Energy Storage Arbitrage Under Day-Ahead and Real-Time Price Uncertainty

Dheepak Krishnamurthy, *Member, IEEE*, Canan Uckun, Zhi Zhou, *Member, IEEE*, Prakash R. Thimmapuram, and Audun Botterud, *Member, IEEE*

***Abstract*—Electricity markets must match real-time supply and demand of electricity. With increasing penetration of renewable resources, it is important that this balancing is done effectively, considering the high uncertainty of wind and solar energy. Storing electrical energy can make the grid more reliable and efficient and energy storage is proposed as a complement to highly variable renewable energy sources. However, for investments in energy storage to increase, participating in the market must become economically viable for owners. This paper proposes a stochastic formulation of a storage owner's arbitrage profit maximization problem under uncertainty in day-ahead and real-time market prices. The proposed model helps storage owners in market bidding and operational decisions and in estimation of the economic viability of energy storage. Case study results on realistic market price data show that the novel stochastic bidding approach does significantly better than the deterministic benchmark.**

***Index Terms*—Battery storage plants, energy storage, markets, price arbitrage.**

Nomenclature

A. Indices and Sets

s_{DA} Scenario index for DA price scenarios
s_{RT} Scenario index for RT price scenarios
t Time index

B. Parameters

$C^{\max}$ Maximum state of charge (MWh)
$C^{\min}$ Minimum state of charge (MWh)
C^{init} Initial state of charge (MWh)
L^{in} Losses during charging (%)
L^{out} Losses during discharging (%)
N_{DA} Number of DA price forecast scenarios
N_{RT} Number of RT price forecast scenarios
N_{DA}^{sample} Sampled number of DA price forecast scenarios
$N_{DA}^{reduced}$ Reduced number of DA price forecast scenarios
R^c Maximum rate of charge (MW)
R^d Maximum rate of discharge (MW)
τ End of horizon wrap-up tolerance for state of charge
$f_{DA}(t)$ Probability weighted average of forecasted prices over all DA price scenarios at time t ($/MWh)
$f_{DA}(t, s_{DA})$ Forecasted price at hour t for DA price scenario s_{DA} ($/MWh)
$f_{RT}(t, s_{RT})$ Forecasted price at hour t for RT price scenario s_{RT} ($/MWh)
$p_{DA}(s_{DA})$ Probability of DA price forecast scenario s_{DA}
$p_{RT}(s_{RT})$ Probability of RT price forecast scenario s_{RT}

C. Decision Variables

$B_{DA}^{in}(t)$ Purchase bid price in day-ahead market (DAM) at hour t ($)
$B_{DA}^{out}(t)$ Sell bid price in DAM at hour t ($)
$E_{DA}^{in}(t)$ Energy purchased from the DAM by storage during hour t (MWh)
$E_{DA}^{out}(t)$ Energy sold to the DAM by storage during hour t (MWh)
$E_{RT}^{in}(t)$ Energy purchased from the real-time market (RTM) by storage during hour t (MWh)
$E_{RT}^{out}(t)$ Energy sold to the RTM by storage during hour t (MWh)
$C(t)$ State of charge during hour t (MWh, Quantity-Only bid model)
$C(t, s_{DA})$ State of charge during hour t in DA price scenario s_{DA} (MWh, Price-Quantity bid model)
$E_{stor}^{in}(t)$ Energy supplied to storage during hour t (MWh, Quantity-Only bid model)
$E_{stor}^{out}(t)$ Energy supplied from storage during hour t (MWh, Quantity-Only bid model)
$E_{stor}^{in}(t, s_{DA})$ Energy supplied to storage during hour t in DA price scenario s_{DA} (MWh, Price-Quantity bid model)
$E_{stor}^{out}(t, s_{DA})$ Energy supplied from storage during hour t (MWh, Price-Quantity bid model)
$z^{in}(t, s_{DA})$ Binary variable that indicates if purchase bid is accepted or rejected in hour t in DA price scenario s_{DA} (0,1)
$z^{out}(t, s_{DA})$ Binary variable that indicates if sell bid is accepted or rejected in hour t in DA price scenario s_{DA} (0,1)

Manuscript received April 18, 2016; revised September 14, 2016 and February 1, 2017; accepted March 4, 2017. Date of publication April 4, 2017; date of current version December 20, 2017. This work was supported by the Laboratory Directed Research and Development funding from Argonne National Laboratory (Argonne), provided by the Director, Office of Science, of the U.S. Department of Energy under Contract DEAC02-06CH11357. The submitted manuscript has been created by UChicago Argonne, LLC, Operator of Argonne. Paper no. TPWRS-00608-2016.

D. Krishnamurthy was with the Energy Systems Division, Argonne National Laboratory, Lemont, IL 60439 USA. He is now with the Strategic Energy Analysis Center, National Renewable Energy Laboratory, Golden, CO 80401 USA (e-mail: dheepak.krishnamurthy@nrel.gov).

C. Uckun, Z. Zhou, P. R. Thimmapuram, and A. Botterud are with the Energy Systems Division, Argonne National Laboratory, Lemont, IL 60439 USA (e-mail: cuckun@anl.gov; zzhou@anl.gov; prakash@anl.gov; abotterud@anl.gov).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TPWRS.2017.2685347

0885-8950 © 2017 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission.
See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

Authorized licensed use limited to: University Library Utrecht. Downloaded on October 03,2024 at 12:41:54 UTC from IEEE Xplore. Restrictions apply.

I. Introduction

ONE of the greatest challenges of the 21st century is to introduce more sustainable sources of energy. The penetration of renewable resources, such as wind power and solar energy, has been increasing at a global scale in the last decade. These investments are driven, in part, by policy incentives, such as renewable portfolio standards that set requirements to have a certain percentage of installed capacity from renewable energy sources. For example, the state of California requires that 33% of the supply mix should be provided from renewable sources of energy by 2020 [1]. Falling costs of renewable energy technologies, in particular solar cells in recent years, also contributes to further increase of their penetration. The large-scale expansion of wind and solar power can result in situations where the net demand of power can vary widely in a short period of time due to rapid and sometimes unexpected changes in wind and solar output. This can cause reliability issues in a power system if not adequately addressed. Many proposed energy systems for the future make the assumption that energy storage will be available to assist with this balancing act. Grid-level storage can reduce supply and demand mismatch by shifting energy from times of low demand to high demand, or from times when generation is cheap to when it is expensive. Additionally, storage can be charged or discharged rapidly, which can reduce the dependency on fast generation units. Energy storage can provide power quality, load shifting, load leveling, energy management, frequency regulation, backup power, voltage support, grid stabilization [2]. Hence, integrating energy storage devices into a power system can prove extremely useful in increasing reliability and performance. In electricity markets, grid level storage can take advantage of market operations and generate profits using energy arbitrage. By exploiting the difference in market prices, i.e., a storage owner may buy power when the price is low, store this energy, and sell when the price is high, thereby making it economical over time to provide such load shifting energy services to the market. Energy storage can also benefit by providing other services to the grid, but energy arbitrage is by far the largest business opportunity. At present, grid-level energy storage comprises of 2.3% of total electric production capacity in the United States, of which 95% is pumped storage hydro (PSH) [3]. PSH is considered to be a conventional technology due to its long track record. However, the large scale construction, concerns about local environmental impacts, and few locations with the required topography, limits the expansion of PSH units.

