Online Adaptive Real-Time Optimal Dispatch of Privately Owned Energy Storage Systems Using Public-Domain Electricity Market Prices

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***Abstract*—This paper aims to evaluate and improve the usefulness of publicly available electricity market prices for real-time optimal dispatching (RTOD) of a privately owned energy storage system (ESS) in a competitive electricity market. The RTOD algorithm seeks to maximize the revenue by exploiting arbitrage opportunities available due to the inter-temporal variation of electricity prices in the day-ahead market. The pre-dispatch prices, issued by the Ontario independent electricity system operator, and the corresponding ex-post hourly Ontario energy prices are employed as the forecast and the actual prices. A compressed-air ESS is sized and employed for evaluations due to its lower capital expenditure and its ability to be positively influenced by the availability of waste heat. First, the conventional RTOD algorithm is developed by formulating a mixed integer linear programming problem. It is demonstrated that the forecast inaccuracy of publicly available market prices significantly reduces the ESS revenue. Then, a new adaptive algorithm is proposed and evaluated which adapts the objective function of the optimization problem online based on historical market prices available before real-time. The outcomes reveal that the proposed adaptive RTOD can significantly increase the ESS revenue compared to the conventional algorithm as well as the back-casting method proposed in prior studies.**

***Index Terms*—Adaptive real-time optimal dispatch, electricity market, price forecasting, privately owned energy storage system.**

NOMENCLATURE

Indices:

i, t	Indices for time.
T	Optimization/prediction horizon (h).
T_c	Calibration horizon (h).
Δt	Optimization/calibration time interval (h).
N	Length of optimization horizon $= T/\Delta t$.
M	Length of calibration horizon $= T_c/\Delta t$.

Sets:

$\mathcal{T}$	Set of time steps in the optimization horizon.
$\mathcal{T}_c$	Set of time steps in the calibration horizon.

Parameters:

$P_{\min}^{Chg}$	Minimum allowed charging power (MW).
$P_{\max}^{Chg}$	Maximum allowed charging power (MW).
$P_{\min}^{Dhg}$	Minimum allowed discharging power (MW).
$P_{\max}^{Dhg}$	Maximum allowed discharging power (MW).
$S_{\min}$	Minimum allowed state of the charge (MWh).
$S_{\max}$	Maximum allowed state of the charge (MWh).
η_{Chg}	Charging efficiency (%).
η_{Dhg}	Discharging efficiency (%).
η_{Dsp}	Energy dissipation rate (%/h).
C_{Main}	Maintenance cost per hour of operation ($/h).
C_{ChgO}	Charging operating cost ($/MWh).
C_{DhgO}	Discharging operating cost ($/MWh).
E_t	Electricity price ($/MWh).

Variables:

P_t^{Chg}	Charging power (MW).
P_t^{Dhg}	Discharging power (MW).
M_t^{Chg}	Charging mode, 0: OFF and 1: ON.
M_t^{Dhg}	Discharging mode, 0: OFF and 1: ON.
S_t	State of the charge (MWh).

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I. INTRODUCTION

IN the Ontario power system, several coal power plants have been recently closed. The major power generation in Ontario is currently provided by nuclear power plants which cannot turn down their generation quickly when the load demand is low, mostly during nighttime. Additionally, in many geographical locations, wind generation is maximum at night, a time period when the demand is minimum [1]. This raises the idea of deployment of large-scale energy storage systems (ESSs) in Ontario to shift the surplus energy from the nighttime to peak hours

during the day. This is also a common concern of many other utilities across the world.

On the other hand, in today's competitive electricity markets, utility regulators and policy makers are encouraging private investors to build, own, and operate large-scale ESSs as merchant operators [2]. In such a case, the main objective of the ESS from private owner's perspective would be to generate profit by exploiting arbitrage opportunities. This is achieved mainly by optimally storing inexpensive electric energy during off-peak periods and releasing it when the electricity is expensive during on-peak periods [2].

The optimal dispatching algorithms proposed in some prior studies have been developed for ESSs where the ESS operation is governed to benefit operation of renewable generating resources as part of a grid/microgrid or to achieve some technical objectives for the grid [1], [3]–[6]. A branch of research aims to optimally operate an ESS in the electricity market to generate revenue while it is combined with a wind farm [7]–[9]. In these studies, the ESS is considered as part of the wind farm and, therefore, the wind farm owner must invest in the storage unit. In this way, the ESS cannot be operated as a single entity in the market. Another thread of research seeks to develop deterministic or stochastic optimization tools for energy storage units operating as single entities in an electricity market. They aim to generate different financial benefits in a competitive market [2], [10]–[13]. Another branch of research aims to investigate the economic viability and profitability of two types of storage technologies (i.e., pumped-hydroelectric and compressed-air ESSs) operating in an electricity market to generate revenue [14]–[26].

In the prior optimization algorithms, either deterministic or stochastic techniques are employed to formulate the optimization problem. The deterministic model uses the point forecasts of market prices in the optimization to find the bid schedule. However, it suffers from price forecast inaccuracy [10]. The stochastic programming approach is employed to deal with price forecast inaccuracy to some extent. However, stochastic models are computationally challenging due to the large number of scenarios that have to be considered. The model also requires knowledge of the probability distribution of uncertain variables, which may not be available [9]. In this paper, deterministic optimization approaches have been used.

