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Impact of Optimal Storage Allocation on Price Volatility in Energy-only Electricity Markets

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***Abstract*—Recent studies show that the fast growing expansion of wind power generation may lead to extremely high levels of price volatility in wholesale electricity markets. Storage technologies, regardless of their specific forms, e.g. pump-storage hydro, large-scale or distributed batteries, are capable of alleviating the extreme price volatility levels due to their energy usage time shifting, fast-ramping and price arbitrage capabilities. In this paper, we propose a stochastic bi-level optimization model to find the optimal nodal storage capacities required to achieve a certain price volatility level in a highly volatile energy-only electricity market. The decision on storage capacities is made in the upper level problem and the operation of strategic/regulated generation, storage and transmission players is modeled in the lower level problem using an extended stochastic (Bayesian) Cournot-based game. The South Australia (SA) electricity market, which has recently experienced high levels of price volatility, and a 30-bus IEEE system are considered as the case studies. Our numerical results indicate that 50% price volatility reduction in SA electricity market can be achieved by installing either 430 MWh regulated storage or 530 MWh strategic storage. In other words, regulated storage firms are more efficient in reducing the price volatility than strategic storage firms.**

***Index Terms*—Price volatility, Electricity market, Bi-level optimization model, Storage technologies, Strategic and regulated firms.**

I. Introduction

A. Impotance of price volatility problem and storage allocation

A high level of intermittent wind generation may result in frequent high prices and high levels of price volatility in electricity markets [1]–[3]. High levels of price volatility in a market refers to a situation in which the market price varies in a wide range. For example, one hundred hours with highest levels of electricity prices resulted in 21% of the annual monetary market share in 2015 in South Australia, which is a highly price volatile region in Australia's National Electricity Market (NEM) [4]. Price volatility makes the task of price prediction highly uncertain, which consequently imposes large financial risks on the market participants.

In the long term, extreme levels of price volatility can lead to undesirable consequences such as bankruptcy of retailers [5] and market suspension. In a highly volatile electricity market, the participants, such as generators, utility companies and large industrial consumers, are exposed to a high level of financial risk as well as costly risk management strategies [6]. In some electricity markets, such as the NEM, the market is suspended if the sum of spot prices over a certain period of time is more than cumulative price threshold (CPT). A highly volatile market is subject to frequent CPT breaches due to the low conventional capacity and high level of wind variability. Storage solutions with price arbitrage capabilities can resolve the problem of high electricity prices and consequently prevent high levels of price volatility. We note that recently a large scale storage installation has been announced in South Australia for resolving the price volatility problem.

Using a proper storage allocation framework, the policy makers and market/system operators can compute the required nodal storage capacities for managing the price volatility level in electricity markets. Although the current cost of storage systems is relatively high, the support from governments (in the form of subsidies) and the eventual decline of the technology cost can lead to large scale integration of storage systems in electricity markets.

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B. Related Works

The problem of optimal storage operation or storage allocation for facilitating the integration of intermittent renewable energy generators in electricity networks has been studied in [7]–[14], with total cost minimization objective functions, and in [15]–[20], with profit maximization goals. However, the price volatility management problem using optimal storage allocation has not been investigated in the literature.

The operation of a storage system is optimized, by minimizing the total operation costs in the network, to facilitate the integration of intermittent renewable resources in power systems in [7]. Minimum (operational/installation) cost storage allocation problem for renewable integrated power systems is studied in [8]–[10] under deterministic wind models, and in [11] under a stochastic wind model. The minimum-cost storage allocation problem is studied in a bi-level problem in [12], [13], with the upper and lower levels optimizing the allocation and the operation, respectively. The paper [14] investigates the optimal sizing, siting, and operation strategies for a storage system to be installed in a distribution company controlled area. We note that these works only study the minimum cost storage allocation or operation problems, and do not investigate the interplay between the storage firms and other participants in the market.

The paper [15] studies the optimal operation of a storage unit, with a given capacity, which aims to maximize its profit in the market from energy arbitrage and provision of regulation and frequency response services. The paper [16] computes the optimal supply and demand bids of a storage unit so as to maximize the storage's profit from energy arbitrage in the

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day-ahead and the next 24 hour-ahead markets. The paper [17] investigates the profit maximization problem for a group of independently-operated investor-owned storage units which offer both energy and reserve in both day-ahead and hour-ahead markets. In these works, the storage is modeled as a price taker firm due to its small capacity.

The operation of a price maker storage device is optimized using a bi-level stochastic optimization model, with the lower level clearing the market and the upper level maximizing the storage profit by bidding on price and charge/discharge in [18]. The storage size in addition to its operation is optimized in the upper level problem in [19] when the lower level problem clears the market. Note that the price bids of market participants other than the storage firm are treated exogenously in these models. The paper [20] also maximizes the day-ahead profit of a load serving entity which owns large-scale storage capacity, assuming the price bids in the wholesale market as exogenous parameters.

The paper [21] maximizes a large-scale energy storage system's profit considering the storage as the only strategic player in the market. Using Cournot-based electricity market models, the generation and storage firms are considered as strategic players in [22], [23]. However, they do not study storage sizing problem and the effect of intermittent renewables on the market. Therefore, to the best of our knowledge, the problem of finding optimal storage capacity subject to a price volatility management target in electricity markets has not been addressed before.

C. Contributions

The current paper proposes a stochastic optimization framework for finding the required nodal storage capacities in electricity markets with high levels of wind penetration such that the price volatility in the market is kept below a certain level. The contributions of this paper are summarized as follows:

1) A bi-level optimization model is proposed to find the optimal nodal storage capacities required for avoiding the extreme price volatility levels in a nodal electricity market.
2) In the upper level problem, the total storage capacity is minimized subject to a price volatility target constraint in each node and at each time.
3) In the lower level problem, the non-cooperative interaction between generation, transmission and storage players in the market is modeled as a stochastic (Bayesian) Cournot-based game with an exponential inverse demand function. Note that the equilibrium prices at the lower level problem are functions of the storage capacities. The operation of storage devices at the lower level problem is modeled without introducing binary variables.
4) The existence of Bayesian Nash Equilibrium (Bayes-NE) [24] under the exponential inverse demand function is established for the lower level problem.

Under the proposed framework, the size of storage devices at two nodes of South Australia (SA) and Victoria (VIC) in NEM and also the size of storage in a 30-bus IEEE system is determined such that the market price volatility is kept below a desired level at all times. The desired level of price volatility can be determined based on various criteria such as net revenue earned by the market players, occurrence frequency of undesirable prices, number of CPT breaches, etc [25].

The rest of the paper is organized as follows. The system model and the proposed bi-level optimization problem are formulated in Section II. The equilibrium analysis of the lower level problem and the solution method are presented in Section III. The simulation results are presented in Section IV. The conclusion remarks are discussed in Section V.

II. System Model

Consider a nodal electricity market with I nodes. Let $\mathcal{N}_i^{\text{cg}}$ be the set of classical generators, such as coal and gas power plants, located in node i and $\mathcal{N}_i^{\text{wg}}$ be the set of wind generation firms located in node i. The set of neighboring nodes of node i is denoted by $\mathcal{N}_i$. Since the wind availability is a stochastic parameter, a scenario-based model, with N_{w} different scenarios, is considered to model the wind availability in the electricity network. The nodal prices in our model are determined by solving a stochastic (Bayesian) Cournot-based game among all market participants, that is, classical generators, wind firms, storage firms and transmission interconnectors which are introduced in detail in the lower level problem, given the wind power availability scenarios. The decision variables, feasible region, and objective function for each player in our game model are discussed in Section II-B. In a Cournot game, each producer (generator) competes for maximizing its profit which is defined as its revenue minus its production cost, given the generation of other players. The revenue of each player is its production level times the market price. Also, the market price is a function of total generation. Following the standard Cournot game models, any player in our model maximizes its objective function given the decision variables of other players (generation, transmission, and storage firms). Considering different wind power availability scenarios with given probabilities makes our game model consistent with the Bayesian game definition. In a Bayesian game, players maximize their expected utility over a set of scenarios with a given probability distribution [24].

In this paper, we present a bi-level optimization approach for finding the minimum required total storage capacity in the market such that the market price volatility stays within a desired limit at each time.