Extensive research has been conducted on combined optimization of energy storage and variable renewable generation [4]–[6]. The integration of grid level energy storage to provide load shifting, primary or/and secondary reserve in a centralized cost-based energy market is analyzed in [7]. A stochastic unit commitment model with energy storage and wind power for system scheduling at day-ahead and real-time stages is proposed in [8]. A method combining a genetic algorithm with linear programming to determine the best capacity and operating status of an energy storage system is proposed in [9]. Scheduling strategies for PSH have been studied for a long time. Examples of energy arbitrage strategies proposed for PSH include [10]–[12], where the first two look at income from energy arbitrage and regulation and the latter from arbitrage only. All three studies use deterministic bidding models under a price taker assumption. Other analyses have been performed to determine the optimal dispatch of other storage technologies with respect to spot market prices [13]–[15]. In particular, with recent improvements in cost and performance, battery storage is receiving increasing attention for grid applications. The authors in [16] propose a stochastic model for optimal energy and reserve bids in power systems with high wind penetration, where prices are derived from a stochastic unit commitment model. The authors in [17] propose a stochastic battery arbitrage model for day-ahead and real-time prices. In case studies based on historical prices from California, it is shown that economic bidding outperforms a self-scheduling strategy. However, price forecast information is not used in the study. There is also a growing literature examining the use of battery storage for arbitrage maximization in distribution markets [18], [19].

This paper focuses on the time domain arbitrage opportunities for grid level battery storage in the DAM with the possibility of making corrections in the RTM. The storage-owner is a price taker, the proposed optimization model provides the bids a grid level storage owner can submit to the DAM in order to maximize the expected profit taking into consideration uncertainty in market prices by using a stochastic programming approach without recourse. The contributions of the paper includes: 1) We present a novel storage bidding strategy into the DAM that includes price and quantity bids based on stochastic price forecasts for the DAM, 2) We reformulate the original optimization problem, which is non-linear, into a mixed integer linear programming (MILP) problem, which can be solved efficiently by commercial solvers, 3) We conduct a case study based on historical price data from California, which show benefits of the proposed stochastic model compared to a deterministic quantity bidding strategy benchmark under different forecasting methods.

This paper is organized as follows. Section II introduces the mathematical formulation for the battery storage bidding model where Section II-A explains the price scenario generation methodology, Section II-B discusses the energy storage representation and Section II-C introduces the bidding models for both DAM and RTM. Section III presents case studies and results with the novel storage model and presents the results. Section IV summarizes the conclusions and provides directions for future work.

II. Mathematical Formulation

A. Price Forecast Scenario Generation and Scenario Reduction

1) Price Generation Framework: The objective is to generate scenarios for DAM and RTM electricity prices, which are used to determine the bids in the DAM and the RTM. The procedure consists of multiple steps, as illustrated in Fig. 1 and outlined below.

2) ARIMA Point Forecast: A point forecast for prices is implemented by using an ARIMA model with seasonality to

Authorized licensed use limited to: University Library Utrecht. Downloaded on October 03,2024 at 12:41:54 UTC from IEEE Xplore. Restrictions apply.

Fig. 1. Framework for price scenario generation.

capture daily, weekly and seasonal fluctuations in the price profile. Both the DA and RT prices are forecasted for 24 hours upfront to comply with the decision procedure of energy storage owners that the bids are submitted for a whole day. The parameters of the ARIMA model are optimized based on selected historical prices information, which are usually determined separately for weekday and weekend days. The ARIMA point forecast is used as an input to the probabilistic forecasting model.

3) Probabilistic Price Forecasting: Probability density functions (pdfs) of prices are estimated using a quantile-copula kernel density estimator (KDE) [20]. The KDE model estimates the empirical pdf of prices for each look-ahead hour based on a set of explanatory variables, from which quantiles and scenarios of prices can be derived. In the case study, the point forecasts of prices and the hour of the day are used as explanatory variables to estimate pdfs for DAM and RTM prices. The problem can therefore be formulated, given a set of explanatory variables to estimate the conditional pdf of electricity prices at a time for each look-ahead time step.

4) Scenario Generation and Reduction: The forecasted pdfs express the empirical probability distribution of the price forecast for a specific point in time. However, for energy storage, it is important to take inter-temporal relationships in the forecast uncertainty into consideration. This makes scenarios a more appropriate representation for the price distribution over a whole day. We use the scenario generation approach described in [21] to generate forecast scenarios from the estimated pdfs. In this approach, scenario sampling is performed using a Monte Carlo simulation. The inter-temporal correlation (hour-to-hour) is represented by a covariance matrix, which is estimated on the basis of covariance of historical data. To reduce the computational complexity of the decision problem for energy storage, it is necessary to use a reduced set of scenarios as input. The price distributions represented by the reduced scenario set should be as close as possible to the original set. Towards this end, we use the standard scenario reduction method from [22]. This method reduces the set based on the Kantorovich distance between the original and reduced sets of scenarios, taking scenario probabilities and distances of scenario values into account.

B. Electric Energy Storage Model

We model the battery by considering its energy storage capacity, maximum charging rate, maximum discharging rate, charging efficiency, discharging efficiency, initial charge state and final charge state, as expressed in the following equations.

$$E_{DA}^{in}(t) = E_{stor}^{in}(t) \div \left(1 - \frac{L^{in}}{100}\right) \tag{1}$$

$$E_{DA}^{out}(t) = E_{stor}^{out}(t) \times \left(1 - \frac{L^{out}}{100}\right) \tag{2}$$

$$E_{stor}^{in}(t) \leq R^{c} \tag{3}$$

$$E_{stor}^{out}(t) \leq R^{d} \tag{4}$$

$$C(1) = C^{init} - E_{stor}^{out}(1) + E_{stor}^{in}(1) \tag{5}$$

$$C(t) = C(t-1) - E_{stor}^{out}(t) + E_{stor}^{in}(t) \tag{6}$$

$$C(t) \leq C^{max} \tag{7}$$

$$C(t) \geq C^{min} \tag{8}$$

$$C(24) \geq C^{init}\left(1 - \frac{\tau}{100}\right) \tag{9}$$

$$C(24) \leq C^{init}\left(1 + \frac{\tau}{100}\right) \tag{10}$$

where constraints (1) and (2) ensure that the energy charged or discharged at a particular time period t is equal to the purchased or sold energy bid that is accepted at time t after accounting for efficiency losses. Constraints (3) and (4) ensure that the charging and discharging of the storage device in a given time period are limited by the maximum charging and discharing rates. Constraints (5) and (6) represent that the state of charge is a function of the state of charge in the previous period and the amount of energy charged or discharged in the current period. Constraints (7) and (8) make sure that the energy stored in the battery is less than the size of the battery, C^{max} and greater than C^{min}. Finally, we assume that the final state of charge at the end of the day lies within a tolerance band of the initial condition, as shown in (9) and (10).