Among those studies which aim to investigate the economic profitability of ESSs in real-world markets, some studies have estimated the ESS revenue of single or multiple applications, using simplified dispatch assumptions and actual historical market prices [14]–[18]. In [14], three simple strategies are proposed which aim to optimally dispatch the ESS in the day-ahead electricity market based on historical actual prices. The first strategy, called back-casting approach, duplicates the actual prices of the day-behind. The others take the average of last actual and future prices in a user-specified period and bid on the market correspondingly; such strategies require the presence of accurate price forecasts, which may not be available. Simple back-basting approach has been used in some other studies as a practical operation strategy since it would not assume the optimal operation of the ESS with perfect/accurate price forecast. In [15]–[18], the revenue captured using back-casting approach in different markets has been compared with the ideal revenue generated with the assumption of the availability of the perfect price forecast. They have concluded that a considerable amount of revenue can be captured using the back-casting method because off-peak and on-peak periods of prices have fairly consistent daily and seasonal patterns.

However, when the ESS operation is optimized using the back-casting technique, only the lower bound of the revenue could be captured. To obtain a better operation, short-term scheduling of ESSs or other market participants could be carried out using a price forecast. One of the options is that each market player uses its own forecasting algorithm for short-term scheduling. Although various techniques have been reported in the literature to improve price forecast accuracy, short-term operation scheduling in a liberalized electricity market is still a very challenging task due to the uncertainty associated with future electricity prices [27].

The other option would be to employ the public-domain price forecast issued by the system operator. In such a case, the following question will be answered in the present paper: *How useful are these public-domain price forecasts, and what kind of improvement could be applied on them to capture higher revenue for the ESS operation in a competitive electricity market?* The main contributions of this paper are as follows:

1) To evaluate the usefulness of public-domain market price forecasts for real-time optimization of a privately owned ESS operating in a competitive market to generate revenue by exploiting arbitrage opportunities in the day-ahead market.
2) To formulate and evaluate a new adaptive RTOD which calibrates public-domain price forecasts online, based on historical market prices available before real-time, to reduce the adverse impact of forecast inaccuracy on the ESS revenue, thereby capturing higher revenue.

The main goal of this paper would be, therefore, to mine practically available market data, improve them, and use them for real-time optimization of an ESS which is operating in that market. The performance of the proposed method is compared with previous approaches concerning optimal dispatch of ESSs using historical data of real-world markets, including conventional and back-casting methods.

In the Ontario market, several market participants employ the public-domain day-ahead price forecast, named pre-dispatch prices (PDPs), for short-term scheduling in the day-ahead market. However, their optimal operations suffer from forecast inaccuracy [28]. In order for an ESS to be operated in this market based on these public data, the proposed adaptive RTOD could be of great interest. Although the proposed technique has relevance for ESSs, the concept could be used for other market players as well.

The rest of the paper is organized as follows: The conventional RTOD is formulated in Section II. The sizing and modeling of the ESS is described in Section III. The performance of the conventional RTOD is analyzed in Section IV. The proposed adaptive RTOD is presented in Section V. The performance of the adaptive RTOD is evaluated and compared with the conventional RTOD and the back-casting method in Section VI. Section VII summarizes the main findings.

II. Conventional RTOD for a Privately Owned ESS

To develop an RTOD algorithm for a privately owned ESS, a mixed integer linear programming (MILP) optimization problem is formulated as explained in this section. The optimization horizon of 24 h with 1-h time step is considered to determine optimal charging and discharging power set-points. The time step of 1 h is selected since market prices are updated every hour in the case-market of this paper, i.e., the Ontario market. Since optimal decisions are made for the present and future time steps (i.e., optimization horizon), the optimal dispatch problem is a multi-interval optimization problem. Decisions are also updated by re-running the optimization calculations every hour to account for the time-varying nature of electricity prices in the market. In this case, the optimal dispatch problem will include $T/\Delta t = 24\,h/1\,h = 24$ time~steps, each of which represents one hour time interval. In this case, all of the optimization variables will be 1-D arrays with 24 elements decided by the end of each hour of the dispatch time. The aforementioned method is commonly referred to as the rolling time horizon or model predictive control [29], [30].

The objective function of the optimization problem which aims to maximize the ESS revenue by exploiting arbitrage opportunities available due to the price volatility is as follows:

$$\underset{P_t^{Chg},\,P_t^{Dhg}}{\text{Maximize}} \sum_{t=1}^{N}\Big((P_t^{Dhg}-P_t^{Chg})\cdot E_t - C_{DhgO}\cdot P_t^{Dhg} - C_{ChgO}\cdot P_t^{Chg}\Big)\cdot \Delta t \quad (1)$$

including the following terms:

$$\text{Energy price arbitrage benefit}: (P_t^{Dhg}-P_t^{Chg})\cdot E_t \quad (2)$$

$$\text{ESS operating costs}: C_{DhgO}\cdot P_t^{Dhg} + C_{ChgO}\cdot P_t^{Chg} \quad (3)$$

and subject to the following operational constraints of the ESS:

$$M_t^{Chg}\cdot P_{\min}^{Chg} \le P_t^{Chg} \le M_t^{Chg}\cdot P_{\max}^{Chg} \quad \forall t\in\mathcal{T} \quad (4)$$

$$M_t^{Dhg}\cdot P_{\min}^{Dhg} \le P_t^{Dhg} \le M_t^{Dhg}\cdot P_{\max}^{Dhg} \quad \forall t\in\mathcal{T} \quad (5)$$

$$S_{\min} \le S_t \le S_{\max} \quad \forall t\in\mathcal{T} \quad (6)$$

$$S_{t+1} = S_t + \left(\eta_{Chg}\cdot P_t^{Chg} - \frac{P_t^{Dhg}}{\eta_{Dhg}} - \eta_{Dsp}\cdot S_t\right)\cdot\Delta t \quad \forall t\in\mathcal{T} \quad (7)$$

where $\mathcal{T}$ is the set of time steps defined as follows:

$$\mathcal{T} = \{1,\ldots,N\} \text{ where } N = \frac{T}{\Delta t} = \frac{24\,h}{1\,h} = 24. \quad (8)$$