A. Upper-level Problem

In the upper-level optimization problem, we determine the nodal storage capacities such that a price volatility constraint is satisfied in each node at each time. In this paper, estimates of variances are used to capture the volatilities [26], i.e., the variance of market price is considered as a measure of price volatility. The variance of the market price in node i at time t, i.e., $\text{Var}\big(P_{itw}\big)$, can be written as:

$$\begin{aligned}\text{Var}\left(P_{itw}\right) &= \mathsf{E}_w\Big[\left(P_{itw}\left(\boldsymbol{q}_{itw}\right)\right)^2\Big] - \left(\mathsf{E}_w\left[P\left(\boldsymbol{q}_{itw}\right)\right]\right)^2 \\ &= \sum_w \Big(P_{itw}\left(\boldsymbol{q}_{itw}\right)\Big)^2 \Psi_w - \Big(\sum_w P_{itw}\left(\boldsymbol{q}_{itw}\right)\Psi_w\Big)^2 \quad (1)\end{aligned}$$

where Ψ_w is the probability of scenario w, and $P_{itw}\left(\boldsymbol{q}_{itw}\right)$ is the market price in node i at time t under the wind availability scenario w, which is a function of the collection of all players' strategies $\boldsymbol{q}_{itw}$, i.e., the decision variables in the lower level game.

The notion of variance quantifies the *effective* variation range of random variables, i.e. a random variable with a small variance has a smaller effective range of variation when compared with a random variable with a large variance.

Given the price volatility relation (1) based on the Bayes-NE strategy collection of all firms $\boldsymbol{q}^{\star}_{itw}$, the upper-level optimization problem is given by:

$$\min_{\{Q^{\mathrm{s}}_i\}_i} \sum_{i=1}^{I} Q^{\mathrm{s}}_i$$

s.t.

$$Q^{\mathrm{s}}_i \geq 0 \quad \forall i \tag{2a}$$

$$\mathrm{Var}\left(P_{itw}\left(\boldsymbol{q}^{\star}_{itw}\right)\right) \leq \sigma_0^2 \quad \forall i, t \tag{2b}$$

where Q^{s}_i is the storage capacity in node i, $P_{itw}\left(\boldsymbol{q}^{\star}_{itw}\right)$ is the market price in node i at time t under the wind availability scenario w, and σ_0^2 is the price volatility target. The price volatility of the market is defined as the maximum variance of market price, *i.e.* $\max_{it} \mathrm{Var}(P_{itw}(\boldsymbol{q}^{\star}_{itw}))$.

B. Lower-level Problem

In the lower-level problem, the nodal market prices and the Bayes-NE strategies of firms are obtained by solving an extended stochastic Cournot-based game between wind generators, storage firms, transmission firms, and classical generators. Our model differs from a standard Cournot game, such that it includes regulated players in addition to strategic players in generation, storage and transmission levels.

Definition 1: A strategic (price maker) firm decides on its strategies over the operation horizon $\{1, ..., N_{\mathrm{T}}\}$ such that its aggregate expected profit, over the operation horizon, is maximized. On the other hand, a regulated (price taker) firm aims to maximize the net market value, i.e. the social welfare [27].

The market price in node i at time t under the wind availability scenario w is given by an exponential inverse demand function (Appendix B):

$$P_{itw}(\boldsymbol{q}_{itw}) = \alpha_{it} e^{-\beta_{it}\left(q^{\mathrm{s}}_{itw} + \sum\limits_{m\in\mathcal{N}^{\mathrm{wg}}_i} q^{\mathrm{wg}}_{mitw} + \sum\limits_{n\in\mathcal{N}^{\mathrm{cg}}_i} q^{\mathrm{cg}}_{nitw} + \sum\limits_{j\in\mathcal{N}_i} q^{\mathrm{tr}}_{ijtw}\right)} \tag{3}$$

where α_{it}, β_{it} are positive real values in the inverse demand function, q^{cg}_{nitw} is the generation strategy of the nth classical generator located in node i at time t under scenario w, q^{wg}_{mitw} is the generation strategy of the mth wind generator located in node i at time t under scenario w, q^{s}_{itw} is the charge/discharge strategy of the storage firm in node i at time t under scenario w, q^{tr}_{ijtw} is the strategy of transmission firm located between node i and node j at time t under scenario w. The collection of strategies of all firms located in node i at time t under the scenario w is denoted by $\boldsymbol{q}_{itw}$. Note that the total amount of power supply from the generation and storage firms plus the net import/export, i.e., $q^{\mathrm{s}}_{itw} + \sum_{m\in\mathcal{N}^{\mathrm{wg}}_i} q^{\mathrm{wg}}_{mitw} + \sum_{n\in\mathcal{N}^{\mathrm{cg}}_i} q^{\mathrm{cg}}_{nitw} + \sum_{j\in\mathcal{N}_i} q^{\mathrm{tr}}_{ijtw}$, is equal to the net electricity demand in each node, at each time and under each scenario, which represents the nodal electricity balance in our model.

In what follows, the variable μ is used to indicate the associated Lagrange variable with its corresponding constraint in the model.

1) Wind Generators: The Bayes-NE strategy of the mth wind generator in node i is obtained by solving the following optimization problem:

$$\max_{\left\{q^{\mathrm{wg}}_{mitw}\right\}_{tw} \succeq 0} \sum_{w} \Psi_w \sum_{t=1}^{N_{\mathrm{T}}} P_{itw}\left(\boldsymbol{q}_{itw}\right) q^{\mathrm{wg}}_{mitw}\left(1-\gamma^{\mathrm{wg}}_{mi}\right) + \gamma^{\mathrm{wg}}_{mi}\left(\frac{P_{itw}\left(\boldsymbol{q}_{itw}\right)}{-\beta_{it}}\right)$$

s.t.

$$q^{\mathrm{wg}}_{mitw} \leq Q^{\mathrm{wg}}_{mitw} \quad : \quad \mu^{\mathrm{wg,max}}_{mitw} \quad \forall t, w \tag{4a}$$

$$P_{itw}\left(\boldsymbol{q}_{itw}\right) \leq P^{\mathrm{cap}} \quad : \quad \mu^{\mathrm{wg,cap}}_{mitw} \quad \forall t, w \tag{4b}$$

where q^{wg}_{mitw} and Q^{wg}_{mitw} are the generation level and the available wind capacity of the mth wind generator located in node i at time t under scenario w. The parameter P^{cap} represents the price cap in the market, which is, for instance, 11000 \$/MWh in the NEM market. Setting cap price in electricity markets also aims to limit the price levels and price volatility levels. Note that the wind availability changes in time in a stochastic manner, and the wind firm's bids depend on the wind availability. As a result, the nodal prices and decisions of the other firms become stochastic in our model [28].

The mth wind firm in node i acts as a strategic firm in the market if $\gamma^{\mathrm{wg}}_{mi}$ is equal to zero and acts as a regulated firm if $\gamma^{\mathrm{wg}}_{mi}$ is equal to one. The difference between regulated and strategic players corresponds to the strategic price impacting capability. In fact, a regulated firm behaves as a price taker player while a strategic firm behaves as a price maker player.

2) Storage Firms: Storage firms benefit from price difference at different times to make profit, i.e. they sell the off-peak stored electricity at higher prices at peak times. The Bayes-NE strategy of storage firm located in node i is determined by solving the following optimization problem:

$$\max_{\substack{\left\{q^{\mathrm{dis}}_{itw}, q^{\mathrm{ch}}_{itw}\right\}_{tw} \succeq 0 \\ ,\left\{q^{\mathrm{s}}_{itw}\right\}_{tw}}} \sum_{w} \Psi_w \sum_{t=1}^{N_{\mathrm{T}}} P_{itw}\left(\boldsymbol{q}_{itw}\right) q^{\mathrm{s}}_{itw}\left(1-\gamma^{\mathrm{s}}_i\right) - c^{\mathrm{s}}_i\left(q^{\mathrm{dis}}_{itw} + q^{\mathrm{ch}}_{itw}\right) + \gamma^{\mathrm{s}}_i\left(\frac{P_{itw}\left(\boldsymbol{q}_{itw}\right)}{-\beta_{it}}\right)$$

s.t.