C. Electricity Market Stages

We assume that storage owners are price-takers that can make hourly price and quantity bids into the DAM given the price forecast scenarios, and can make quantity bids into the RTM. A storage owner must consider how to allocate energy resources between the two markets such as to maximize profits along with potential other objectives such as reducing risk exposure. After the DAM bid period ends, the independent system operator (ISO) calculates the DA schedule for the market participants and energy prices for all hours of the next day, based on a security-constrained unit commitment and economic dispatch. Market participants can usually revise their bids ahead of the RTM clearing. RTM prices are calculated based on actual system operating conditions. The rules for submitting bids to the RTM are different than that of the DAM, i.e., the RTM is settled sequentially and as time progresses. Moreover, electricity prices in the RTM are highly volatile and unpredictable since they are affected by various factors such as weather, contingencies in the power system and all the physical constraints in the power system. A storage owner needs to decide whether to keep the energy stored for the RTM or sell in the DAM. We introduce different storage optimization models for DAM and RTM. An illustrative comparison of these models is shown in Fig. 2 and is outlined in detail below. Both stages are simulated in the case study.

Authorized licensed use limited to: University Library Utrecht. Downloaded on October 03,2024 at 12:41:54 UTC from IEEE Xplore. Restrictions apply.

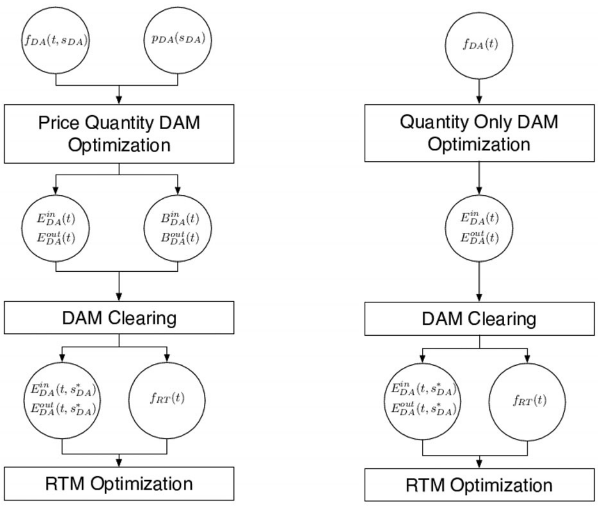

Fig. 2. Operating methodology comparing quantity-price and quantity only DAM optimization.

1) Day-Ahead Market Optimization:

a) Quantity-only bid model (LP): Our first model assumes that the storage owner submits only quantity bids into the DAM. The problem is formulated as follows:

$$\max \sum_{t=1}^{24} \left(f_{DA}(t) \times \left(E_{DA}^{out}(t) - E_{DA}^{in}(t) \right) \right) \tag{11}$$

subject to:

$$(1) - (10)$$

$$E_{DA}^{in}(t) \geq 0 \qquad \forall t \tag{12}$$

$$E_{DA}^{out}(t) \geq 0 \qquad \forall t \tag{13}$$

$$C(t) \geq 0 \qquad \forall t \tag{14}$$

$$E_{stor}^{in}(t) \geq 0 \qquad \forall t \tag{15}$$

$$E_{stor}^{out}(t) \geq 0 \qquad \forall t \tag{16}$$

where the expected DAM clearing price $f_{DA}(t)$ at a given time t is calculated using the probability weighted average of all scenarios at the same time t. The objective function in (11) is to maximize the expected profit subject to the storage constraints described in Section II-B, (1)–(10) and non-negativity constraints (12)–(16). This model is a linear program (LP) and can be solved using a standard LP solver.

b) Price-quantity bid model (MILP): When we include price and quantity bids into the offer, the DAM problem becomes a stochastic programming problem. The objective is to maximize the expected profit:

$$\max \sum_{t=1}^{24} \left(\sum_{s_{DA}=1}^{N_{DA}} p_{DA}(s_{DA}) \times f_{DA}(t, s_{DA}) \times \left(z^{out}(t, s_{DA}) \times E_{DA}^{out}(t) - z^{in}(t, s_{DA}) \times E_{DA}^{in}(t) \right) \right) \tag{17}$$

The use of binary variables, $z^{out}(t, s_{DA})$ and $z^{in}(t, s_{DA})$, in the objective function leads to a mixed integer non-linear problem (MINLP). The MINLP can be converted into a mixed integer linear program (MILP) by defining the continuous variables $X^{in}(t, s_{DA})$ and $X^{out}(t, s_{DA})$ using the following constraints:

$$X^{in}(t, s_{DA}) \leq z^{in}(t, s_{DA}) \times \left(R^c \div \left(1 - \frac{L^{in}}{100} \right) \right) \tag{18}$$

$$X^{out}(t, s_{DA}) \leq z^{out}(t, s_{DA}) \times \left(R^d \times \left(1 - \frac{L^{out}}{100} \right) \right) \tag{19}$$

$$E_{DA}^{in}(t) - X^{in}(t, s_{DA}) \leq (1 - z^{in}(t, s_{DA})) \times \left(R^c \div \left(1 - \frac{L^{in}}{100} \right) \right) \tag{20}$$

$$E_{DA}^{out}(t) - X^{out}(t, s_{DA}) \leq (1 - z^{out}(t, s_{DA})) \times \left(R^d \times \left(1 - \frac{L^{out}}{100} \right) \right) \tag{21}$$

$$E_{DA}^{in}(t) - X^{in}(t, s_{DA}) >= 0 \tag{22}$$

$$E_{DA}^{out}(t) - X^{out}(t, s_{DA}) >= 0 \tag{23}$$

From (18)–(23), it readily follows that

$$X^{in}(t, s_{DA}) = z^{in}(t, s_{DA}) \times E_{DA}^{in}(t) \tag{24}$$

$$X^{out}(t, s_{DA}) = z^{out}(t, s_{DA}) \times E_{DA}^{out}(t) \tag{25}$$

Then the problem we need to solve is:

$$\max \sum_{t=1}^{24} \left(\sum_{s_{DA}=1}^{N_{DA}} p_{DA}(s_{DA}) \times f_{DA}(t, s_{DA}) \times \left(X^{out}(t, s_{DA}) - X^{in}(t, s_{DA}) \right) \right) \tag{26}$$

subject to:

(1)–(10)

(18)–(23)

$$B_{DA}^{in}(t) \leq f_{DA}(t, s_{DA}) + M'' \times z^{in}(t, s_{DA}) \qquad \forall t, \forall s_{DA} \tag{27}$$

$$B_{DA}^{in}(t) \geq f_{DA}(t, s_{DA}) - M'' \times (1 - z^{in}(t, s_{DA})) \qquad \forall t, \forall s_{DA} \tag{28}$$

$$B_{DA}^{out}(t) \geq f_{DA}(t, s_{DA}) - M' \times z^{out}(t, s_{DA}) \qquad \forall t, \forall s_{DA} \tag{29}$$

$$B_{DA}^{out}(t) \leq f_{DA}(t, s_{DA}) + M' \times (1 - z^{out}(t, s_{DA})) \qquad \forall t,\ s_{DA} \tag{30}$$

$$C(t, s_{DA}) \geq 0 \qquad \forall t \tag{31}$$

Authorized licensed use limited to: University Library Utrecht. Downloaded on October 03,2024 at 12:41:54 UTC from IEEE Xplore. Restrictions apply.

$$E_{DA}^{in}(t), E_{DA}^{out}(t) \geq 0 \qquad \forall t \qquad (32)$$

$$B_{DA}^{in}(t), B_{DA}^{out}(t) \geq 0 \qquad \forall t \qquad (33)$$

$$X_{DA}^{in}(t, s_{DA}), X_{DA}^{out}(t, s_{DA}) \geq 0 \qquad \forall t, \forall s_{DA} \qquad (34)$$

$$E_{stor}^{in}(t, s_{DA}), E_{stor}^{out}(t, s_{DA}) \geq 0 \qquad \forall t,\ \forall s_{DA} \qquad (35)$$

$$z^{in}(t, s_{DA}), z^{out}(t, s_{DA}) \in \{0, 1\} \qquad \forall t, \forall s_{DA} \qquad (36)$$