Thus, the optimization variables fall in the following ranges:

$$P_t^{Chg}, P_t^{Dhg} \ge 0 \quad \forall t\in\mathcal{T} \quad (9)$$

$$S_t > 0 \quad \forall t\in\mathcal{T} \quad (10)$$

$$M_t^{Chg}, M_t^{Dhg} = 0 \text{ or } 1 \text{ (binary variables)} \quad \forall t\in\mathcal{T}. \quad (11)$$

The objective function, expressed in (1), includes the financial benefit of selling electricity to the market, the cost of purchasing electricity from the market, and the ESS operating cost for charging and discharging within the optimization horizon, i.e., 24 h. In (1), E_t is the electricity price forecast at the time step t while it is equal to the actual price at the present moment, i.e., $t = 1$. Equations (4)–(6) state charging and discharging powers and state of the charge (SOC) constraints for the ESS. Equation (7) expresses the energy balance of ESS defining the relation of SOC at time steps t and $t+1$.

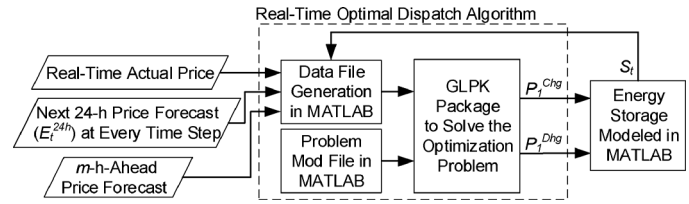

Fig. 1. Flowchart for implementation of the conventional RTOD.

Fig. 1 represents how the proposed RTOD is implemented in this study. The ESS is modeled in MATLAB. The optimization problem including variables, parameters, constraints, and the objective function are defined in a file, which is called hereafter problem mod file, using GNU MathProg modeling language in MATLAB. The values for the problem parameters are generated at each time step by a MATLAB code in another file, hereafter called data file. The data file includes ESS parameters such as minimum and maximum charging/discharging powers, SOC at the present time step, etc. The real-time actual and 24-h-ahead forecasted prices are also inputted to the data file as E_t. If more accurate price forecast is available up to the first few hours (e.g., m hours), it could substitute for the first few hours of the 24-h-ahead forecast. For instance, in the Ontario market, the next 3-h price forecast is published and updated every 1 h [31]. Both data and mod files are inputted to the GNU linear programming kit (GLPK) [32]. Then, the optimization problem is solved by the GLPK package to find the optimal values of charging and discharging power set-points. The charging and discharging power set-points at the present time (i.e., P_1^{Chg} and P_1^{Dhg}) will provide the required commands to the ESS. In the next time step, the SOC (i.e., S_t) is calculated based on the latest power set-point commands. Then, the RTOD algorithm is executed to derive new power set-point commands. This process continues until the end of the simulation period.

III. Sizing and Modeling of a Compressed-Air ESS

Due to its lower capital expenditure and its capability to be positively influenced by the availability of waste heat, a compressed-air energy storage (CAES) unit is sized and used for evaluations. A CAES unit is basically composed of three main plants as follows: Charging plant, compressed-air reservoir plant, and discharging plant. Based on its application, a CAES unit can have different ratings for each of these three plants. These ratings for the overall plant can be specified based on a feasibility study to meet the power available during off-peak time periods versus the power needed during on-peak time periods in the market [33]. In this paper, a CAES unit is sized and modeled based on the parameters reported in Table I. The capital cost of the plant has been assumed to be $1 Million/MW of discharging power [33]. In sizing of the CAES unit, different capacities have been tried based on the proposed ranges in the

TABLE I
OPERATING PARAMETERS OF THE CAES UNIT

$P_{min}^{Chg} = 80\% \times P_{max}^{Chg}$	$\eta_{Chg} = \eta_{Dhg} = 84\%$
$P_{min}^{Dhg} = 3\% \times P_{max}^{Dhg}$	$C_{Main} = 5\% \times$ Capital Cost$/(30 \times 365 \times 24)$
$S_{min} = 10\% \times S_{max}$	$C_{ChgO} = 60\% \times C_{Main}/P_{max}^{Chg}$
$\eta_{Dsp} = 0.0416\% \times S_t$	$C_{DhgO} = 40\% \times C_{Main}/P_{max}^{Dhg}$

TABLE II
RATINGS OF THE CAES UNIT SIZED AND USED IN THIS STUDY

Capital Cost	P_{max}^{Chg}	P_{max}^{Dhg}	S_{max}
\$100 Million	100 MW	100 MW	2000 MWh

literature, such as [34]. The optimal capacity is then selected as 2000 MWh. The compression and generation power ratings, reservoir capacity, and the capital cost of the CAES unit are calculated and reported in Table II.

The operating parameters, used for modeling and simulation of the CAES in this study, are reported in Table I. The values of these parameters are typical and can be different for different types of CAES technologies. In large-scale ESSs including the CAES technology, to maintain rated efficiently, it is required to operate the compression plant close to its rated value. Therefore, $P_{\min}^{Chg}$ is set to 80% of $P_{\max}^{Chg}$. However, the generating turbine and its supplying pump can efficiently operate at very low power set-points [2]. Energy storage dissipation is assumed to be 1% per day resulting in $1/24\% = 0.0416\%$ per hour. The charging efficiency (i.e., η_{Chg}) and discharging efficiency (i.e., η_{Dhg}) have been assumed to be 0.84%, causing a round-trip efficiency of 70% [34], a typical value for a highly efficient unit. With a lower efficiency, the ESS will not be scheduled to exploit lower arbitrage benefits since it might not be able to overcome the energy losses during the process. Hence, it will generate less revenue. Additionally, a higher portion of the energy will be lost during the process. Thus, the absolute value of revenue capture (in terms of \$) will decrease with a lower efficiency for all methods. Nevertheless, a reasonable variation of the parameters reported in Table I will not affect the ultimate outcome of the present study. Using these parameters, the CAES is modeled, and the optimization problem is solved to obtain optimization variables.