$$q^{\mathrm{s}}_{itw} = \eta^{\mathrm{dis}}_i q^{\mathrm{dis}}_{itw} - \frac{q^{\mathrm{ch}}_{itw}}{\eta^{\mathrm{ch}}_i} \quad : \quad \mu^{\mathrm{s}}_{itw} \quad \forall t, w \tag{5a}$$

$$q^{\mathrm{dis}}_{itw} \leq \zeta^{\mathrm{dis}}_i Q^{\mathrm{s}}_i \quad : \quad \mu^{\mathrm{dis,max}}_{itw} \quad \forall t, w \tag{5b}$$

$$q^{\mathrm{ch}}_{itw} \leq \zeta^{\mathrm{ch}}_i Q^{\mathrm{s}}_i \quad : \quad \mu^{\mathrm{ch,max}}_{itw} \quad \forall t, w \tag{5c}$$

$$0 \leq \sum_{k=1}^{t}\left(q^{\mathrm{ch}}_{ikw} - q^{\mathrm{dis}}_{ikw}\right)\Delta \leq Q^{\mathrm{s}}_i : \mu^{\mathrm{s,min}}_{itw}, \mu^{\mathrm{s,max}}_{itw} \quad \forall t, w \tag{5d}$$

$$P_{itw}\left(\boldsymbol{q}_{itw}\right) \leq P^{\mathrm{cap}} \quad : \quad \mu^{\mathrm{s,cap}}_{itw} \quad \forall t, w \tag{5e}$$

where q^{dis}_{itw} and q^{ch}_{itw} are the discharge and charge levels of the storage firm in node i at time t under scenario w, respectively, c^{s}_i is the unit operation cost, η^{ch}_i ,η^{dis}_i are the charging and discharging efficiencies, respectively, and q^{s}_{itw} is the net supply/demand of the storage firm in node i. The parameter ζ^{ch}_i (ζ^{dis}_i) is the percentage of storage capacity Q^{s}_i, which can be charged (discharged) during time period

Δ. It is assumed that the storage devices are initially fully discharged. The energy level of the storage device in node i at each time is limited by its capacity Q_i^{s}. Note that the nodal market prices depend on the storage capacities, *i.e.* Q_i^{s}s, through the constraints (5b)-(5d). This dependency allows the market operator to meet the volatility constraint using the optimal values of the storage capacities. The storage capacity variables are the only variables that couple the scenarios in the lower level problem. Therefore, each scenario of the lower lever problem can be solved separately for any storage capacity amount. The storage firm in node i acts as a strategic firm in the market if γ_i^{s} is equal to zero and acts as a regulated firm if γ_i^{s} is equal to one.

Proposition 1: At the Bayes-NE of the lower level game, each storage firm is either in the charge mode or discharge mode at each scenario, i.e. the charge and discharge levels of each storage firm cannot be simultaneously positive at the NE of each scenario.

Proof: See Appendix A.

3) Classical Generators: Classical generators include coal, gas, hydro and nuclear power plants. The Bayes-NE strategy of nth classical generator located in node i is determined by solving the following optimization problem:

$$\max_{\{q_{nitw}^{\mathrm{cg}}\}_{tw}\succeq 0} \sum_w \Psi_w \sum_{t=1}^{N_{\mathrm{T}}} P_{itw}\left(\boldsymbol{q}_{itw}\right) q_{nitw}^{\mathrm{cg}}\left(1-\gamma_{ni}^{\mathrm{cg}}\right) - c_{ni}^{\mathrm{cg}} q_{nitw}^{\mathrm{cg}} + \gamma_{ni}^{\mathrm{cg}}\left(\frac{P_{itw}\left(\boldsymbol{q}_{itw}\right)}{-\beta_{it}}\right)$$

s.t.

$$q_{nitw}^{\mathrm{cg}} \leq Q_{ni}^{\mathrm{cg}} \quad : \quad \mu_{nitw}^{\mathrm{cg,max}} \quad \forall t, w \tag{6a}$$

$$q_{nitw}^{\mathrm{cg}} - q_{ni(t-1)w}^{\mathrm{cg}} \leq R_{ni}^{\mathrm{up}} \quad : \quad \mu_{nitw}^{\mathrm{cg,up}} \quad \forall t, w \tag{6b}$$

$$q_{ni(t-1)w}^{\mathrm{cg}} - q_{nitw}^{\mathrm{cg}} \leq R_{ni}^{\mathrm{dn}} \quad : \quad \mu_{nitw}^{\mathrm{cg,dn}} \quad \forall t, w \tag{6c}$$

$$P_{itw}\left(\boldsymbol{q}_{itw}\right) \leq P^{\mathrm{cap}} \quad : \quad \mu_{nitw}^{\mathrm{cg,cap}} \quad \forall t, w \tag{6d}$$

where q_{nitw}^{cg} is the generation level of the nth classical generator in node i at time t under scenario w, Q_{ni}^{cg} and c_{ni}^{cg} are the capacity and the short term marginal cost of the nth classical generator in node i, respectively. The constraints (6b) and (6c) ensure that the ramping limitations of the nth classical generator in node i are always met. The nth classical generator in node i acts as a strategic firm in the market if $\gamma_{ni}^{\mathrm{cg}}$ is equal to zero and acts as a regulated firm if $\gamma_{ni}^{\mathrm{cg}}$ is equal to one.

4) Transmission Firms: The Bayes-NE strategy of the transmission firm between nodes i and j is determined by solving the following optimization problem:

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

s.t.

$$q_{ijtw}^{\mathrm{tr}} = -q_{jitw}^{\mathrm{tr}} \quad : \quad \mu_{ijtw}^{\mathrm{tr}} \quad \forall t, w \tag{7a}$$

$$-Q_{ij}^{\mathrm{tr}} \leq q_{ijtw}^{\mathrm{tr}} \leq Q_{ij}^{\mathrm{tr}} \quad : \quad \mu_{ijtw}^{\mathrm{tr,min}}, \mu_{ijtw}^{\mathrm{tr,max}} \quad \forall t, w \tag{7b}$$

$$P_{ktw}\left(\boldsymbol{q}_{ktw}\right) \leq P^{\mathrm{cap}} : \mu_{kk'tw}^{\mathrm{tr,cap}} \quad k, k' \in \{i, j\}, k \neq k' \quad \forall t, w \tag{7c}$$

where q_{ijtw}^{tr} is the electricity flow from nodes j to i at time t under scenario w, and Q_{ij}^{tr} is the capacity of the transmission line between node i and node j. The transmission firm between nodes i and j behaves as a strategic player when $\gamma_{ij}^{\mathrm{tr}}$ is equal to zero and behaves as a regulated player when $\gamma_{ij}^{\mathrm{tr}}$ is equal to one. Note that the term $P_{jtw}\left(\boldsymbol{q}_{jtw}\right) q_{jitw}^{\mathrm{tr}} + P_{itw}\left(\boldsymbol{q}_{itw}\right) q_{ijtw}^{\mathrm{tr}}$ in the objective function of the transmission firm is equal to $\left(P_{jtw}\left(\boldsymbol{q}_{jtw}\right) - P_{itw}\left(\boldsymbol{q}_{itw}\right)\right) q_{jitw}^{\mathrm{tr}}$ which implies that the transmission firm between two nodes makes profit by transmitting electricity from the node with lower market price to the node with higher market price. Moreover, the price difference between the paired nodes indicates the congestion on the transmission lines and can be used to set the value of Financial Transmission Rights (FTR) [29] in electricity markets.

Transmission lines or interconnectors are usually controlled by the market operator and are regulated to maximize the social welfare in the market. The markets with regulated transmission firms are discussed as electricity markets with transmission constraints in the literature, e.g., see [30]–[32]. However, some electricity markets allow the transmission lines to act strategically, i.e. to make revenue by trading electricity across the nodes [33].

III. Solution Approach

In this section, we first provide a game-theoretic analysis of the lower-level problem. Next, the bi-level price volatility management problem is transformed to a single optimization Mathematical Problem with Equilibrium Constraints (MPEC).

A. Game-theoretic Analysis of the Lower-level Problem

To solve the lower-level problem, we need to study the best response functions of firms participating in the market. Then, any intersection of the best response functions of all firms in all scenarios will be a Bayes-NE. In this subsection, we first establish the existence of Bayes-NE for the lower-level problem. Then, we provide the necessary and sufficient conditions which can be used to solve the lower-level problem.

To transform the bi-level price volatility management problem to a single level problem, we need to ensure that for every vector of storage capacities, *i.e.* $\boldsymbol{Q}^{\mathrm{s}} = [Q_1^{\mathrm{s}}, \cdots, Q_I^{\mathrm{s}}]^\top \geq \mathbf{0}$, the lower-level problem admits a Bayes-NE. At the Bayes-NE strategy of the lower-level problem, no single firm has any incentive to unilaterally deviate its strategy from its Bayes-NE strategy. Note that the objective function of each firm is quasi-concave in its strategy and constraint set of each firm is closed and bounded for all $\boldsymbol{Q}^{\mathrm{s}} = [Q_1^{\mathrm{s}}, \cdots, Q_I^{\mathrm{s}}]^\top \geq \mathbf{0}$. Thus, the lower level game admits a Bayes-NE. This result is formally stated in Proposition 2.

Proposition 2: For any vector of storage capacities, $\boldsymbol{Q}^{\mathrm{s}} = [Q_1^{\mathrm{s}}, \cdots, Q_I^{\mathrm{s}}]^\top \geq \mathbf{0}$, the lower level game admits a Bayes-NE.