If z^{in} is 1, then constraint (27) is no longer binding, given M' and M'' are two big numbers. Constraint (28) is binding, and effectively limits the value of the bid price B_{DA}^{in} to greater than the f_{DA}. If the purchase bid price is higher than the clearing price, the bid is accepted. If the purchase bid is lower than the clearing price, the bid is rejected. Similarly, if z^{in} is 0, then Constraint (28) is no longer binding. Constraint (27) forces the bid price to be below the clearing price. Hence, when the bid price is below the clearing price, the bid is rejected and when the bid price is above the clearing price the bid is accepted. Similarly, z^{out} is the decision variable that governs if a sell bid is accepted or rejected. A sell bid will only be accepted if the sell bid price is lower than the clearing price. If z^{out} is 1, Constraint (29) is no longer binding, and Constraint (30) is active, making the sell bid price lesser than the f_{DA}. Similarly, if z^{out} is 0, Constraint (30) is no longer binding and constraint (29) is binding, making the sell bid price greater than f_{DA}. Hence, when the market is cleared, depending on which DAM price scenario is realized, a bid may be accepted or rejected. As described above, constraints (27)–(30) are used to determine whether a bid is accepted or rejected. A selling bid is accepted when the market clearing price is higher than the bid price. A purchasing bid is accepted when the market clearing price is lower than the bid price. The DAM formulations do not take into consideration the ability to change bids in the RTM explicitly. This assumption is needed to prevent the DAM model from exploiting DA-RT arbitrage opportunities that may be present in the price forecast scenarios. Note that the variables $C(t)$, $E_{stor}^{in}(t)$ and $E_{stor}^{out}(t)$ now depend on the DA scenario.

2) Real-Time Market Optimization (LP): Storage owners can make additional quantity bids into the RTM, to make up for rejected DAM bids or to make additional profits based on the forecasted RTM prices. The accepted DAM bids are considered as input to the RTM optimization. Assume DA price scenario s_{DA}^* is realized. Then the RTM optimization problem is a linear program. The formulation is

$$\max \quad \sum_{t=1}^{24} \Bigg(f_{DA}(t, s_{DA}^*) \times \left(z^{out}(t, s_{DA}^*) \times E_{DA}^{out}(t) - z^{in}(t, s_{DA}^*) \times E_{DA}^{in}(t) \right) + \sum_{s_{RT}=1}^{N_{RT}} p_{RT}(s_{RT}) \times \Big(f_{RT}(t, s_{RT}) \times \left(E_{RT}^{out}(t, s_{DA}^*) - E_{RT}^{in}(t, s_{DA}^*) \right) \Big) \Bigg) \qquad (37)$$

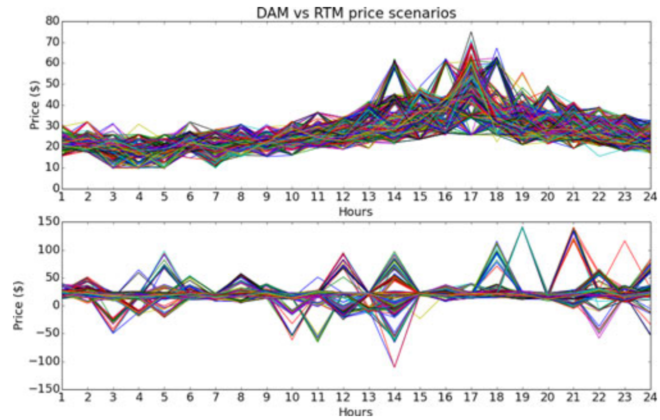

Fig. 3. Price scenarios in DAM and RTM.

subject to:

(3)–(10)

$$z^{in}(t, s_{DA}^*) \times E_{DA}^{in}(t) + E_{RT}^{in}(t, s_{DA}^*) = E_{stor}^{in}(t, s_{DA}^*) \div \left(1 - \frac{L^{in}}{100}\right) \qquad \forall t \qquad (38)$$

$$z^{out}(t, s_{DA}^*) \times E_{DA}^{out}(t) + E_{RT}^{out}(t, s_{DA}^*) = E_{stor}^{out}(t, s_{DA}^*) \times \left(1 - \frac{L^{out}}{100}\right) \qquad \forall t \qquad (39)$$

$$C(t, s_{DA}^*) \geq 0 \qquad \forall t \qquad (40)$$

$$E_{RT}^{in}(t, s_{DA}^*), E_{RT}^{out}(t, s_{DA}^*) \geq 0 \qquad \forall t \qquad (41)$$

$$E_{stor}^{in}(t, s_{DA}^*), E_{stor}^{out}(t, s_{DA}^*) \geq 0 \qquad \forall t \qquad (42)$$

The objective is to maximize the sum of DAM profit and the expected RTM profit. Although DAM profit is constant at this point, we add it in the formulation for completeness. We update the battery constraints (1)–(2) to accommodate for RTM charge/discharge decisions to get constraints (38) and (39). We ensure non-negativity by constraints (40)–(42). Note that the variables in the RTM model depends on the realized DA price scenario. RTM produces additional profits (or losses) as well as takes into consideration the feasibility of the solution, in case the accepted DAM bids are infeasible. We do not consider price-quantity bids in the RTM, since it may result in infeasible schedules that cannot be corrected.

III. Case Studies

Three cases are presented to show the effectiveness of the proposed Price-Quantity MILP model compared to the Quantity-Only LP model in the DAM. Case I presents a detailed Monte Carlo analysis of 1000 price scenarios for a selected day, with the characteristics of the battery defined as 50MW/50MWh (i.e., a 1 hour battery) with 10% charge/discharge losses, no variable or fixed operational costs, with a zero initial state of charge. In Case II, the same analysis is repeated with a 25MW/50MWh (i.e., 2 hour) battery. Case III presents results from running 130 days of simulation using real world historical price data (out of sample). DAM and RTM price scenarios were generated

Authorized licensed use limited to: University Library Utrecht. Downloaded on October 03,2024 at 12:41:54 UTC from IEEE Xplore. Restrictions apply.

TABLE I
COMPARISON OF AVERAGE AND STANDARD DEVIATION OF DAM AND RTM PROFITS WITH A ONE HOUR BATTERY

Type of Optimization	DAM Profits		RTM Profits		DAM+RTM Profits	
	Avg.	Std. Dev.	Avg.	Std. Dev.	Avg.	Std. Dev.
Price-Quantity (MILP)	6209.76	1283.66	170.30	661.10	6380.07	1285.64
Quantity-Only (LP)	3125.88	523.88	731.54	113.12	3737.26	504.40

TABLE II
COMPARISON OF NUMBER OF CYCLES OF ONE HOUR STORAGE DEVICE

Type of Optimization	Charge Cycles	
	Avg.	Std. Dev.
Price-Quantity (MILP)	4.37	2.01
Quantity-Only (LP)	2.13	0.52

for the Palo Verde Hub in CAISO using the procedure described in Section II-A under the assumption that that DAM and RTM price scenarios are independent. Specifically, the ARIMA models are picked as $(0; 1; 1)(2; 1; 1)_s$ for DAM prices of weekday and $(0; 1; 1)(1; 1; 0)_s$ for RTM prices of weekday. The seasonality component is based on a daily cycle.

