Real-Time Optimal Dispatch and Economic Viability of Cryogenic Energy Storage Exploiting Arbitrage Opportunities in an Electricity Market

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***Abstract*—In this paper, the economic viability and profitability of a newly emerging storage technology, i.e., cryogenic energy storage (CES), is investigated. A real-time optimal dispatching algorithm is proposed and developed to optimally dispatch a privately owned CES unit to generate revenue by exploiting arbitrage opportunities in the day-ahead/week-ahead electricity market. Due to its special characteristics, CES can provide significantly more financial and technical benefits in a weekly scheduling compared with common daily scheduling. The electricity price modulation is proposed as a new approach to competitively offer subsidy by the utility regulator to CES owners to fill the gap between current and a stable expected rate of return. Using real-world price data from the Ontario wholesale electricity market, the method is validated. The results reveal significant benefits of weekly usage as compared to daily usage of CES. The efficacy and feasibility of the proposed approach to subsidize CES owners are validated through simulation studies.**

***Index Terms*—Cryogenic energy storage (CES), energy shifting, real-time optimal dispatching (RTOD), subsidy, weekly and daily usages.**

NOMENCLATURE

Indices:

t	Index for time.
T	Optimization/prediction horizon (h).
Δt	Optimization time interval (h).
N	Length of optimization horizon = $T/\Delta t$.

Sets:

$\mathcal{N}$	Set of time steps in the optimization horizon.

Parameters:

I	Electricity price modulation factor.
$P_{\min}^{\mathrm{Chg}}$	Minimum allowed charging power (MW).
$P_{\max}^{\mathrm{Chg}}$	Maximum allowed charging power (MW).
$P_{\min}^{\mathrm{Dhg}}$	Minimum allowed discharging power (MW).
$P_{\max}^{\mathrm{Dhg}}$	Maximum allowed discharging power (MW).
$S_{\min}$	Minimum allowed state of the charge (MWh).
$S_{\max}$	Maximum allowed state of the charge (MWh).
S_{Int}	Initial state of the charge (MWh).
T^{Chg}	Charging period (h).
T^{Dhg}	Discharging period (h).
W^{Chg}	Charging energy (MWh).
W^{Dhg}	Discharging energy (MWh).
η_{Chg}	Charging efficiency (%).
η_{Dhg}	Discharging efficiency (%).
η_{Dsp}	Energy dissipation rate (%/h).
C_{Cap}	Capital cost (total investment) per hour ($/h).
C_{Main}	Maintenance cost per hour of operation ($/h).
C_{ChgO}	Charging operating cost ($/MWh).
C_{DhgO}	Discharging operating cost ($/MWh).
C_{EInc}	Hourly expected income due to investment ($/h).
E_t	Electricity price ($/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, almost all coal power plants have been recently closed. The major power generation in Ontario is currently provided by nuclear power plants (NPPs) (base-load generation) which cannot turn down their generation quickly when the load demand decreases mostly during nighttime [1]. Additionally, the costs of energy generation from such a capital-intensive power plant (i.e., NPP) can be sizable if facilities are operated at less than full capacity [2]. Moreover, wind generation typically is maximum at night, a time period when the demand is minimum [3]. This raises the idea of deploying large-scale energy storage systems (ESSs) in Ontario to shift the excess energy from nighttime to peak hours during the day. While the amount of surplus power available during off-peak periods and the amount of load demand during on-peak periods are not still significant for generating an attractive energy price arbitrage benefit to make any ESS investments economical today, it is expected that more arbitrage opportunities become available in the market in the near future. This is because as the wind power penetration in the Ontario market increases and more push is applied to minimize the use of hydrocarbons for electric energy generation, there would be more surplus power available during off-peak periods and more demand during on-peak periods. In addition, as the technology grows, more efficient ESSs with lower capital costs are expected to emerge in the near future. Although price arbitrage benefits in current electricity markets do not offer an attractive rate of return (ROR) to make any ESS investments economical today, ESS diffusion for large-scale energy shifting can be still justified due to several technical benefits of ESSs for the system.