Proof: Note that the objective function of each firm is continuous and quasi-concave in its strategy. Also, the strategy space is non-empty, compact and convex. Therefore, according to Theorem 1.2 in [34], the lower level game admits a Bayes-NE. ■

1) Best responses of wind firm mi: Let $\boldsymbol{q}_{-(mi)}$ be the strategies of all firms in the market except the wind generator m located in node i. Then, the best response of the wind generator m in node i to $\boldsymbol{q}_{-(mi)}$ satisfies the necessary and sufficient

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Karush-Kuhn-Tucker (KKT) conditions ($t \in \{1, ..., N_{\mathrm{T}}\}; w \in \{1, ..., N_{\mathrm{w}}\}$):

$$P_{itw}(\boldsymbol{q}_{itw}) + (1-\gamma_{mi}^{\mathrm{wg}})\frac{\partial P_{itw}(\boldsymbol{q}_{itw})}{\partial q_{mitw}^{\mathrm{wg}}} q_{mitw}^{\mathrm{wg}} - \frac{\mu_{mitw}^{\mathrm{wg,max}}}{\Psi_w} - \frac{\frac{\partial P_{itw}(\boldsymbol{q}_{itw})}{\partial q_{mitw}^{\mathrm{wg}}}\mu_{mitw}^{\mathrm{wg,cap}}}{\Psi_w} \leq 0 \perp q_{mitw}^{\mathrm{wg}} \geq 0 \tag{8a}$$

$$q_{mitw}^{\mathrm{wg}} \leq Q_{mitw}^{\mathrm{wg}} \perp \mu_{mitw}^{\mathrm{wg,max}} \geq 0 \tag{8b}$$

$$P_{itw}(\boldsymbol{q}_{itw}) \leq P^{\mathrm{cap}} \perp \mu_{itw}^{\mathrm{wg,cap}} \geq 0 \tag{8c}$$

where the perpendicularity sign, $\perp$, means that at least one of the adjacent inequalities must be satisfied as an equality [35].

2) Best responses of storage firm i: To study the best response of the storage firm in node i, let $\boldsymbol{q}_{-i}$ denote the collection of strategies of all firms except the storage firm in node i. Then, the best response of the storage firm in node i is obtained by solving the following KKT conditions ($t \in \{1, ..., N_{\mathrm{T}}\}; w \in \{1, ..., N_{\mathrm{w}}\}$):

$$P_{itw}(\boldsymbol{q}_{itw}) + (1-\gamma_i^{\mathrm{s}})\frac{\partial P_{itw}(\boldsymbol{q}_{itw})}{\partial q_{itw}^{\mathrm{s}}} q_{itw}^{\mathrm{s}} + \frac{\mu_{itw}^{\mathrm{s}} - \frac{\partial P_{itw}(\boldsymbol{q}_{itw})}{\partial q_{itw}^{\mathrm{s}}}\mu_{itw}^{\mathrm{s,cap}}}{\Psi_w} = 0 \tag{9a}$$

$$\frac{-\eta_i^{\mathrm{dis}}\mu_{itw}^{\mathrm{s}} - \mu_{itw}^{\mathrm{dis,max}} - \Delta\sum_{k=t}^{N_{\mathrm{T}}}\left(\mu_{ikw}^{\mathrm{s,min}} - \mu_{ikw}^{\mathrm{s,max}}\right)}{\Psi_w} - c_i^{\mathrm{s}} \leq 0 \perp q_{itw}^{\mathrm{dis}} \geq 0 \tag{9b}$$

$$\frac{\frac{\mu_{itw}^{\mathrm{s}}}{\eta_i^{\mathrm{ch}}} - \mu_{itw}^{\mathrm{ch,max}} + \Delta\sum_{k=t}^{N_{\mathrm{T}}}\left(\mu_{ikw}^{\mathrm{s,min}} - \mu_{ikw}^{\mathrm{s,max}}\right)}{\Psi_w} - c_i^{\mathrm{s}} \leq 0 \perp q_{itw}^{\mathrm{ch}} \geq 0 \tag{9c}$$

$$q_{itw}^{\mathrm{s}} = \eta_i^{\mathrm{dis}} q_{itw}^{\mathrm{dis}} - \frac{q_{itw}^{\mathrm{ch}}}{\eta_i^{\mathrm{ch}}} \tag{9d}$$

$$q_{itw}^{\mathrm{dis}} \leq \zeta_i^{\mathrm{dis}} Q_i^{\mathrm{s}} \perp \mu_{itw}^{\mathrm{dis,max}} \geq 0 \tag{9e}$$

$$q_{itw}^{\mathrm{ch}} \leq \zeta_i^{\mathrm{ch}} Q_i^{\mathrm{s}} \perp \mu_{itw}^{\mathrm{ch,max}} \geq 0 \tag{9f}$$

$$0 \leq \sum_{k=1}^{t}\left(q_{ikw}^{\mathrm{ch}} - q_{ikw}^{\mathrm{dis}}\right)\Delta \perp \mu_{itw}^{\mathrm{s,min}} \geq 0 \tag{9g}$$

$$\sum_{k=1}^{t}\left(q_{ikw}^{\mathrm{ch}} - q_{ikw}^{\mathrm{dis}}\right)\Delta \leq Q_i^{\mathrm{s}} \perp \mu_{itw}^{\mathrm{s,max}} \geq 0 \tag{9h}$$

$$P_{itw}(\boldsymbol{q}_{itw}) \leq P^{\mathrm{cap}} \perp \mu_{itw}^{\mathrm{s,cap}} \geq 0 \tag{9i}$$

3) Best responses of classical generation firm ni: The best response of the classical generator n in node i to $\boldsymbol{q}_{-(ni)}$, i.e. the collection of strategies of all firms except the classical generator n in node i, is obtained by solving the following KKT conditions ($t \in \{1, ..., N_{\mathrm{T}}\}; w \in \{1, ..., N_{\mathrm{w}}\}$):

$$P_{itw}(\boldsymbol{q}_{itw}) - c_{ni}^{\mathrm{cg}} + (1-\gamma_{ni}^{\mathrm{cg}})\frac{\partial P_{itw}(\boldsymbol{q}_{itw})}{\partial q_{nitw}^{\mathrm{cg}}} q_{nitw}^{\mathrm{cg}} - \frac{\mu_{nitw}^{\mathrm{cg,max}}}{\Psi_w} - \frac{\frac{\partial P_{itw}(\boldsymbol{q}_{itw})}{\partial q_{nitw}^{\mathrm{cg}}}\mu_{nitw}^{\mathrm{cg,cap}}}{\Psi_w} + \frac{\mu_{ni(t+1)w}^{\mathrm{cg,up}} - \mu_{nitw}^{\mathrm{cg,up}} + \mu_{nitw}^{\mathrm{cg,dn}} - \mu_{ni(t+1)w}^{\mathrm{cg,dn}}}{\Psi_w} \leq 0 \perp q_{nitw}^{\mathrm{cg}} \geq 0 \tag{10a}$$

$$q_{nitw}^{\mathrm{cg}} \leq Q_{ni}^{\mathrm{cg}} \perp \mu_{nitw}^{\mathrm{cg,max}} \tag{10b}$$

$$q_{nitw}^{\mathrm{cg}} - q_{ni(t-1)w}^{\mathrm{cg}} \leq R_{ni}^{\mathrm{up}} \perp \mu_{nitw}^{\mathrm{cg,up}} \geq 0 \tag{10c}$$

$$q_{ni(t-1)w}^{\mathrm{cg}} - q_{nitw}^{\mathrm{cg}} \leq R_{ni}^{\mathrm{dn}} \perp \mu_{nitw}^{\mathrm{cg,dn}} \geq 0 \tag{10d}$$

$$P_{itw}(\boldsymbol{q}_{itw}) \leq P^{\mathrm{cap}} \perp \mu_{nitw}^{\mathrm{cg,cap}} \geq 0 \tag{10e}$$