A. *Case I*

A single day is chosen as the operating period. A visual representation of the N_{DA} and N_{RT} price scenarios in the DAM and RTM in this single day are shown in Fig. 3. The testing procedure is described in detail below.

Testing Procedure:

1) The input contains N_{DA} price scenarios. Using a random sampler, a "test case" of N_{DA}^{sample} price scenarios is generated.
2) The model decides the optimal DAM bid based on these N_{DA}^{sample} price scenarios as input, and produces quantity and price (MILP) or quantity only (LP) bids for 24 hours.
3) A single clearing price scenario is chosen from the N_{DA} price scenarios in the input file, and the DAM is cleared.
4) With the DAM results as an input, the model then produces RTM quantity bids based on expected RT prices, i.e., the average of the N_{RT} RT price scenarios. This RT bid is cleared with each N_{RT} RT price scenarios.
5) Steps 3-4 are repeated for every clearing price scenario in the N_{DA} scenarios to complete the "test case".
6) Another random sample of N_{DA}^{sample} price scenarios is generated to produce a different "test case" and steps 2 to 5 are repeated. This process is repeated for 1000 different test cases.

In the above described testing procedure, N_{DA} is 1000, N_{DA}^{sample} is 10 and N_{RT} is 1000.

The results for Case I are summarized in Tables I and II.[1] The analysis shows that the stochastic optimization strategy (MILP) provides a substantially higher combined average profit from the DAM and RTM markets, but also a higher standard deviation in profits indicating a higher risk exposure as seen in Table I. Moreover, the storage unit is required to cycle more often under the price-quantity (MILP) strategy as seen from Table II.

Fig. 4 compares the bids submitted into the DAM in both models. Note that in the Quantity-Only bid model shown in Fig. 4(a), the price for the purchase bid is higher than the highest price in the scenarios, and the price for the sell bid is lower than the lowest price in the scenarios. This means that this purchase and sell bid will always be accepted in the DAM clearing process. Fig. 4(b) shows price and quantity bids in the Price-Quantity bidding (MILP) model for the same day. It shows that the stochastic optimization may result in multiple DAM bids in the same hour. Under this strategy, the bids are accepted (or rejected) depending on the realized clearing price. Hence, the cleared DAM bids may not be feasible and the storage owner submits additional bids into the RTM to make up for the infeasibility while also considering additional profits from expected real time prices as shown in Fig. 4(c). For example, in hour 5 a sell bid of 45 MW was cleared in the DAM. However, this is infeasible given that the initial state of charge is 0. In the RTM, a Quantity-Only purchase bid of 55 MW is made in hour 3, so that the DAM market schedule can be met in hour 5.

Depending on the realized DAM clearing price and how well it is aligned with the reduced price scenarios used in the optimization, the result may also be that the accepted DAM bids are always feasible. In this case, no infeasibility constraints needs to be resolved in the RTM. However, the storage profits can be improved by bidding into the RTM considering the expected RT price.

Fig. 5 shows a comparison of the combined DAM and RTM profits in the individual 1000 cases. We can see that the stochastic MILP algorithm provides a higher DAM profit in almost all cases, but with higher standard deviation. The realized DAM profit is dependent on the proximity of realized clearing prices to the price scenarios used as input to the MILP algorithm. The standard deviation of the RTM profits with the DAM MILP algorithm is also larger than with the DAM LP algorithm. The higher standard deviation is due to the additional task of compensating for infeasible solutions produced after the DAM clearance.

B. *Case II*

We perform the same analysis as in Case I for a two hour battery (25 MW/50 MWh) using the same price scenarios as shown in Fig. 3. Tables III and IV show that stochastic MILP formulation provides a higher profit than the deterministic one, while

[1] Charge cycle is calculated by counting the number of times the battery has entered a state of charge or a state of discharge.

Authorized licensed use limited to: University Library Utrecht. Downloaded on October 03,2024 at 12:41:54 UTC from IEEE Xplore. Restrictions apply.

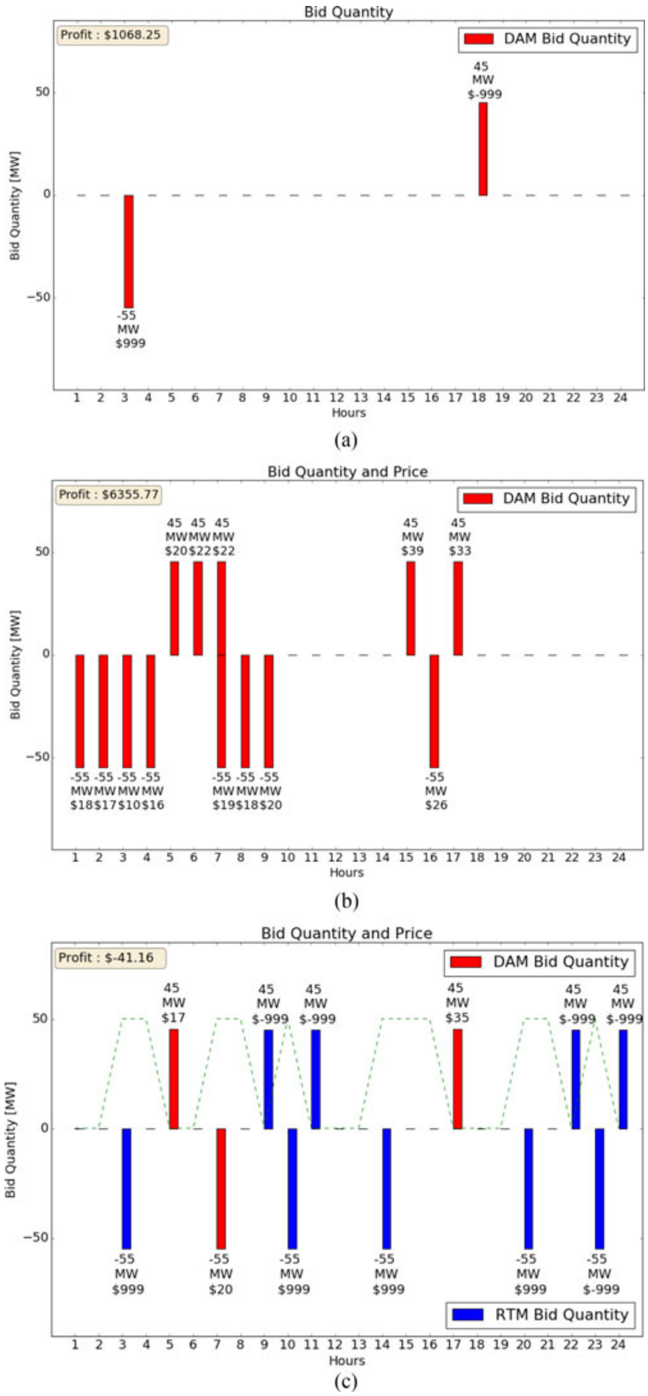

Fig. 4. Example of bids submitted to DAM and RTM. (a) DAM bids submitted in quantity-only bid model. (b) DAM bids submitted in price-quantity bid model. (c) Realized DAM schedule (red) and RTM bids (blue) along with charge state of battery (green) where RTM bids fix DAM bid infeasibilities as well as improve total profits.