On the other hand, in today's competitive electricity markets, utility regulators are encouraging private investors to build, own, and operate large-scale ESSs. In such a case, the main objective of an ESS from private owner's perspective would be to generate revenue. This is achieved mainly by optimally storing inexpensive electricity and releasing it when the electricity is expensive. This is the main concept of energy shifting which also results in peak shaving [1], [4].

The energy storage operation in some prior studies is governed to benefit operation of renewable generation resources as part of a grid/microgrid or to achieve technical objectives for the grid [3], [5]–[8]. A branch of research aims to optimally operate an energy storage unit in the electricity market to generate revenue while it is combined with a wind farm [9]–[11]. In this way, the ESS cannot be operated as a single entity in the market. Another branch of research seeks to develop deterministic or stochastic optimization tools for ESSs operating as single entities in an electricity market to generate different financial benefits [12]–[14]. Another thread of research aims to investigate the profitability of two types of storage technologies (i.e., pumped-hydroelectric and compressed-air ESSs) operating in an electricity market to generate revenue [1], [15]–[18].

There are also few studies in the literature about cryogenic energy storage (CES) applications as peak-shaving solutions. For instance, in [19], off-peak electricity is used to produce liquid nitrogen and oxygen in air separation and liquefaction units, respectively. During on-peak periods, natural gas is burned by the oxygen from the air separation unit to generate electricity. In [20], the energy use of the air separation unit of a 530 MW coal-fired power plant has been shifted from on-peak to off-peak periods to obtain financial benefits. A model is proposed in [2] by integrating a NPP with a large-scale CES unit to achieve time shifting of the electric power output. The combination of the nuclear power generation and

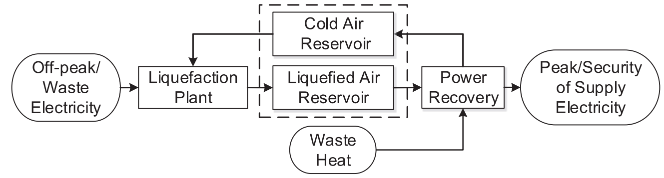

Fig. 1. Generic block diagram of a CES unit [4], [28].

the CES technology provides an efficient way to use significant thermal energy of the NPP during the power extraction process.

The prior studies, however, do not address the challenges of CES operation in an electricity market. Further work is, therefore, needed to study the economic aspects associated with this newly emerging technology. In this paper, a comprehensive economic study is conducted on the feasibility of the CES deployment in the Ontario electricity market.

Compared to [4], which uses a nonreal-time optimal dispatching algorithm and the generic price profile, in this paper, a real-time optimal dispatching (RTOD) algorithm is applied with a new technique of price modulation to subsidize ESS owners. Moreover, the findings are validated using real-world price data from the Ontario electricity market.

The main contributions of this paper are listed as follows.

1) To propose and develop RTOD for weekly scheduling of a certain type of ESS (i.e., CES) compared to common daily scheduling.
2) To propose and develop the electricity price modulation as part of the real-time optimization algorithm to competitively offer subsidy by utility regulators to private investors in ESSs to fill the gap between current and a stable expected ROR.
3) To comprehensively study the economic viability of the operation of a newly emerging energy storage technology (i.e., CES) in competitive electricity markets.

While weekly scheduling is proposed for the CES technology, the proposed methodology for optimal dispatching of privately owned ESSs to exploit energy price arbitrage opportunities as well as the use of modulation factor to subsidize ESSs can be applied to other storage technologies.

The rest of this paper is organized as follows. The CES is introduced in Section II. The methodology for the ESS sizing, formulation of the RTOD algorithm, and subsidy provision for the ESS are described in Section III. The performance of the CES is analyzed in Section IV. Real-world price data are used for evaluations in Section V. Finally, Section VI summarizes the main findings of this paper.