4) Best responses of transmission firm ij: Finally, the best response of the transmission firm between nodes i and j, to $\boldsymbol{q}_{-(ij)}$, i.e. the set of all firms' strategies except those of the transmission line between nodes i and j, can be obtained using the KKT conditions ($t \in \{1, ..., N_{\mathrm{T}}\}; w \in \{1, ..., N_{\mathrm{w}}\}$):

$$P_{itw}(\boldsymbol{q}_{itw}) + \left(1-\gamma_{ij}^{\mathrm{tr}}\right)\frac{\partial P_{itw}(\boldsymbol{q}_{itw})}{\partial q_{ijtw}^{\mathrm{tr}}} q_{ijtw}^{\mathrm{tr}} + \frac{\mu_{jitw}^{\mathrm{tr}} + \mu_{ijtw}^{\mathrm{tr}}}{\Psi_w} + \frac{\mu_{ijtw}^{\mathrm{tr,min}} - \mu_{ijtw}^{\mathrm{tr,max}} - \frac{\partial P_{itw}(\boldsymbol{q}_{itw})}{\partial q_{ijtw}^{\mathrm{tr}}}\mu_{ijtw}^{\mathrm{tr,cap}}}{\Psi_w} = 0 \tag{11a}$$

$$q_{ijtw}^{\mathrm{tr}} = -q_{jitw}^{\mathrm{tr}} \tag{11b}$$

$$-Q_{ij}^{\mathrm{tr}} \leq q_{ijtw}^{\mathrm{tr}} \perp \mu_{ijtw}^{\mathrm{tr,min}} \geq 0 \tag{11c}$$

$$q_{ijtw}^{\mathrm{tr}} \leq Q_{ij}^{\mathrm{tr}} \perp \mu_{ijtw}^{\mathrm{tr,max}} \geq 0 \tag{11d}$$

$$P_{itw}(\boldsymbol{q}_{itw}) \leq P^{\mathrm{cap}} \perp \mu_{ijtw}^{\mathrm{tr,cap}} \geq 0 \tag{11e}$$

B. The Equivalent Single-level Problem

Here, the bi-level price volatility management problem is transformed into a single-level MPEC. To this end, note that for every vector of storage capacities the market price can be obtained by solving the firms' KKT conditions. Thus, by imposing the KKT conditions of all firms as constraints in the optimization problem (2), the price volatility management problem can be written as the following single-level optimization problem:

$$\min \sum_{i=1}^{I} Q_i^{\mathrm{s}} \tag{12}$$

$$\text{s.t.}$$
$$(2a-2b), (8a-8c), (9a-9i), (10a-10e), (11a-11e)$$
$$m \in \{1, ..., N_i^{\mathrm{wg}}\}, n \in \{1, ..., N_i^{\mathrm{cg}}\}, i, j \in \{1, ..., I\},$$
$$t \in \{1, ..., N_{\mathrm{T}}\}; w \in \{1, ..., N_{\mathrm{w}}\}$$

where the optimization variables are the storage capacities, the bidding strategies of all firms and the set of all Lagrange multipliers. Because of the nonlinear complementary constraints, the feasible region is not necessarily convex or even connected. Therefore, increasing the storage capacities stepwise, ΔQ^{s}, we solve the lower level problem, which is convex.

Remark 1: It is possible to convert the equivalent single level problem (12) to a Mixed-Integer Non-Linear Problem (MINLP). However, the large number of integer variables potentially makes the resulting MINLP computationally infeasible.

The MPEC problem (12) can be solved using extensive search when the number of nodes is small. For large electricity networks, the greedy algorithm proposed in [36] can be used to find the storage capacities iteratively while the other variables are calculated as the solution of the lower level problem. In each iteration, the lower level problem is solved as a Mixed Complementarity Problem (MCP) [37], which is sometimes termed as rectangular variational inequalities. The optimization solution method is illustrated in Algorithm 1. The storage capacity variable is discretized and the increment storage capacity of ΔQ^{s} is added to the selected node i^* at each iteration of the algorithm. Once the price volatility constraint is satisfied with equality, the optimum solution is found.

Although our greedy algorithm just guarantees a locally optimal storage capacity, we obtained the same results in NEM market using the extensive search.

Algorithm 1 The greedy algorithm for finding the storage allocation

while $\max_{it} \mathrm{Var}(P_{itw}(\boldsymbol{q}^\star_{itw})) > \sigma_0^2$ **do**
  iteration=iteration+1
  for $i' = 1 : I$ **do**
    $Q^{\mathrm{s}}_{i'}(\text{iteration}) \leftarrow \mathrm{Q}^{\mathrm{s}}_{\mathrm{i}'}(\text{iteration}-1) + \Delta\mathrm{Q}^{\mathrm{s}}$
    $Q^{\mathrm{s}}_{-i'}(\text{iteration}) \leftarrow \mathrm{Q}^{\mathrm{s}}_{-\mathrm{i}'}(\text{iteration}-1)$
    $\boldsymbol{q}^\star \leftarrow$ Lower level problem Bayes–NE
    Price Volatility$(i') \leftarrow \max_{it} \mathrm{Var}(P_{itw}(\boldsymbol{q}^\star_{itw}))$
  end for
  $i^* \leftarrow \underset{i}{\mathrm{find}}(\min(\text{Price Volatility(i)}))$
  $Q^{\mathrm{s}}_{i^*}(\text{iteration}) \leftarrow \mathrm{Q}^{\mathrm{s}}_{\mathrm{i}^*}(\text{iteration}-1) + \Delta\mathrm{Q}^{\mathrm{s}}$
end while

IV. Case Study and Simulation Results

In this section, we apply our price volatility management framework to two different types of electricity markets: (i) the NEM market, which has a regional pricing mechanism, (ii) a 30-bus electricity system with a Locational Marginal Pricing (LMP) mechanism [38]. The most important difference between LMP and regional pricing markets is the number of settlement prices. Tens or hundreds of pricing nodes may be required to implement a LMP market whereas in a regional pricing only few settlement prices are considered. Note that the optimization problem (12) can model both regional and LMP markets.

A. Simulations in NEM

In this subsection, we study the impact of storage installation on price volatility in two nodes of Australia's National Electricity Market (NEM), South Australia (SA) and Victoria (VIC), with regional pricing mechanism, which sets the marginal value of demand at each region as the regional prices. SA has a high level of wind penetration and VIC has high coal-fueled classical generation. Real data for price and demand from the year 2015 is used to calibrate the inverse demand function in the model. Different types of generation firms, such as coal, gas, hydro, wind and biomass, with generation capacity (intermittent and dispatchable) of 3.7 GW and 11.3 GW were active in SA and VIC, respectively, in 2015. The transmission line interconnecting SA and VIC, which is a regulated line, has the capacity of 680 MW but currently is working with just 70% of its capacity. The generation capacities in our numerical results are gathered from Australian Electricity Market Operator's (AEMO's) website (aemo.com.au) and all the prices are shown in Australian dollar.

In our study, we consider a set of scenarios each representing a 24-hour wind power availability profile. In order to guarantee a high level of accuracy, we do not employ scenario reduction methods [39] and instead consider 365 daily wind power availability scenarios, with equal probabilities, using the realistic data from the year 2015 in different regions of NEM (source of data: AEMO). Fig. 1 shows the hourly wind power availability in SA. On each box in Fig. 1, the central mark indicates the average level and the bottom and top edges of the box indicate the 25th and 75th percentiles of wind power availability from the 365 scenarios, respectively. It can be seen that in SA the wind power capacity is about 1200 MW and the wind capacity factor is about 33-42% at different hours.

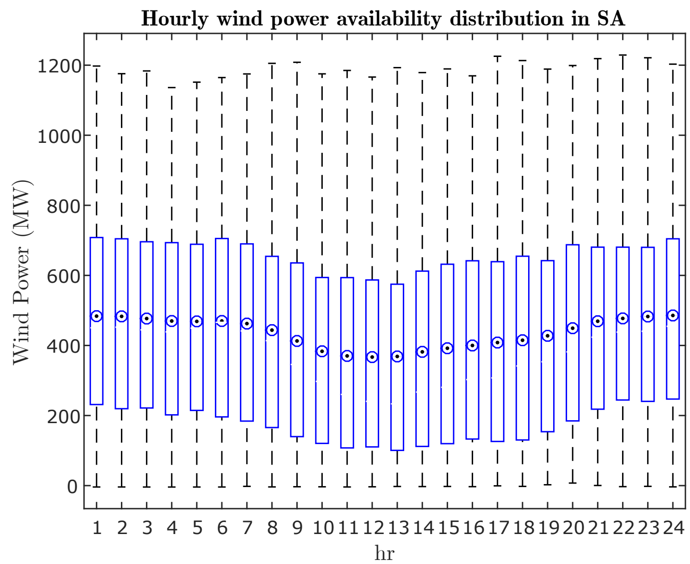

Fig. 1: SA's Hourly wind power availability distribution in 2015 (the central marks show the average levels and the bottom and top edges of the boxes indicate the 25th and 75th percentiles).

In what follows, by price volatility we mean the maximum variance of market price, i.e. $\max_{it} \mathrm{Var}(P_{itw}(\boldsymbol{q}^\star_{itw}))$. Also, by square root of price volatility we mean the maximum standard deviation of market price, i.e. $\max_{it} \sqrt{\mathrm{Var}(P_{itw}(\boldsymbol{q}^\star_{itw}))}$.