IV. PERFORMANCE ANALYSES OF CONVENTIONAL RTOD

In this section, Ontario's wholesale market prices have been used for evaluations. The Ontario independent energy system operator (IESO) publishes two sets of pre-dispatch prices (PDPs) as follows: 24-h-ahead and 3-h-ahead PDPs both with 1-h time resolutions (i.e., $\Delta t = 1$) [31]. The first set is the next day PDPs (starting from 1 am) published at 3:30 pm Eastern Time every day while the second set is the next 3-h PDPs published every hour. The challenge of using IESO-generated PDPs is that the complete next 24-h forecast is not available for every time step between 1 am to 3 pm of each day. For instance, at 10 am, only the next 15 h, i.e., from 10 am to midnight is available. To mitigate this issue, it is proposed to duplicate PDPs at the same hours of the last day for the missing hours.

TABLE III
IDEAL REVENUE OF ESS (MILLION \$) USING ONTARIO'S WHOLESALE MARKET PRICES, AVERAGE PURCHASE AND SALE PRICES (\$/MWh), AND THE ARBITRAGE BENEFIT (\$/MWh)

Year	Ideal Revenue	Average Annual Purchase Price	Average Annual Sale Price	Arbitrage Benefit
2006	6.03	24.98	63.26	38.28
2007	7.21	29.99	75.20	45.21
2008	8.86	27.40	82.29	54.89
2009	5.26	10.76	41.63	30.87
2011	4.62	16.72	42.96	26.24
Average	6.39	21.97	61.07	39.10

TABLE IV
% OF IDEAL REVENUE CAPTURE FOR CONVENTIONAL AND BACK-CAST METHODS USING ONTARIO'S WHOLESALE MARKET PRICES

Year	Conventional Method	Back-Casting Method
2006	53.99	68.28
2007	51.11	66.03
2008	39.61	69.28
2009	51.36	73.22
2011	43.25	71.69
Average	47.37	69.35

Equations (19) and (20) are formulated in the Appendix A to translate IESO-generated PDPs into the next 24-h price forecast at every time step (i.e., E_t^{24h}).

The real-time simulation is executed using Ontario's market prices from 2006 to 2009 and 2011 for three following cases:

A. Optimal Dispatch Using a Perfect Price Forecast

The price forecasts are substituted with the actual prices. In this case, the resulted revenue would be equal to the ideal revenue. The ideal revenue (Million \$), average purchase and sale prices (\$/MWh), and the average arbitrage benefit (\$/MWh), i.e., the difference between sale and purchase prices, are reported in Table III. The differences in ideal revenue for different years, stemmed from different arbitrage potentials in the Ontario market for different years. The higher the arbitrage benefit is, the higher revenue could be generated by the ESS.

B. Optimal Dispatch by Directly Used PDPs

This approach is called conventional algorithm in this study. In this case, the PDPs issued by the Ontario's IESO are used (imperfect forecasting). Table IV reports the annual revenue capture in percent of the ideal revenue for each year as well as the five-year average. As it is demonstrated, a significant portion of the annual revenue is lost due to forecast error in each year.

C. Optimal Dispatch Using Back-Casting Method

As defined earlier in the introduction section, in this approach, the ESS scheduling for the next 24 h is performed using the actual prices in the last 24 h. Table IV reports the annual revenue capture in percent of the ideal revenue by this approach. It can be observed that back-casting method has been more effective than the conventional method in capturing higher revenue, yet a considerable amount of revenue has been lost due to inconsistency of inter-day electricity market prices.

V. Proposed Adaptive RTOD

Studying the actual and forecasted electricity prices issued by different markets especially the Ontario market, authors realized that the average error of publicly available price forecasts does not change abruptly in the market. For instance, if the price in a typical day is under-forecasted, the next day price will also be under-forecasted with a high probability. In order to reveal the consistency of the inter-day forecast error, the forecast error of 24-h-ahead as well as 24-h-behind market prices in each time step has been calculated for the Ontario's wholesale market prices (in 2007 as a sample year) and plotted in Fig. 2. In Fig. 2(a) the results have been represented for the entire year (i.e., 8760 h), whereas the same results for the first month (i.e., 720 h) have been highlighted in Fig. 2(b) for the sake of clarity. It can be observed in Fig. 2 that the forecast errors of 24-h-ahead and 24-h-behind market prices are very close in each time step. This characteristic of the price forecast make it amendable to the proposed adaptive method. Since the amount of forecast error is time-variant, it cannot be compensated using a constant value, but rather it should be dynamically predicted and compensated which is the concern of the proposed adaptive algorithm. Since the RTOD is more sensitive to the arbitrage than absolute values of prices, it is proposed to adapt the objective function of the RTOD by online calibration of the price forecast (i.e., E_t) based on the amount of price under-forecasting/over-forecasting in the past several hours or days, as follows:

$$\underset{P_t^{Chg},\,P_t^{Dhg}}{\text{Maximize}} \sum_{t=1}^{N}\Big(\big(P_t^{Dhg}-P_t^{Chg}\big)\,.\,\big((1+A_t)\,.\,E_t+B_t\big) -C_{DhgO}\cdot P_t^{Dhg}-C_{ChgO}\cdot P_t^{Chg}\Big)\cdot\Delta t \quad (12)$$

in which the calibrated electricity price forecast is as follows:

$$\text{Calibrated price forecast}:\big((1+A_t)\cdot E_t+B_t\big) \quad (13)$$

where A_t and B_t are scaling and offset calibration coefficients, respectively. As per observations, publicly available PDPs are generally acceptable in forecasting off-peak and on-peak periods of prices. For this reason, the calibration methods in this study are only focused on price forecast level correction, but not price forecast time correction. Several historical data lengths such as 1, 2, 7, and 30 days have been considered to estimate the level of the expected under-forecasting or over-forecasting for the next 24 h based on which A_t and B_t are determined. According to the simulation results performed in this study for the Ontario market, increasing the window length beyond 24 h does not improve the outcomes for the studied years. Therefore, in this paper, the results of different methods to estimate calibration coefficients are only presented for 1-day historical data length. However, changing the historical data length to track the behavior of the price forecast could be considered as an option which may help to improve the results for other electricity markets.

Generally, in real-time price forecasting, the forecasting algorithm operates at each time step. Hence, the next T-h price is forecasted at every time step. Thus, for each time step, $N = T/\Delta t$ values of price forecast are available. Additionally,

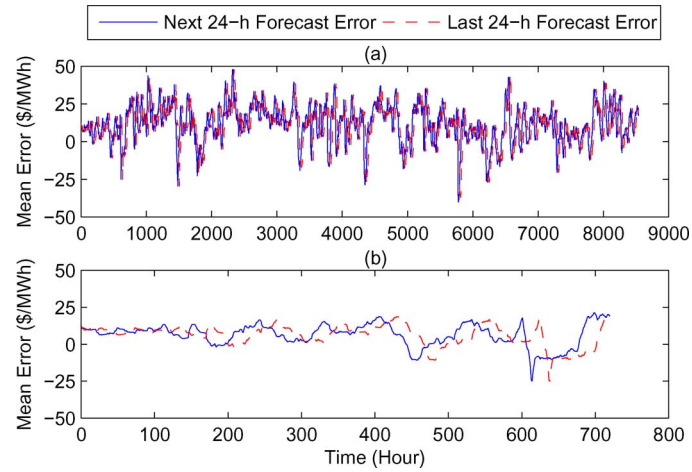

Fig. 2. Forecast error of Ontario's wholesale market prices in the next and last 24 h. (a) In the entire year of 2007. (b) In the first month of 2007.

since the calibration length is $M = T_c/\Delta t$, the forecasted data for the past M time steps should be stored in an $M \times N$ data buffer. Fig. 3 shows how the proposed adaptive RTOD is implemented online. As shown in this figure, the real-time actual and next $N = 24$ forecasted prices are inputted to the data buffer. The data of the 2-D buffer is represented with $E_{i,t}^h$ where i is the time index for the last 24 h, and t points to the next time steps in each time index. Since for every time step in the real-time simulation, the last 24 h data shall be picked from the buffer, i is considered equal to the present time in the 24-h time notation divided by Δt. For instance, at 3 pm, in the real-time simulation, $i = 15/1 = 15$ if Δt is considered 1 h. Therefore, $E_{15,t}^h$ represents historical market prices issued at 3 pm of the last day and stored in the buffer. The scaling and offset calibration coefficients, i.e., A_t and B_t are calculated using historical market prices available in the 2-D historical data buffer as discussed later in this section. Once calibration coefficients are calculated, a limiter is applied to each coefficient to avoid undesired calibration in case of the spurious market behavior. In general, the lower and upper limits can be different, but they are considered identical for the sake of simplicity in this study. The outputs of the limiters are further adjusted by forcing $A_1 = 0$ and $B_1 = 0$ to avoid calibration for the present time step in which the actual price value is available. The values of A_t and B_t for $t = 2$ to m can be forced to zero if a more accurate price forecast is available up to the first few hours (e.g., m hours). For instance, in the Ontario market, a 3-h-ahead price forecast is issued hourly [31]. Hence, the calibration can be performed on the remaining hours since the error of 3-h-ahead PDPs is considerably smaller as compared to 24-h-ahead PDPs. The final coefficients A_t and B_t are inputted to the data file generation block. As per (12), A_t and B_t are used in the objective function of the adaptive RTOD for online calibration of the price forecast (i.e., E_t). Other steps are the same as the conventional RTOD, described in Section II.

In general, two different categories of definitions can be considered for measuring the error of historical price forecast available before real-time. It should be noted that in this paper, the historical forecast error refers to the difference between historical actual prices and historical forecasted prices which are

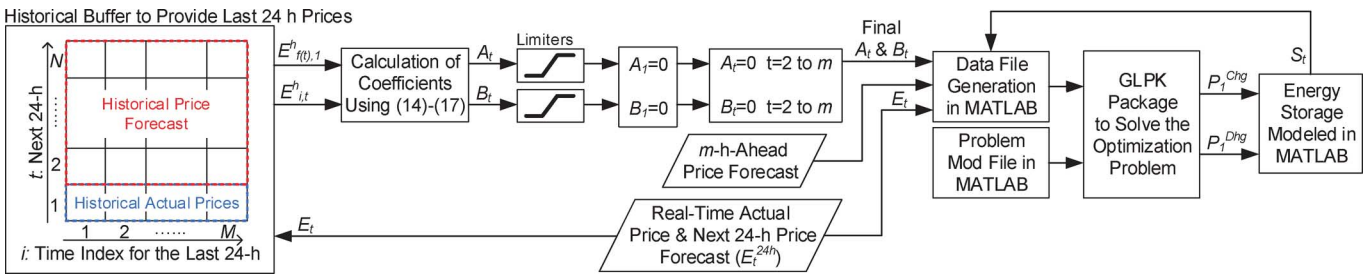

Fig. 3. Flowchart for implementation of the proposed online adaptive RTOD developed for a privately owned energy storage unit.