II. CES: Background and Description

The concept of storing energy in the form of liquefied air (i.e., CES) was first investigated in 1977 [21]. Later on, numerous theoretical and experimental studies were conducted on the subject by both industries, such as [22]–[25] and academic institutes, such as [2], [19], [20], and [26]. Finally, all of these efforts led to a completely operational grid-tied pilot plant in U.K., in 2011 [27].

As represented in Fig. 1, a CES unit comprises of three major components: liquefaction plant, liquefied and cold air reservoirs, and power recovery plant [4], [28]. In this technology, cryogen (liquid air) is produced using electric energy in the liquefaction plant. The resultant cryogen, which is around $-190\,°\mathrm{C}$, is stored at low pressure in the liquefied air reservoir which is vacuum insulated. The dissipation rate is usually very small, i.e., around 0.1%–0.2% of the reservoir capacity per day. During power recovery, auxiliary heat (i.e., waste heat from any source or even from ambient conditions) is added to the cryogen converting it into the superheated vapor (gaseous phase) at a high pressure. The high-pressure gas then expands in a series of expansion turbines driving synchronous generator(s) to generate electricity. In this technology, low-grade heat from industrial process plants can be effectively used to improve the system efficiency. While the production of cryogen has a relatively low efficiency, i.e., about 30%, but this is greatly increased to around 50% when a low-grade cold storage is used. Use of auxiliary waste heat could increase the round-trip efficiency level up to 70% range [4], [29].

Two key advantages of the CES technology which discriminate it from other energy storage technologies (e.g., battery, pumped-hydro, and compressed-air ESSs) are as follows.

1) The CES reservoir is significantly inexpensive compared to liquefaction and power recovery plants and does not occupy large space due to its higher energy density (100–200 W.h/kg) [4], [28], [29]. Thus, it would be significantly inexpensive to increase the storage capacity. This is especially important to allow economic weekly usage of CES compared to the common daily usage. Further, this makes the CES technology superior to other technologies for long-term energy storing.
2) The CES technology has a highly efficient heat-to-power conversion in energy extraction process using cryogen itself as a working fluid [30], [31]. This capability makes the CES technology a more economically viable solution compared to common technologies when significant waste heat is available (e.g., in combination with NPPs [2]). In such a case, the round trip efficiency of CES can even reach to around 70% (a very high efficiency value for a large-scale ESS) due to the elevated topping temperature in superheating process [2].

III. METHODOLOGY

In this paper, the CES is considered as a single entity which can freely purchase/sell electricity from/to the day-ahead or week-ahead electricity market. An RTOD algorithm is developed to optimally dispatch the CES to generate revenue by utilizing energy price volatility. The RTOD also modulates the electricity prices using the modulation factor offered by the utility regulator to subsidize the ESS owner, based on a new approach proposed in this paper. The framework of the proposed model in this paper is briefly depicted in Fig. 2. This model is described in detail throughout this paper.

A. Daily and Weekly Sizing of Two CES Units

In order to fairly compare financial benefits of weekly and daily usages of CES, two equally expensive CES units are sized in this section using a simple method. Several parameters

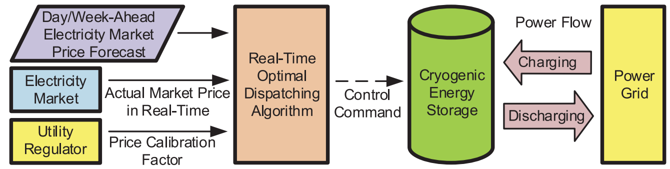

Fig. 2. Framework of the proposed model in this paper.