1) One-region model simulations in South Australia: In our one-region model simulations, we first study the impacts of peak demand levels and supply capacity shortage on the standard deviation of hourly electricity prices (or square root of hourly price volatilities) in SA with no storage. Next, we study the effect of storage on the price volatility in SA. Fig. 2 shows the average and standard deviation of hourly prices for a day in SA (with no storage) for three different cases: (i) a regular demand day, (ii) a high demand day, (iii) a high demand day with coal-plant outage. An additional load of 1000 MW is considered in the high demand case during hours 16, 17 and 18 to study the joint effect of wind intermittency and large demand variations on the price volatility. The additional loads are sometimes demanded in the market due to unexpected high temperatures happening in the region. The coal-plant outage case is motivated by the recent retirement of two coal-plants in SA with total capacity of 770 MW [40]. This allows us to investigate the joint impact of wind indeterminacy and low base-load generation capacity on the price volatility.

According to Fig. 2, wind power fluctuation does not create much price fluctuation in a regular demand day. The square root of the price volatility in the regular demand day is equal to 65 \$/MWh. Depending on the wind power availability level, the peak price varies from 92 \$/MWh to 323 \$/MWh, with average of 210 \$/MWh, in a regular demand day. Based on Fig. 2, the square root of the price volatility in the high demand day is equal to 1167 \$/MWh. The maximum price in a high demand day in SA changes from 237 \$/MWh to 4466 \$/MWh, with average of 1555 \$/MWh, because of wind power availability fluctuation. The extra load at peak times and the wind power fluctuation create a higher level of price volatility during a high demand day compared with a regular demand day.

The retirement (outage) of coal-plants in SA beside the extra load at peak hours increases the price volatility due to the wind power fluctuation. The maximum price during the high demand day with coal-plant outage varies from 377 \$/MWh to the cap price of 11000 \$/MWh, with average of 5832 \$/MWh. The square root of the price volatility during the high demand day with coal-plant outage is equal to 4365 \$/MWh. The square root of the price volatility during the high demand day with coal-plant outage is almost 67 times more than the regular demand day due to the simultaneous variation in both supply and demand.

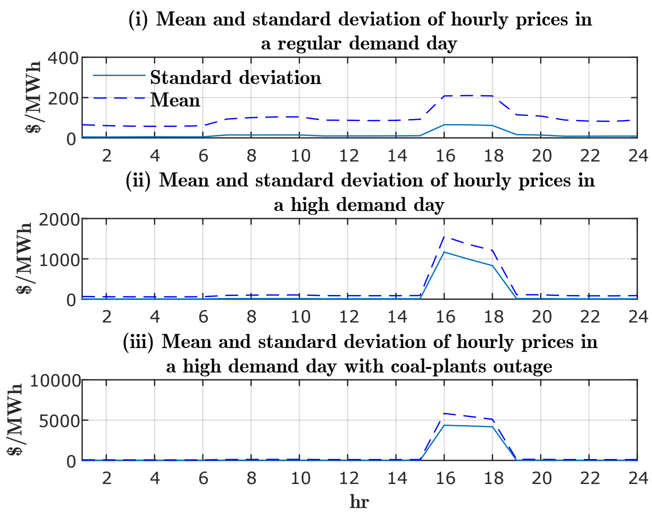

Fig. 2: Standard deviation and mean of hourly wholesale electricity prices in SA with no storage.

Fig. 3 shows the minimum required (strategic/regulated) storage capacities for achieving various levels of price volatility in SA during a high demand day with coal-plant outage. The minimum storage capacities are calculated by solving the optimization problem (12) for the high demand day with coal-plant outage case. According to Fig. 3, a strategic storage firm requires a substantially larger capacity, compared with a regulated storage firm, to achieve a target price volatility level due to the selfish behavior of the storage firms. In fact, the strategic storage firms may sometimes withhold their available capacities and do not participate in the price volatility reduction as they do not always benefit from reducing the price. The price volatility in SA can be reduced by 50% using either 530 MWh strategic storage or 430 MWh regulated storage. Note that AEMO has forecasted about 500 MWh battery storage to be installed in SA until 2035 [41].

According to our numerical results, storage can displace the peaking generators, with high fuel costs and market power, which results in reducing the price level and the price volatility. A storage capacity of 500 MWh (or 500 MW given the discharge coefficient $\eta^{\text{dis}} = 1$) reduces the square root of the price volatility from 4365 \$/MWh to 2692 \$/MWh, almost 38%

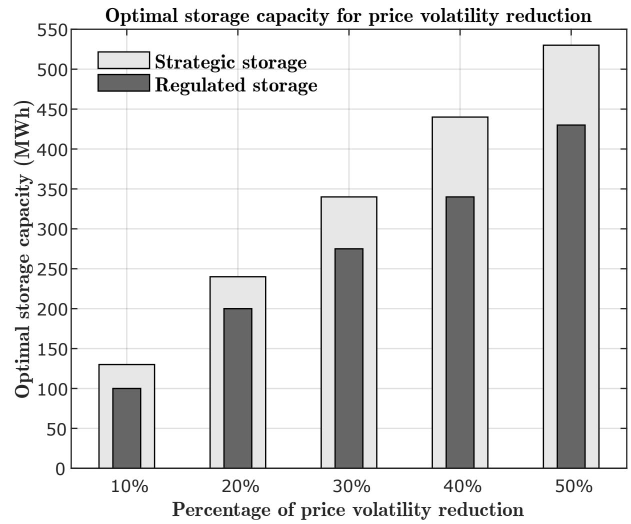

Fig. 3: Optimal strategic and regulated storage capacity for achieving different price volatility levels in SA region for a high demand day with coal-plant outage.

reduction, during a high demand day with coal-plant outage in SA.

The behaviour of the peak and the daily average prices for the high demand day with coal-plant outage in SA is illustrated in Fig. 4. In this figure, the peak price represents the average of highest prices over all scenarios during the day, i.e. $\sum_w \Psi_w \left(\max_t P_{tw}(\boldsymbol{q}^\star_{tw})\right)$ and the daily average price indicates the average of price over time and scenarios, i.e. $\frac{1}{N_T}\sum_{tw} P_{tw}(q^\star_{tw})\Psi_w$. Sensitivity analysis of the peak and the daily average prices in SA with respect to storage capacity indicates that high storage capacities lead to relatively low prices in the market. At very high prices, demand is almost inelastic and a small amount of excess supply leads to a large amount of price reduction. According to Fig. 4, the rate of peak price reduction decreases as the storage capacity increases since large storage capacities lead to lower peak prices which make the demand more elastic.

Based on Fig. 4, the impact of storage on the daily average and peak prices depends on whether the storage firm is strategic or regulated. It can be observed that the impacts of strategic and regulated storage firms on the daily peak/average prices are almost similar for small storage capacities, i.e. when the storage capacity is smaller than 100 MWh (or 100 MW given $\eta^{\text{dis}} = 1$). However, a regulated firm reduces both the peak and the average prices more efficiently compared with a strategic storage firm as its capacity becomes large. A large strategic storage firm in SA does not use its excess capacity beyond 500 MWh to reduce the market price since it acts as a strategic profit maximizer, but a regulated storage firm contributes to the price volatility reduction as long as there is potential for price reduction by its operation.

Fig. 5 depicts the square root of price volatility versus storage capacity in SA during the high demand day with coal-plant outage. According to this figure, the price volatility in the market decreases by installing either regulated or strategic storage devices. To reduce the square root of price volatility to 3350 \$/MWh, the required strategic capacity is about 100 MWh more than that of a regulated storage. Moreover, a strategic storage firm stops reducing the price volatility when

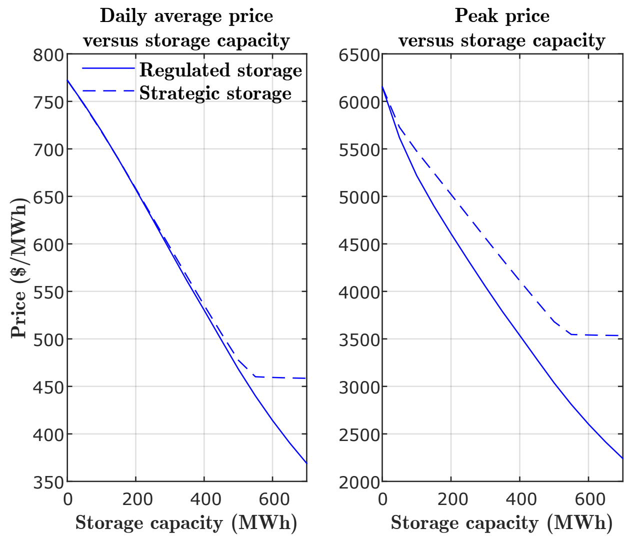

Fig. 4: Daily peak and average prices in SA versus storage capacity in a high demand day with coal-plant outage.

its capacity exceeds a threshold value. In our study, a strategic storage firm does not reduce the square root of price volatility more than 32%, but a regulated firm reduces it by 89%. These observations confirm that regulated storage firms are more efficient than strategic firms in reducing the price volatility.