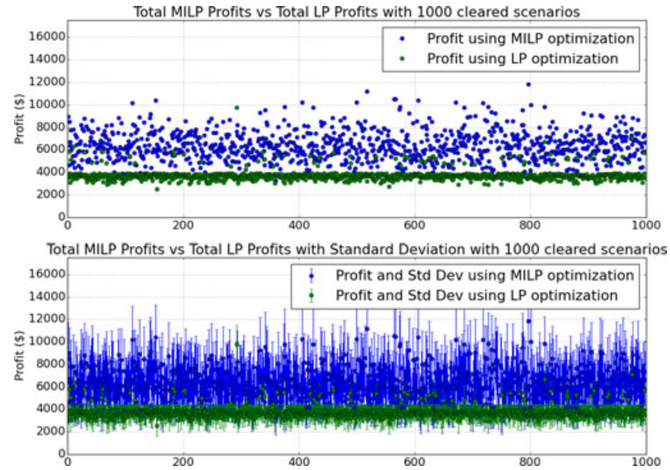

Fig. 5. Total profit in DAM and RTM for 1000 scenarios.

TABLE III
COMPARISON OF AVERAGE AND STANDARD DEVIATION OF DAM AND RTM PROFITS WITH A TWO HOUR BATTERY

Type of Optimization	DAM Profits		RTM Profits		DAM+RTM Profits	
	Avg.	Std. Dev.	Avg.	Std. Dev.	Avg.	Std. Dev.
Price-Quantity (MILP)	4500.35	699.68	53.29	422.10	4553.64	709.63
Quantity-Only (LP)	2711.66	198.44	345.03	66.88	3056.69	211.50

TABLE IV
COMPARISON OF NUMBER OF CYCLES OF TWO HOUR STORAGE DEVICE

Type of Optimization	Charge Cycles	
	Avg.	Std. Dev.
Price-Quantity (MILP)	6.54	2.07
Quantity-Only (LP)	4.08	0.40

requiring more cycling of the storage device. However, since the battery is a two hour battery with smaller power capacity, the profits are less on average compared to Case I.

C. Case III

In Case III, the performance of the proposed stochastic Price-Quantity bid MILP algorithm is tested and compared to the Quantity-Only bid LP strategy using real world realized price data under different forecasting methods. Three cases are presented, each identical in terms of optimization models, but with different price forecasting inputs. A total of 130 weekdays are simulated. The 130 days represent weekdays from the second half of the year. Each day is provided with a set of forecasted price scenarios as well as realized prices. A visual representation of the price scenarios in the DAM along with the actual DAM price for that day are shown in Fig. 6. The test procedure, outlined below, simulated how the two different storage strategies would perform in a real-world setting under the three different forecasting methods.

Testing Procedure:

1) Generate price forecasts for a given case
2) Decide the optimal DAM bids based on the N_{DA} price scenarios for 24 h using the Price-Quantity bids (MILP) and Quantity-Only (LP) optimization
3) Clear the DAM based on the historical realized DAM price

Authorized licensed use limited to: University Library Utrecht. Downloaded on October 03,2024 at 12:41:54 UTC from IEEE Xplore. Restrictions apply.

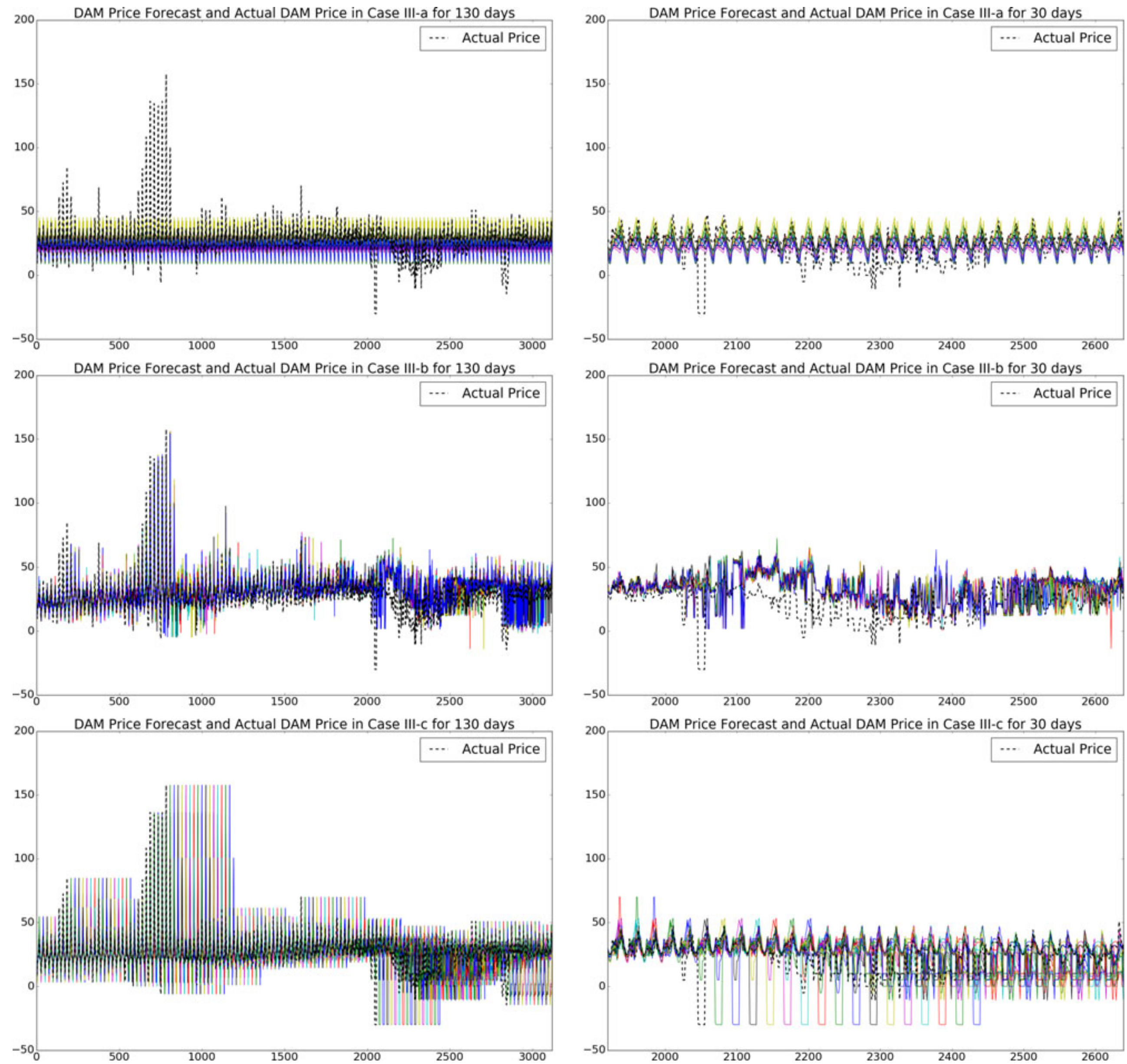

Fig. 6. Hourly forecasted price scenarios and actual realizations in DAM for 130 days and a sample for 30 day period.