available before real-time, i.e., in the last 24 h. The first category presents this error in terms of \$/MWh, and the other one presents it in terms of the percentage of the actual price. Each of these categories of definitions can be formulated either as a 1-D array of error with M elements at every time instance or as a single value which is the average of the error array. These definitions, proposed in this paper, are formulated in (14) – (17) for every time index i, as follows:

$$\mathrm{HFME} = \frac{1}{M}\sum_{t=1}^{M}(E^h_{f(t),1} - E^h_{i,t}) \tag{14}$$

$$\mathrm{HFE}_t = E^h_{f(t),1} - E^h_{i,t} \tag{15}$$

$$\mathrm{HFMPE} = \frac{\sum_{t=1}^{M}(E^h_{f(t),1} - E^h_{i,t})}{\sum_{t=1}^{M} E^h_{f(t),1}} \times 100 \tag{16}$$

$$\mathrm{HFPE}_t = \frac{E^h_{f(t),1} - E^h_{i,t}}{\frac{1}{M}\sum_{t=1}^{M} E^h_{f(t),1}} \times 100. \tag{17}$$

In HFME (Historical Forecast Mean Error) and HFE_t (Historical Forecast Error) definitions, the error is in terms of \$/MWh. In HFMPE (Historical Forecast Mean Percentage Error) and HFPE_t (Historical Forecast Percentage Error) definitions, the error is in terms of the percentage of the actual price. Equations (15) and (17) result in 1-D arrays with M elements while (14) and (16) result in single numbers which are the average of (15) and (17), respectively. In (14) – (17), $E^h_{f(t),1}$ is a 1-D array representing historical actual prices in the calibration horizon stored in the first row of the 2-D data buffer (see Fig. 3), where $f(t)$ is a 1-D array with M elements as follows:

$$f(t) = \{i, \ldots, M \,\&\, 1, \ldots, i-1\} \quad \forall i \in \mathcal{T}_c. \tag{18}$$

In the following, four calibration methods are proposed based on the four above-mentioned definitions in (14)–(17).

In Method 1, HFME is calculated based on the definition presented in (14). Then, the calculated HFME is assigned to B_t for the entire prediction horizon while A_t is assumed to be zero. As presented in Fig. 3, B_t can be limited to a certain value such as $\pm\$10$ or $\pm\$20$ which is called calibration limit.

In Method 2, the historical forecast error based on the definition presented in (15) is calculated for every time step t. In this method, the lengths of calibration horizon and prediction horizon shall be selected identical, i.e., $M = N$. The calculated HFE_t is assigned to B_t for every t while A_t is assumed to be zero. In this case, the forecasted price at each t is calibrated online by using the historical forecast error at t of the day before. For instance, the price forecast at 1:00 pm in the next day is calibrated using the historical forecast error at 1:00 pm of the day before and so on for the other time steps.

In Method 3, HFMPE is calculated based on the definition presented in (16). The calculated HFMPE is assigned to A_t for the entire prediction horizon while B_t is assumed to be zero. Similar to prior methods, the value of A_t can be limited to a certain value such as $\pm 30\%$ or $\pm 50\%$.

In Method 4, the percentage error of the historical forecast based on the definition presented in (17) is calculated for every time step t. Similar to Method 2, the lengths of the calibration horizon and prediction horizon shall be selected identical, i.e., $M = N$. Then, the calculated HFPE_t is assigned to A_t for every t while B_t is assumed to be zero.

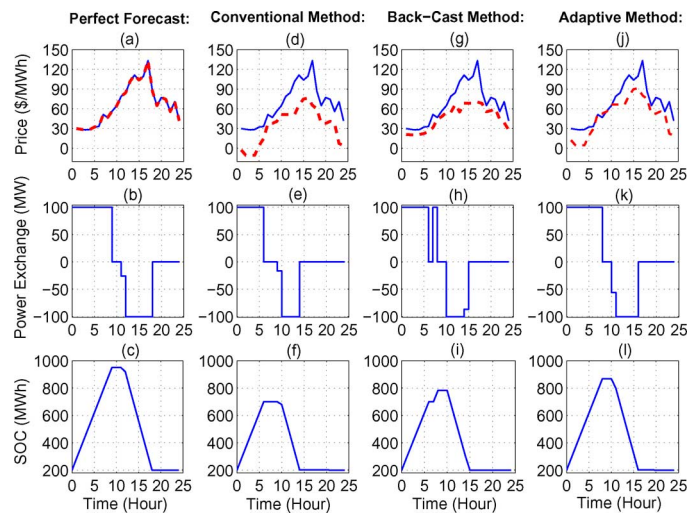

Fig. 4. (a), (d), (g), and (j): Ontario's wholesale market prices in May 15, 2007 (bold line: actual and red dotted line: forecast). (b), (e), (h), and (k): ESS power exchange. (c), (f), (i), and (l): ESS SOC. (a), (b), and (c): For perfect price forecast. (d), (e), and (f): For conventional method. (g), (h), and (i): For back-casting method. (j), (k), and (l): For adaptive algorithm (Method1).