The impact of the regulated storage firm in reducing the price volatility can be divided into three ranges of initial, efficient, and saturated, as shown in Fig. 5. In the initial range, an increment in the capacity of the regulated firm slightly reduces the price volatility. Then the price volatility reduces sharply with storage capacity in the second region. Finally, the price volatility reduction gradually stops in the saturated region. This observation implies that although storage alleviates the price volatility in the market, it is not capable to eliminate it completely.

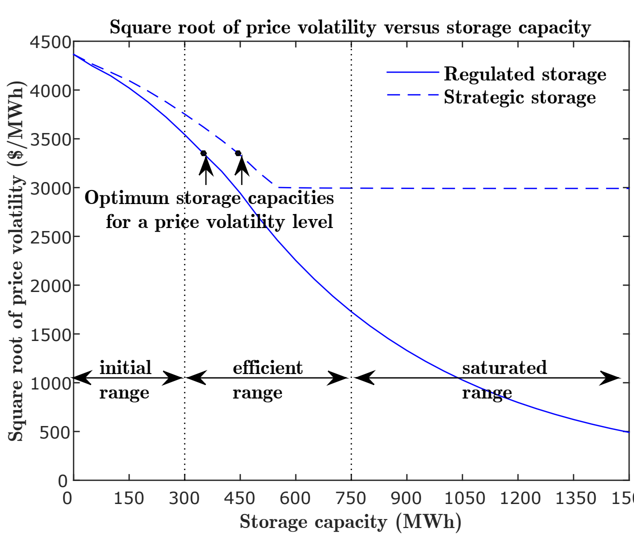

Fig. 5: Square root of price volatility in SA versus storage capacity during a high demand day with coal-plant outage.

2) Two-region model simulations in South Australia and Victoria:

In the one-region model simulations, we analysed the impact of storage on the price volatility in SA when the SA-VIC interconnector is not active. In this subsection, we first study the effect of the interconnector between SA and VIC on the price volatility in the absence of storage firms. Next, we investigate the impact of storage firms on the price volatility when the SA-VIC transmission line operates at various capacities. In our numerical results, SA is connected to VIC using a 680 MW interconnector which is currently operating with 70% of its capacity, i.e. 30% of its capacity is under maintenance. The numerical results in this subsection are based on the two-node model for a high demand day with coal-plant outage in SA. To investigate the impact of transmission line on price volatility, it is assumed that the SA-VIC interconnector operates with 60% and 70% of its capacity.

According to our numerical results, the peak price (the average of highest prices over all scenarios) in SA is equal to 6154 $/MWh when the SA-VIC interconnector is completely in outage. However, the peak price reduces to 3328 $/MWh and 2432 $/MWh when the interconnector operates at 60% and 70% of its capacity. The square root of price volatility is 4365 $/MWh, 860 $/MWh, and 614 $/MWh when the capacity of the SA-VIC transmission line is equal to 0%, 60%, and 70%, respectively, which emphasizes the importance of interconnectors in price volatility reduction.

Simulation results show that as long as the interconnector is not congested, the line alleviates the price volatility phenomenon in SA by importing electricity from VIC to SA at peak times. Since the market in SA compared to VIC is much smaller, about three times, the price volatility abatement in SA after importing electricity from VIC is much higher than the price volatility increment in VIC. Moreover, the price volatility reduces as the capacity of transmission line increases.

Fig. 6 shows the optimum storage capacity versus the percentage of price volatility reduction in the two-node market. According to our numerical results, storage is just located in SA, which witnesses a high level of price volatility as the capacity of transmission line decreases. According to this figure, the optimum storage capacity becomes large as the capacity of transmission line decreases. Note that a sudden decrease of the transmission line capacity may result in a high level of price volatility in SA. However, based on Fig. 6, storage firms are capable of reducing the price volatility during the outage of the interconnecting lines.

B. Simulations for a 30-bus System

In order to assess the functionality of our optimal storage allocation model for markets consisting relatively high number of nodes, we simulate a standard IEEE 30-bus (30-node) electricity network with LMP pricing mechanism, which sets the marginal value of demand at each bus or node as the nodal prices, in this subsection. The generation and transmission data is based upon [42], which includes six classical generators introduced in Table I. We assume the first two generators are regulated in our system. To consider the impact of supply scarcity, we retire the classical generator at node 5 and install the wind power generation capacity of 2.5 MW at each node, i.e., the total capacity of 75 MW in the system, in our study.

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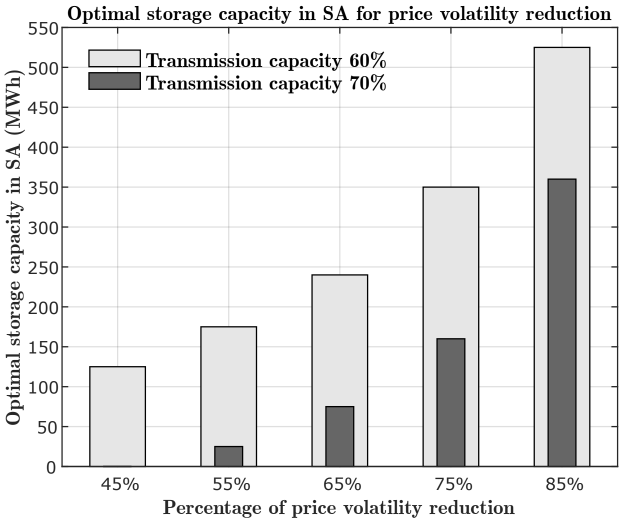

Fig. 6: Optimal regulated storage capacity versus the percentage of price volatility reduction in the two-node market in a high demand day with coal-plant outage in SA.

The transmission line limits are set to 50% of their values so that some lines would be binding in the solutions.

TABLE I: Location, capacity and generation cost of classical generators in the 30-bus electricity system.

Unit	1	2	3	4	5	6
Bus	1	2	5	8	11	13
Capacity (MW)	200	80	50	35	30	40
Cost ($/MWh)	15	15	35	35	35	35

We divide a day into the off-peak period (10 hours), the peak period (4 hours) and the shoulder period (10 hours) times. The demand in the off-peak is 10% more than the demand in the shoulder period whereas the peak demand is 25% more than the shoulder demand. Given the demand values in [42], we assume the electricity prices are equal to 40, 75 and 50 $/MWh during off-peak, peak, and shoulder periods, respectively.

In the absence of storage, the square root of the price volatility is equal to 250 $/MWh in the market due to the joint effect of wind power fluctuation and the power-plant retirement. To compute the storage capacity, we use Algorithm 1 with the increment storage capacity of 15 MWh. According to our numerical results, Algorithm 1 installs the storage only at node 5, which is the highest price volatile node in the system, in order to meet the required price volatility level. Fig (7) represents the price volatility level after allocating the storage capacity, calculated by the greedy algorithm 1. The step size of the increment storage capacity is considered as 15 MWh in each iteration of the algorithm. For instance, the total storage capacity of 60 MWh at the node 5 is calculated to address the square root of the price volatility limit of 90 $/MWh. The joint effect of capacity retirement and high electricity demand at node 5 leads to high level of price volatility after installing the intermittent wind power capacities in the market and makes the node 5 the likely candidate for storage allocation to meet the price volatility requirement.

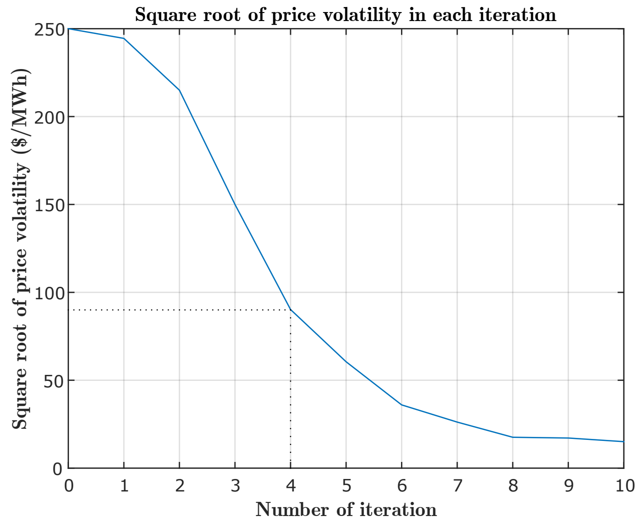

Fig. 7: Square root of price volatility level in the 30-bus system after ten iterations of Algorithm 1 with $\Delta Q^{\mathrm{s}} = 15\mathrm{MWh}$.