TABLE I
PARAMETERS USED TO SIZE CES FOR WEEKLY AND DAILY USAGES

T^{Chg} in Weekends for Weekly Usage	48 h per week
T^{Chg} in Weekends for Daily Usage	0 h per week
T^{Dhg} in Weekends for Weekly and Daily Usages	0 h per week
T^{Chg} in Weekdays for Weekly and Daily Usages	5 h per day
T^{Dhg} in Weekdays for Weekly and Daily Usages	3 h per day
Maximum Charging Efficiency	83%
Maximum Discharging Efficiency	83%
Capital Cost of Charging Plant	$1.68 Million/MW
Capital Cost of Discharging Plant	$0.56 Million/MW
Capital Cost of Reservoir Plant	$0.007 Million/MWh

are assumed in the sizing process. Since CES is a very new technology, no accurate parameters such as efficiency and cost have been found in literature. Some approximate parameters are provided by the manufacturer [29] for this paper. Table I presents the parameters used to size the CES unit. The charging/discharging periods reported in Table I have been specified to meet the power available during off-peak time periods versus the power needed during on-peak time periods in the Ontario electricity market.

As mentioned in Section II, the efficiency of the CES unit can vary from 30% to 70% depending on the size, use of low-grade cold reservoir, and use of waste heat. Maximum efficiency is used for CES sizing to allow performance comparison at high and low efficiencies. The round-trip efficiency has been equally split between charging and discharging plants. In practice, charging and discharging efficiencies are based on the ESS technology, provided by the ESS manufacturer. Since the main purpose of this paper would be to compare weekly and daily usages, any reasonable variation in typical parameters used in this paper will not impact the ultimate outcomes.

Weekly usage is considered as the base for sizing two equally expensive CES units, i.e., CES_1 and CES_2 for weekly and daily usages, respectively. The maximum discharging power for CES_1 is assumed to be 100 MW. Based on the CES maximum efficiency and desired hours of charging and discharging in weekly usage, maximum charging power (i.e., liquefaction plant rating) and the reservoir size are obtained. Then, the capital cost of CES_1 is calculated. For CES_2, the maximum discharging power is unknown; instead, the capital cost is known and is the one calculated for CES_1. Based on the CES maximum efficiency and desired hours of charging and discharging in daily usage and the cost, three equations and three unknowns including maximum charging and discharging powers and the reservoir size can be written and solved.

In weekly design, i.e., CES_1, the total charging period, i.e., T^{Chg} is 73 h, (two full weekends plus five weekdays each with 5 h of charging opportunity) = 2×24+5×5, while the discharging period, i.e., T^{Dhg} is 15 h, (five weekdays each with 3 h of discharging opportunity) = 5×3. Hence, based on the maximum discharging power (i.e., 100 MW in weekly usage), the total required charging energy (i.e., W^{Chg}) and the rating of liquefaction plant (i.e., $P_{\max}^{\text{Chg}}$) can be calculated as follows:

$$W^{\text{Chg}} = \frac{W^{\text{Dhg}} = P_{\max}^{\text{Dhg}} \times T^{\text{Dhg}}}{\eta_{\text{Chg}} \times \eta_{\text{Dhg}}} = 2177\,\text{MWh} \tag{1}$$

$$P_{\max}^{\text{Chg}} = \frac{W^{\text{Chg}}}{T^{\text{Chg}}} = 30\,\text{MW}. \tag{2}$$

To determine maximum state of the charge (SoC), 20% extra size is considered to maintain minimum 10% charge and 10% to take benefit in cases where the electricity price suddenly increases. Larger reservoir capacities could deal with market price forecast uncertainties to some extent, thereby increasing ESS revenue capture [1]. Since, this paper does not mainly aim to deal with price forecast inaccuracy, the maximum reservoir capacity is determined only based on full charging on two days of the weekend and off-peak charging on the following Monday which equals $2 \times 24 + 5 = 53$ h, as follows:

$$S_{\max} = 53 \times P_{\max}^{\text{Chg}} \times \eta_{\text{Chg}} \times 1.2 = 1575\,\text{MWh}. \tag{3}$$

The total capital cost of CES_1 can be calculated as follows:

$$1.68P_{\max}^{\text{Chg}} + 0.56P_{\max}^{\text{Dhg}} + 0.007S_{\max} = \$117\,\text{Million}. \tag{4}$$