4) Using the DAM schedule as input, produce RTM quantity bids based on expected RT prices i.e., the average of the N_{RT} RT price scenarios. Clear the RTM using the historical realized RTM price of that day.
5) Repeat this process for 130 days.

Storage levels are set to zero at the beginning of each simulated day.

N_{DA} is 15 and N_{RT} is 1000.

1) Case III-a: The price forecasts are generated performing a scenario reduction on historical prices for 130 days from the first half of the year. In this case, the forecasts of prices, i.e., the 15 price forecast profiles, are identical for all 130 days, as seen in Fig. 6. All price forecast profiles are weighted equally.

2) Case III-b: N_{DA}^{total} price scenarios were generated for each day using the method described in Section II-A3. Using scenario reduction, the N_{DA}^{total} price scenarios are reduced to $N_{DA}^{reduced}$ price scenarios. In the above described testing procedure, N_{DA}^{total} is 250, $N_{DA}^{reduced}$ is 15 and N_{RT} is 1000. Price forecasts for all days and for a 30–day period are shown in Fig. 6.

3) Case III-c: The price forecasts are generated using prices from the previous 15 days, with all forecasts being weighted equally. This case evaluates the performance of a a persistence rolling forecast.

The tests are conducted for the 1-hour battery (50 MW/ 50 MWh). The results in Table V show that the proposed stochastic MILP algorithm produces a higher cumulative profit under different forecasting techniques, when compared to the LP algorithm for real world price data. Case III-a uses an identical forecast for each simulated day, and hence do not accurately

Authorized licensed use limited to: University Library Utrecht. Downloaded on October 03,2024 at 12:41:54 UTC from IEEE Xplore. Restrictions apply.

TABLE V
COMPARISON OF AVERAGE AND STANDARD DEVIATION OF DAM AND RTM PROFITS OVER 130 DAYS

Case	Type of Optimization	DAM Profits ($)		RTM Profits ($)		DAM+RTM Profits ($)	
		Avg.	Std. Dev.	Avg.	Std. Dev.	Avg.	Std. Dev.
Case III-a	Price-Quantity (MILP)	1025.57	632.07	−1542.48	7025.75	−516.9	6985.76
	Quantity (LP)	405.3	406.92	−1121.45	7002.19	−716.15	7034.27
Case III-b	Price-Quantity (MILP)	−404.12	3603.03	247.0	7575.36	−157.12	7886.61
	Quantity (LP)	494.22	1109.02	−683.08	7105.92	−188.86	7157.32
Case III-c	Price-Quantity (MILP)	1218.76	1495.84	−840.9	8112.48	377.86	8096.99
	Quantity (LP)	934.31	1135.68	−924.74	7727.71	9.57	7762.76

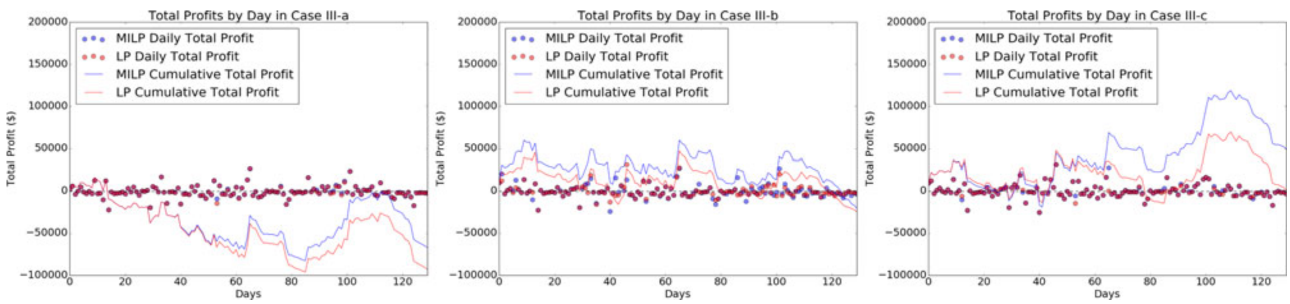

Fig. 7. Daily total profits and cumulative sum of daily profits with MILP and LP algorithm for Case III-a, Case III-b and Case III-c.

forecast the actual realized DAM prices. This naive forecasting methodology results in lower total profits. We can see from Fig. 6 that both the forecasting methodology in Case III-b and Case III-c predicts actual realized DAM prices with a degree of uncertainty. On some days, the forecast in Case III-b does not accurately reflect the actual realized DAM prices, and hence results in a loss in total profit.

This study shows that the proposed MILP algorithm produces a higher average profit, and that when the forecast is better a higher profit can be attained. Fig. 7 shows the daily profits as well as a cumulative sum of daily profits across the simulation for all three cases. We can see that profits for the MILP algorithm are higher than the LP algorithm. When such an algorithm is implemented on a longer time scale, the MILP algorithm tends to outperform the LP algorithm, as inferred from cases I and II.

IV. CONCLUSIONS AND FUTURE WORK

In this paper, we proposed two models for arbitrage maximization in the DAM under price uncertainty. We found that the stochastic Price-Quantity bidding model gives higher profits than the Quantity-Only bidding model on average. However, the standard deviation of profit is higher for the Price-Quantity bidding model, indicating a riskier strategy. Our results also provide insights about how the battery operates in terms of number of charge cycles under the two strategies. With the stochastic Price-Quantity strategy, the battery tends to make more bids in the DAM, which sometimes require that adjustments are made in the RTM for feasibility. This leads to additional cycling of the storage unit. The increased revenue from the energy market must be weighed against the cycling costs for the specific battery. Finally the results show that the profits are lower in general for a longer duration battery as the battery requires longer time to charge/discharge. This is compensated, at least in part, by lower investment costs for longer battery durations. As future work, we plan to extend the proposed models to incorporate the impact of participation in ancillary services markets. Incorporating a representation of risk preferences into our framework, possibly through reducing DAM infeasibilities and thereby exposure to RTM price volatility, is another important extension.

REFERENCES

[1] J. W. Kup, R. M. Gittleman, C. W. Hall, and M. N. Vanko, "California's renewables portfolio standard: Charting the course towards 33% by 2020," *Elect. J.*, vol. 22, no. 4, pp. 79–94, 2009.

[2] J. Eyer and G. Corey, "Energy storage for the electricity grid: Benefits and market potential assessment guide," Sandia Nat. Lab., Livermore, CA, USA, Rep. SAND2010-0815, 2010. [Online]. Available: https://www.smartgrid.gov/sites/default/files/resources/energy_storage.pdf

[3] "Grid energy storage," U.S. Department of Energy, Washington, DC, USA, Rep., Dec. 2013.

[4] J. Garcia-Gonzalez, R. de la Muela, L. Santos, and A. Gonzalez, "Stochastic joint optimization of wind generation and pumped-storage units in an electricity market," *IEEE Trans. Power Syst.*, vol. 23, no. 2, pp. 460–468, May 2008.

[5] M. Korpaas, A. T. Holen, and R. Hildrum, "Operation and sizing of energy storage for wind power plants in a market system," *Int. J. Elect. Power Energy Syst.*, vol. 25, no. 8, pp. 599–606, Oct. 2003. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0142061503000164

[6] P. Denholm and R. Sioshansi, "The value of compressed air energy storage with wind in transmission-constrained electric power systems," *Energy Policy*, vol. 37, no. 8, pp. 3149–3158, Aug. 2009. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0301421509002328

[7] C. Suazo-Martinez, E. Pereira-Bonvallet, R. Palma-Behnke, and X.-P. Zhang, "Impacts of energy storage on short term operation planning under centralized spot markets," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 1110–1118, Mar. 2014.