TABLE V
ESS REVENUE IN 24-h UTILIZATION FOR DIFFERENT METHODS USING ONTARIO'S WHOLESALE MARKET PRICES IN MAY 15, 2007

Methods	ESS Revenue (Thousand \$)	% of Ideal Revenue
Perfect Forecast	32.94	100
Conventional	20.43	62.01
Back-Casting	23.64	71.73
Adaptive (Method 1)	27.34	82.98

TABLE VI
% OF IDEAL REVENUE CAPTURE BY PROPOSED METHODS AT DIFFERENT CALIBRATION LIMITS USING ONTARIO'S WHOLESALE MARKET PRICES

	Method 1				Method 2				Method 3				Method 4			
Year	$\pm\$10$	$\pm\$20$	$\pm\$30$	$\pm\$\infty$	$\pm\$10$	$\pm\$20$	$\pm\$30$	$\pm\$\infty$	$\pm30\%$	$\pm50\%$	$\pm70\%$	$\pm\infty\%$	$\pm30\%$	$\pm50\%$	$\pm70\%$	$\pm\infty\%$
2006	69.13	76.36	76.43	76.27	66.44	74.25	74.18	70.95	67.83	70.50	70.90	70.90	65.33	65.65	64.51	63.82
2007	67.57	76.22	77.10	76.96	65.11	73.81	75.72	74.67	63.17	68.05	67.70	67.63	61.20	65.66	66.18	66.20
2008	56.71	73.23	80.57	80.59	54.76	69.33	76.73	78.25	56.16	64.63	66.20	67.06	53.89	61.68	64.94	66.57
2009	68.81	79.69	79.85	76.02	64.38	75.25	76.88	76.22	58.09	65.37	66.21	67.60	55.83	56.45	56.76	57.65
2011	66.40	71.06	72.05	61.65	59.08	67.05	71.14	72.28	60.81	56.99	53.15	51.02	54.35	55.11	54.89	55.46
Average	64.89	75.24	77.66	75.47	61.50	71.91	75.24	74.87	60.93	65.53	65.54	65.68	58.08	61.52	62.34	62.90

VI. PERFORMANCE EVALUATION OF THE ADAPTIVE RTOD

The CAES, sized in Section III, with 70% round-trip efficiency and the proposed adaptive RTOD are modeled in MATLAB (see Fig. 3). To determine the appropriate values of calibration limit, the average error and average percentage error of the Ontario's price forecasts for five years are calculated as \$20/MWh and 50% approximately. These values are applied as the medium calibration limits to $|B_t|$ and $|A_t|$, respectively. Then, approximately 50% lower and higher of these values are selected as the low and high levels of limits, respectively. The real-time simulation is executed at time steps of 1 h. Fig. 4 shows the ESS operation in a sample day (i.e., May 15, 2007) for different methods, including conventional, back-casting, and proposed adaptive algorithm (calibration Method 1). In Fig. 4(b), (e), (h), and (k), the positive and negative power exchanges indicate charging and discharging, respectively. As shown in Fig. 4(c), (f), (i), and (l), the SOC increases when the ESS is charging; it slowly drops with the ESS dissipation rate when the power exchange is zero; and it decreases when the ESS is discharging. The ESS generates revenue by purchasing and charging inexpensive energy at low prices; then discharging and selling it back to the market at high prices. The ESS operation for each method is different, thereby different percentages of ideal revenue are captured as reported in Table V. As presented in Table V, the proposed adaptive algorithm has outperformed both conventional and back-casting methods in capturing higher revenue in this day.

The values of ESS revenue are computed using proposed adaptive RTOD for Ontario's wholesale market prices in different time periods: $\{2006, \ldots, 2009, 2011\}$, different calibration methods: $\{\text{Method } 1, \ldots, \text{Method } 4\}$, and different calibration limits: $\{\pm30\%, \pm50\%, \pm70\%, \pm\infty\%\}$ for A_t and $\{\pm\$10, \pm\$20, \pm\$30, \pm\$\infty\}$ for B_t; where $\pm\infty$ indicates that there is no calibration limit on A_t and B_t.

To analyze and compare the results of the proposed adaptive RTOD with prior methods (i.e., conventional and back-casting methods), the percent of the ideal revenue capture using the adaptive RTOD has been calculated and reported in Table VI for 96 case studies. As reported in Table VI, in all years, the annual revenue capture is increased considerably by using the proposed adaptive RTOD compared to the conventional RTOD (see Table IV). However, for different calibration methods, the level of the improvement in revenue capture is different. Table VI states that the largest values of revenue for five-year average in the Ontario market can be captured at a specific calibration limit for each method, as follows: Methods 1 and 2 with $\pm\$30/\text{MWh}$ and Methods 3 and 4 with $\pm\infty\%$ limits.

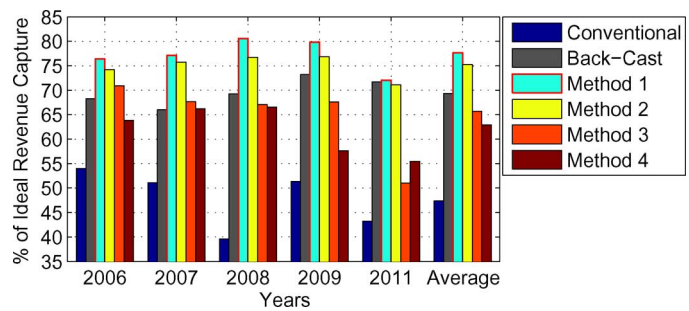

Fig. 5. % of ideal revenue capture for conventional, back-cast, and proposed methods with the optimal calibration limit (Methods 1 and 2 with $\pm\$30/\text{MWh}$ limit and Methods 3 and 4 with $\pm\infty\%$ limit), using Ontario's market prices.