In daily design (i.e., CES_2), the total charging period (i.e., T^{Chg}) is 5 h while the discharging period (i.e., T^{Dhg}) is 3 h. The maximum discharging power is unknown. The total charging energy (i.e., W^{Chg}) and the rating of the liquefaction plant (i.e., $P_{\max}^{\text{Chg}}$) can be calculated as shown in the following:

$$W^{\text{Chg}} = \frac{W^{\text{Dhg}} = P_{\max}^{\text{Dhg}} \times T^{\text{Dhg}}}{\eta_{\text{Chg}} \times \eta_{\text{Dhg}}} = 4.35P_{\max}^{\text{Dhg}}\,\text{MWh} \tag{5}$$

$$P_{\max}^{\text{Chg}} = \frac{W^{\text{Chg}}}{T^{\text{Chg}}} = 0.87P_{\max}^{\text{Dhg}}\,\text{MW}. \tag{6}$$

The same as weekly usage, the maximum reservoir size in the daily usage is calculated as follows:

$$S_{\max} = 5 \times P_{\max}^{\text{Chg}} \times \eta_{\text{Chg}} \times 1.2 = 4.33P_{\max}^{\text{Dhg}}\,\text{MWh}. \tag{7}$$

To maintain the same cost as the CES_1, (4), (6), and (7) can be solved and three unknowns $P_{\max}^{\text{Chg}}$, $P_{\max}^{\text{Dhg}}$, and $S_{\max}$ can be found as reported in Table II. This table presents the charging, discharging, and reservoir plant sizes for CES_1 and CES_2.

B. RTOD for Privately Owned ESS

Either deterministic or stochastic techniques could be employed to formulate the optimization problem. The deterministic model uses the point forecast of market prices for ESS scheduling. The stochastic model does not require the point forecast of market prices, but rather statistical behavior of the energy price is used. As explained in this section, a deterministic optimization model has been developed in this paper since the point forecast of market prices is assumed to be available. Nevertheless, the proposed concepts in this paper could be also applied in stochastic optimization models.

TABLE II
RATINGS OF THE CES SIZED FOR WEEKLY AND DAILY USAGES

Capital	CES_1: Weekly Usage			CES_2: Daily Usage		
Cost	$P_{\max}^{\text{Chg}}$	$P_{\max}^{\text{Dhg}}$	$S_{\max}$	$P_{\max}^{\text{Chg}}$	$P_{\max}^{\text{Dhg}}$	$S_{\max}$
\$117 M	30 MW	100 MW	1575 MWh	50 MW	57 MW	247 MWh

A mixed integer linear programing problem (MILP) is formulated as explained in this section. Optimization horizons with 24 and 168 h are considered for ESS daily and weekly usages, respectively, to determine optimal charging and discharging power set-points for the ESS. The time step of 1 h is selected since electricity 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 within the optimization horizon, the optimal dispatch problem will be a multiinterval optimization problem. Decisions are also updated by rerunning the optimization calculations every hour to account for the time-varying nature of electricity prices in the electricity market. In this case, the multiinterval optimization problem will include $T/\Delta t =$ time steps, equal to 24 for daily usage and 168 for weekly usage; each time step represents a 1 h time interval. In this case, all of the optimization variables will be arrays with 24 or 168 elements depending on daily or weekly usage that are decided by the end of each hour of dispatch time. The aforementioned method is commonly referred to as the rolling time horizon or model predictive control [32], [33].

The objective function of the optimization problem, which aims to maximize CES revenue by exploiting arbitrage opportunities available due to price volatility in the day-ahead/week-ahead electricity market, is formulated as follows:

$$\underset{P_t^{\text{Chg}},\, P_t^{\text{Dhg}}}{\text{Maximize}} \quad \sum_{t=1}^{N} \Big(\Big(P_t^{\text{Dhg}} - P_t^{\text{Chg}} \Big) . E_t - C_{\text{DhgO}} . P_t^{\text{Dhg}} - C_{\text{ChgO}} . P_t^{\text{Chg}} \Big) . \Delta t \tag{8}$$

including the following terms:

$$\text{Electricity price arbitrage benefit: } \Big(P_t^{\text{Dhg}} - P_t^{\text{Chg}} \Big) . E_t \tag{9}$$

$$\text{ESS operating costs: } C_{\text{DhgO}} . P_t^{\text{Dhg}} + C_{\text{ChgO}} . P_t^{\text{Chg}} \tag{10}$$

subject to the following operational constraints of the ESS:

$$M_t^{\text{Chg}} . P_{\min}^{\text{Chg}} \le P_t^{\text{Chg}} \le M_t^{\text{Chg}} . P_{\max}^{\text{Chg}} \quad \forall t \in \mathcal{N} \tag{11}$$

$$M_t^{\text{Dhg}} . P_{\min}^{\text{Dhg}} \le P_t^{\text{Dhg}} \le M_t^{\text{Dhg}} . P_{\max}^{\text{Dhg}} \quad \forall t \in \mathcal{N} \tag{12}$$

$$S_{\min} \le S_t \le S_{\max} \quad \forall t \in \mathcal{N} \tag{13}$$

$$S_{t+1} = S_t + \left(\eta_{\text{Chg}} . P_t^{\text{Chg}} - \frac{P_t^{\text{Dhg}}}{\eta_{\text{Dhg}}} - \eta_{\text{Dsp}} . S_t \right) . \Delta t \quad \forall t \in \mathcal{N} \tag{14}$$

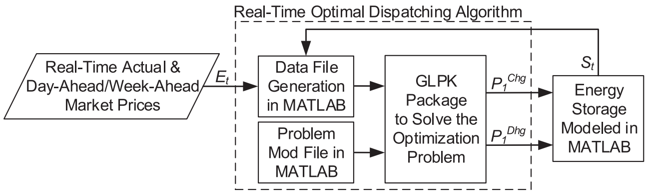

Fig. 3. Flowchart for implementation of the proposed RTOD.

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

$$\mathcal{N} = \{1, \ldots, N\} \text{ where } N = T/\Delta t = 24 \text{ or } 168. \quad (15)$$

Thus, the optimization variables fall in the following ranges:

$$P_t^{\text{Chg}}, P_t^{\text{Dhg}} \geq 0 \quad \forall t \in \mathcal{N} \quad (16)$$

$$S_t > 0 \quad \forall t \in \mathcal{N} \quad (17)$$

$$M_t^{\text{Chg}}, M_t^{\text{Dhg}} = 0 \text{ or } 1 \text{ (binary variables)} \quad \forall t \in \mathcal{N}. \quad (18)$$

E_t is the electricity price defined as follows:

$$E_t = \begin{cases} \text{Forecasted price} & \forall t \in \mathcal{N} \wedge t \neq 1 \\ \text{Actual price in real-time} & \forall t \in \mathcal{N} \wedge t = 1 \end{cases} \quad (19)$$

which means in real-time (i.e., $t = 1$), the actual price is used instead of the forecasted one since it is available at $t = 1$.

Equations (11)–(13) express charging and discharging powers and SoC constraints for the ESS. The energy balance of the ESS is expressed in (14) defining the relation of SoC at time steps t and t+1.

As expressed in (9) and (10), the objective function includes the energy price arbitrage benefit and the ESS operating expenditure (OPEX), including charging and discharging operating costs within the optimization horizon, i.e., 24 or 168 h depending on daily or weekly usages.

Fig. 3 represents how the proposed RTOD is implemented in this paper. The ESS is modeled in MATLAB. The optimization problem is defined in a file, hereafter called problem file, using GNU MathProg modeling language. The values for the optimization parameters are generated at each time step by a MATLAB code in another file, hereafter called data file. The data file includes ESS parameters and the electricity price forecast for the optimization horizon (i.e., E_t). Both files are inputted to the GNU linear programming kit (GLPK) [34]. Then, the optimization problem is solved by GLPK package to find the values of optimization problem variables such as charging and discharging powers. The charging and discharging power set-points in real-time (i.e., P_1^{Chg} and P_1^{Dhg}) will provide the required commands to the ESS. In the next time step, the ESS SoC is calculated based on the latest power set-point commands. After that, the RTOD algorithm is executed to derive the new power set-point commands. This process continues until the end of the simulation period.