V. Conclusion

High penetration of intermittent renewables, such as wind or solar farms, brings high levels of price volatility in electricity markets. Our study presents an optimization model which decides on the minimum storage capacity required for achieving a price volatility target in electricity markets. Based on our numerical results, the impact of storage on the price volatility in one-node electricity market of SA, two-node market of SA-VIC and the standard 30-bus IEEE system can be summarized as:

- Storage alleviates price volatility in the market due to the wind intermittency. However, storage does not remove price volatility completely, i.e. storage stops reducing the price volatility when it is not profitable.
- The effect of a storage firm on price volatility reduction depends on whether the firm is regulated or strategic. Both storage types have similar operation behaviour and price reduction effect when they possess small capacities. For larger capacities, a strategic firm may under-utilize its available capacity and stop reducing the price level due to its profit maximization strategy. On the other hand, a regulated storage firm is more efficient in price volatility reduction because of its social welfare maximization strategy. The price level and volatility reduction patterns observed when storage firms are regulated provide stronger incentives for the market operator to subsidize the storage technologies.
- Both storage devices and transmission lines are capable of reducing the price volatility. High levels of price volatility that may happen due to the line maintenance can be alleviated by storage devices.
- Although many parameters affect the price volatility level of a system, penetration of intermittent wind power generation in a region makes the region or node highly price volatile when a classical generation capacity outage happens or high load level is demanded.

We intend to study the impact of ancillary services markets [43] and capacity markets [44] on the integration of storage systems in electricity networks and study the wind correlation

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analysis to look at volatility reduction effectiveness in our future work. Our future research also includes the optimal storage siting problem subject to the line congestion constraint to alleviate the congestion problem.

APPENDIX A
CHARGING/DISCHARGING

In this appendix, we show that the charge and discharge levels of any storage device cannot be simultaneously positive at the NE of the lower game under each scenario. Consider a strategy in which both charge and discharge levels of storage device i at time t under scenario w, *i.e.* $q^{\rm dis}_{itw}, q^{\rm ch}_{itw}$, are both positive. We show that this strategy cannot be a NE strategy of scenario w as follows. The net electricity flow of storage can be written as $q^{\rm s}_{itw} = \eta^{\rm dis}_i q^{\rm dis}_{itw} - \frac{q^{\rm ch}_{itw}}{\eta^{\rm ch}_i}$. Let $\bar{q}^{\rm dis}_{itw}$ and $\bar{q}^{\rm ch}_{itw}$ be the new discharge and charge levels of storage firm i defined as $\left\{\bar{q}^{\rm dis}_{itw} = q^{\rm dis}_{itw} - \frac{q^{\rm ch}_{itw}}{\eta^{\rm dis}_i \eta^{\rm ch}_i}, \quad \bar{q}^{\rm ch}_{itw} = 0\right\}$ if $q^{\rm s}_{itw} > 0$, or $\left\{\bar{q}^{\rm dis}_{itw} = 0, \quad \bar{q}^{\rm ch}_{itw} = q^{\rm ch}_{itw} - q^{\rm dis}_{itw}\eta^{\rm dis}_i \eta^{\rm ch}_i\right\}$ if $q^{\rm s}_{itw} < 0$. The new net flow of electricity can be written as $\bar{q}^{\rm s}_{itw} = \eta^{\rm dis}_i \bar{q}^{\rm dis}_{itw} - \frac{\bar{q}^{\rm ch}_{itw}}{\eta^{\rm ch}_i}$. Note that the new variables $\bar{q}^{\rm s}_{itw}$, $\bar{q}^{\rm ch}_{itw}$ and $\bar{q}^{\rm dis}_{itw}$ satisfy the constraints (5a-5d).

Considering the new charge and discharge strategies $\bar{q}^{\rm dis}_{itw}$ and $\bar{q}^{\rm ch}_{itw}$, instead of $q^{\rm dis}_{itw}$ and $q^{\rm ch}_{itw}$, the nodal price and the net flow of storage device i do not change. However, the charge/discharge cost of the storage firm i, under the new strategy, is reduces by:

$$c^{\rm s}_i \left(q^{\rm ch}_{itw} + q^{\rm dis}_{itw}\right) - c^{\rm s}_i \left(\bar{q}^{\rm dis}_{itw} + \bar{q}^{\rm ch}_{itw}\right) > 0$$

Hence, any strategy at each scenario in which the charge and discharge variables are simultaneously positive cannot be a NE, i.e. at the NE of the lower game under each scenario each storage firm is either in the charge mode or discharge mode.

APPENDIX B
INVERSE DEMAND FUNCTION

Two most commonly used inverse demand functions in microeconomics literature are the linear and iso-elastic models [45], e.g., in [23], [46]. Exponential inverse demand function has also been used in energy market models [47]. The inverse demand function of most commodities follows a non-linear downward sloping price versus demand relation [48] and a linear inverse demand function is just its first order approximation at an operating price and demand level. The linear function may become invalid when the operating point changes drastically, e.g., when the price plunges from the very high amount of 11000 $/MWh to low level of 50 $/MWh.

The iso-elastic and exponential functions can more accurately illustrate the price and demand relation. In fact, the exponential function, $p = \alpha' e^{-\beta' q}$, is the modified version of the iso-elastic function, $\ln(p) = \alpha - \beta \ln(q)$ or $p = \tilde{\alpha} e^{-\beta \ln(q)}$ with $\tilde{\alpha} = e^{\alpha}$, which substitutes the logarithmic demand levels with nominal levels. We discuss three reasons privileging the exponential inverse demand function over the iso-elastic. Firstly, the KKT conditions of the lower level game become highly non-linear under the iso-elatsic function and it becomes hard to numerically solve them. The derivative of the exponential inverse demand function with respect to demand is $\frac{\partial p}{\partial q} = -\beta' p$, while the derivative of the iso-elastic function with respect to demand is $\frac{\partial p}{\partial q} = -\beta p q^{-1}$. Secondly, the exponential function has a finite price feature while the iso-elastic function goes to infinity for small levels of demand. Lastly, the exponential function partially covers the specifications of both linear and iso-elastic functions. Consequently, we use and calibrate exponential inverse demand functions to characterize the price and demand relations in our model.

In electricity market models, the constant coefficients in the inverse demand functions are usually calibrated based on actual price/demand data , p/q, and price elasticity levels, $\epsilon = \frac{\frac{\partial q}{q}}{\frac{\partial p}{p}}$ [48], which are given as input to our model. Given two equations of price-demand function and elasticity function, i.e., $p = f(q)$ and $\epsilon = \frac{\partial q}{\partial p}\frac{p}{q}$, and two unknowns, we can find the both parameters in all three discussed inverse demand functions. For instance, given the price of $p = 50$ $/MWh, demand of $q = 1500$ MW and price elasticity of demand $\epsilon = -0.3$, the linear function $p = \frac{650}{3} - \frac{1}{9}q$, the iso-elastic function $\ln(p) = 28.28 - \frac{10}{3}\ln(q)$, and the exponential function $p = 50e^{\frac{10}{3}}e^{-\frac{1}{450}q}$ can be extracted. Fig. 8 compares the calibrated linear, exponential and iso-elastic inverse demand functions. The properties of the exponential function lie between the linear and iso-elastic functions.

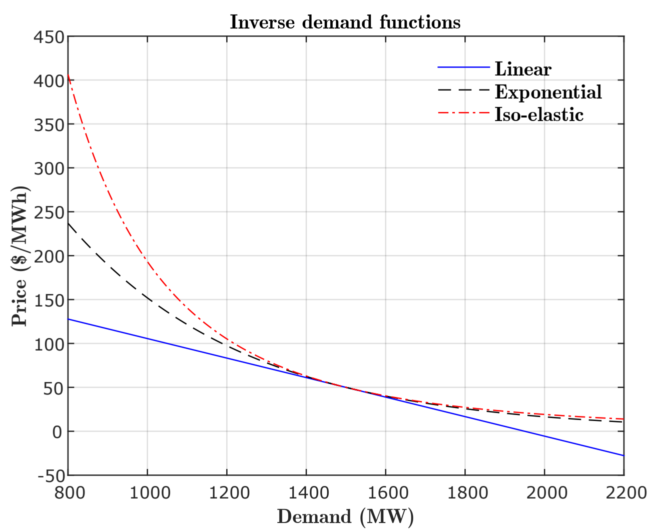

Fig. 8: Calibrated linear, exponential and iso-elastic inverse demand functions at price 50 $/MWh, demand 1500 MW, and elasticity -0.3.

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