Authorized licensed use limited to: University Library Utrecht. Downloaded on October 03,2024 at 12:41:54 UTC from IEEE Xplore. Restrictions apply.

[8] N. Li, C. Uckun, E. M. Constantinescu, J. R. Birge, K. W. Hedman, and A. Botterud, "Flexible operation of batteries in power system scheduling with renewable energy," *IEEE Trans. Sustain. Energy*, vol. 7, no. 2, pp. 685–696, Apr. 2016.

[9] R.-C. Leou, "An economic analysis model for the energy storage systems in a deregulated market," in *Proc. IEEE Int. Conf. Sustain. Energy Technol.*, Nov. 2008, pp. 744–749.

[10] N. Lu, J. H. Chow, and A. A. Desrochers, "Pumped-storage hydro-turbine bidding strategies in a competitive electricity market," *IEEE Trans. Power Syst.*, vol. 19, no. 2, pp. 834–841, May 2004.

[11] P. Kanakasabapathy and K. S. Swarup, "Bidding strategy for pumped-storage plant in pool-based electricity market," *Energy Convers. Manage.*, vol. 51, no. 3, pp. 572–579, 2010. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S019689040900421X

[12] D. Connolly, H. Lund, P. Finn, B. Mathiesen, and M. Leahy, "Practical operation strategies for pumped hydroelectric energy storage (PHES) utilising electricity price arbitrage," *Energy Policy*, vol. 39, no. 7, pp. 4189–4196, 2011. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0301421511003156

[13] A. Awad, J. Fuller, T. El-Fouly, and M. Salama, "Impact of energy storage systems on electricity market equilibrium," *IEEE Trans. Sustain. Energy*, vol. 5, no. 3, pp. 875–885, Jul. 2014.

[14] H. Lund, G. Salgi, B. Elmegaard, and A. N. Andersen, "Optimal operation strategies of compressed air energy storage (CAES) on electricity spot markets with fluctuating prices," *Appl. Therm. Eng.*, vol. 29, no. 56, pp. 799–806, Apr. 2009. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1359431108002469

[15] J. Usaola, "Operation of concentrating solar power plants with storage in spot electricity markets," *IET Renew. Power Gener.*, vol. 6, no. 1, pp. 59–66, Jan. 2012.

[16] H. Akhavan-Hejazi and H. Mohsenian-Rad, "Optimal operation of independent storage systems in energy and reserve markets with high wind penetration," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 1088–1097, Mar. 2014.

[17] H. Mohsenian-Rad, "Optimal bidding, scheduling, and deployment of battery systems in California day-ahead energy market," *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 442–453, Jan. 2016.

[18] R. Sioshansi, P. Denholm, T. Jenkin, and J. Weiss, "Estimating the value of electricity storage in PJM: Arbitrage and some welfare effects," *Energy Econ.*, vol. 31, no. 2, pp. 269–277, Mar. 2009. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0140988308001631

[19] K.-H. Ahlert, "Assessing the economics of distributed storage systems at the end consumer level," in *Proc. 4th Int. Renew. Energy Storage Conf.*, 2009.

[20] R. J. Bessa, V. Miranda, A. Botterud, Z. Zhou, and J. Wang, "Time-adaptive quantile-copula for wind power probabilistic forecasting," *Renew. Energy*, vol. 40, no. 1, pp. 29–39, 2012. [Online]. Available: //www.sciencedirect.com/science/article/pii/S0960148111004587

[21] P. Pinson, H. Madsen, H. A. Nielsen, G. Papaefthymiou, and B. Klckl, "From probabilistic forecasts to statistical scenarios of short-term wind power production," *Wind Energy*, vol. 12, no. 1, pp. 51–62, 2009. [Online]. Available: http://onlinelibrary.wiley.com/doi/10.1002/we.284/abstract

[22] N. Growe-Kuska, H. Heitsch, and W. Romisch, "Scenario reduction and scenario tree construction for power management problems," in *Proc. 2003 IEEE Bologna Power Tech Conf.*, vol. 3, Jun. 2003, pp. 7.

Dheepak Krishnamurthy (M'15) received the B.E. degree in electrical and electronics engineering from the SSN College of Engineering, Anna University, Chennai, India, in 2010. He is working toward the M.S. degree in the Department of Electrical and Computer Engineering, Iowa State University, Ames, IA, USA. He has a research internship with Argonne National Laboratory, working on storage modeling. Since January 2015, he has been with the National Renewable Energy Laboratory, Golden, CO, USA, working as a Research Engineer. His research interests include power system operations, stochastic unit commitment, transmission and distribution modeling, and high-performance computing.

Canan Uckun received the B.Sc. degree in industrial engineering from Marmara University, Istanbul, Turkey, in 2003, the M.Sc. degree in industrial engineering from Ko University, Istanbul, Turkey, in 2006, and the Ph.D. degree in operations management/management science from The University of Chicago Booth School of Business, Chicago, IL, USA, in 2012. She is an STA Engineering Systems Modeling in the Center for Energy, Environmental, and Economic Systems Analysis, Argonne National Laboratory, Lemont, IL, USA. She has done research on electricity markets, smart grid, demand response, revenue management, and inventory systems. Her current work includes stochastic unit commitment, renewable integration, grid-level energy storage, and demand response related projects.

Zhi Zhou (M'09) received the B.Eng. and M.Eng. degrees in computer science from Wuhan University, Wuhan, China, in 2001 and 2004, respectively, and the Ph.D. degree in decision sciences and engineering systems from Rensselaer Polytechnic Institute, Troy, NY, USA, in 2010. He is currently a Computational Scientist in the Energy Systems Division, Argonne National Laboratory, Lemont, IL, USA. His research interests include agent-based modeling and simulation, stochastic optimization, statistical forecasting, electricity markets, and renewable energy.

Prakash R. Thimmapuram received the M.S. degree in chemical engineering from the University of Illinois at Chicago, Chicago, IL, USA, in 1992. He is a Principal Computational Scientist with the Energy Systems division of Argonne National Laboratory, Argonne, IL. He has more than 20 years of experience in developing models for energy, environmental, and economic systems analysis. His current research interests include agent-based modeling and simulation, machine learning, electricity markets, and power system analysis.

Audun Botterud (M'04) received the M.Sc. degree in industrial engineering and the Ph.D. degree in electrical power engineering from the Norwegian University of Science and Technology, Trondheim, Norway, in 1997 and 2004, respectively. He was with the SINTEF Energy Research, Trondheim, Norway. He is a Principal Energy Systems Engineer in the Energy Systems Division, Argonne National Laboratory, Lemont, IL, USA, and a Principal Research Scientist in the Laboratory for Information and Decision Systems, Massachusetts Institute of Technology, Cambridge, MA, USA. His research interests include power systems planning and economics, electricity markets, grid integration of renewable energy, energy storage, and stochastic optimization.

Dr. Botterud is the Co-Chair for the IEEE Task Force on Bulk Power System Operations with Variable Generation.

Authorized licensed use limited to: University Library Utrecht. Downloaded on October 03,2024 at 12:41:54 UTC from IEEE Xplore. Restrictions apply.