Fig. 5 represents the % of the ideal revenue capture for the proposed calibration methods with the above-mentioned calibration limits as well as the revenue capture using conventional and back-casting methods. According to Fig. 5, the outcomes of Methods 1 and 2 are more or less the same; the outcomes of Methods 3 and 4 are also approximately the same. In the Ontario market, the public-domain price forecast in most hours or days has a negative/positive offset. Since this offset is time-variant, it cannot be compensated using a constant value, but rather it should be dynamically predicted and compensated, which is the case in Methods 1 and 2. For this reason, Methods 1 and 2, which are based on price shifting, would be more effective in correcting the arbitrage forecast. However, for other markets, Methods 3 and 4 might be more effective if the forecast has the scaling error. As shown in Fig. 5, while all of the four proposed calibration methods have outperformed the conventional method significantly, the back-casting method has been more effective than Methods 3 and 4 in general. However, in all years, the Method 1 has been more effective than both conventional and back-casting methods in capturing higher revenue (i.e., 30.3% and 8.3% higher revenue compared to conventional and back-casting methods, respectively).

Finally, in order to analyze the profitability level of the investment, the expected rate of return (ROR) needs to be determined, which could be different for each project, e.g., 5%, 8%, and 13% depending on its risk profile. In the following, the ability of the ESS operating under different algorithms to capture an annual net revenue of \$8.34 M is investigated. For a \$100 M investment, this corresponds to an annual capital recovery factor (CRF) of 8.34% and an ROR of 7.35%. The higher the capital cost is, the higher amount of net revenue would be required to achieve any given ROR and, therefore, the chance of being profitable for the plant would be less. However, the main goal of the proposed adaptive RTOD algorithm would be to exploit energy

TABLE VII
PROFITABILITY LEVELS OF THE INVESTMENT (IN %) AND THE BREAK-EVEN TIME (IN YEAR) FOR DIFFERENT METHODS

	Perfect Forecast	Conventional Method	Back-Casting Method	Adaptive Method 1
Profitability Level	77%	36%	53%	60%
Break-Even Time	15.65 Yr	33 Yr	22.57 Yr	20.12 Yr

price arbitrage opportunities in the wholesale electricity market in an optimal fashion, thereby increasing the profitability level of the plant regardless of the capital investment. To fill the gap between current and a stable ROR, some subsidization policies, such as capital cost sharing between the utility regulator and the private investor, may be applied.

While the profitability level of 100% is required for the plant to generate \$8.34 M per year, the profitability levels for different methods based on the five-year average revenue in the Ontario market are calculated and compared in Table VII. In this table, the break-even time is also reported which is the amount of time needed for generated revenue to equal the initial capital cost. As indicated in Table VII, although the plant is not profitable under different algorithms, the proposed adaptive method outperforms the conventional and back-casting methods due to the higher profitability level and lower break-even time.

VII. CONCLUSION

In this paper, the usefulness of publicly available market prices for optimal dispatching of a privately owned ESS in a competitive electricity market was evaluated and improved. A CAES unit was sized, modeled, and employed for evaluations. An RTOD algorithm was developed by formulating an MILP problem which aims to generate revenue by exploiting arbitrage opportunities in the day-ahead electricity market. It was demonstrated that for the five-year average of Ontario's market prices, around 50% of the ideal revenue is lost due to inaccuracy of PDPs. The back-casting method, proposed in prior studies, was evaluated. Although it was more effective than the conventional method, around 30% of the ideal revenue was lost due to inconsistency of inter-day market prices. Then, a new adaptive algorithm was proposed and evaluated which adapts the objective function of the optimization problem online based on 24-h-behind market prices. The percent of the ideal revenue capture using the adaptive, conventional, and back-casting methods was compared. For the five-year average of Ontario's market prices, the proposed adaptive RTOD could generate up to 30.3% and 8.3% higher revenue as compared to the conventional and back-casting methods, respectively.

APPENDIX
TRANSLATING PDPS INTO THE DESIRED PRICE FORECAST

To translate 24-h-ahead PDPs into a 24-h forecast at every time step (i.e., E_t^{24h}), (19) and (20) are formulated as follows:

$$E_t^{24h} = \begin{cases} E_{1,t}^{Tmp} & 1 \le t \le 24 \quad i = 1 \\ E_{1,g(t)}^{Tmp} & 1 \le t \le 24 \quad 2 \le i \le 15 \\ \left(\begin{cases} E_{2,g(t)}^{Tmp} & 1 \le t \le 25 - i \\ E_{1,t-(25-i)}^{Tmp} & 26 - i \le t \le 24 \end{cases} \right) & 16 \le i \le 24 \end{cases} \tag{19}$$

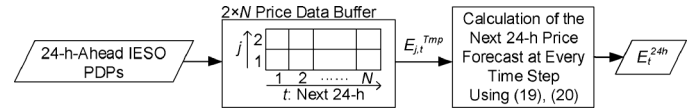

Fig. 6. Translating 24-h-ahead IESO PDPs into the next 24-h price forecast.

where $g(t)$ is defined as follows:

$$g(t) = \begin{cases} \{i, \ldots, 24 \,\&\, 1, \ldots, i-1\} & 2 \le i \le 15 \\ \{i, \ldots, 24\} & 16 \le i \le 24 \end{cases} \tag{20}$$

where i is the time index equal to real-time and t points to next 24 h in each time index. The model is shown in Fig. 6.

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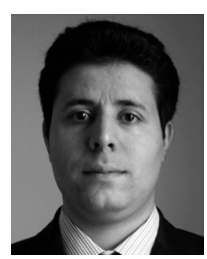

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