C. Proposed Method to Subsidize Privately Owned ESSs

As pointed out in Section I, due to the high capital cost, relatively low round-trip efficiency, and smaller electricity price arbitrage, large-scale ESSs may not be economical in current electricity markets although ESS deployment will be becoming more economical in the near future due to the growing storage technologies and higher arbitrage benefits in future electricity markets. This will be presented in Sections IV and V specifically for a CES unit. According to our studies, employing other storage technologies in current electricity markets might also not be an economically viable option for private investors due to the same reasons.

However, large-scale ESS diffusion for energy shifting can also result in peak shaving. In this way, peak-shaving generators, which usually cause air pollution, can be shut/turned down, thereby generating less CO_2 emission. Moreover, large-scale energy-shifting ESSs can allow a higher penetration of wind and solar energy to electric girds since sporadic availability of renewable resources can be addressed by introducing ESSs to (partially) decouple energy generation from demand, thereby increasing system security [35]. Due to their considerable environmental and technical benefits, privately owned ESSs could be financially supported by utility regulators [36]. One approach to encourage potential investors to invest in ESSs is that utility regulators subsidize ESS owners in contract setting for ESS capital cost. This could be realized through constant monthly/annual payments to ESS owners. In this approach, however, ESS owners are not directly encouraged to operate effectively in the market to obtain their subsidies; this is not appropriate in competitive electricity markets.

In this paper, electricity price modulation is proposed as part of the RTOD algorithm to virtually increase energy price arbitrage to competitively offer subsidy to ESS owners to fill the gap between current and a stable expected ROR. The use of modulation factor also demonstrates how much the energy price arbitrage shall increase until the ESS plant becomes economical. By implementing the proposed approach, the more the ESS operates to support the power gird by means of energy shifting/peak shaving, the more subsidies it can receive from the utility regulator since the amount of subsidy is dependent on the charging in off-peak periods and discharging in on-peak periods which are appropriate for both utility regulator/system operator and ESS investor. One of the advantages of this method is that the level of the price modulation can be adjusted by utility regulators to subsidize all eligible market players, including ESSs, according to their technical and environmental benefits. By including the proposed approach to subsidize the ESS as part of the optimization problem, the objective function would be expressed as follows:

$$\underset{P_t^{\text{Chg}}, P_t^{\text{Dhg}}}{\text{Maximize}} \quad \sum_{t=1}^{N} \left(\left(P_t^{\text{Dhg}} - P_t^{\text{Chg}} \right) . (I) E_t - C_{\text{DhgO}} \, . \, P_t^{\text{Dhg}} - C_{\text{ChgO}} \, . \, P_t^{\text{Chg}} \right) . \, \Delta t. \quad (20)$$

As expressed in (20), the electricity price (i.e., E_t) is multiplied by a constant "I," called modulation factor where $I > 1$. Since $I > 1$, the price arbitrage, the difference between high and low levels of the price, increases. This causes to increase revenue for ESS owners by purchasing and selling electricity. The extra profit is provided for ESS owners indirectly by the utility regulator. The value of modulation factor "I" included in (20) should be so that the total revenue at least covers the expected revenue due to investment. In such a case, the extra revenue at least reaches to zero; the zero extra revenue is the

TABLE III
OPERATING PARAMETERS OF THE CES USED IN THIS PAPER

$P_{min}^{Chg} = 80\% \times P_{max}^{Chg}$	C_{Cap} = Capital Cost/$(30 \times 365 \times 24)$
$P_{min}^{Dhg} = 3\% \times P_{max}^{Dhg}$	$C_{Main} = 5\% \times C_{Cap}$
$S_{min} = 10\% \times S_{max}$	$C_{ChgO} = 60\% \times C_{Main}/P_{max}^{Chg}$
$S_{Int} = 10\% \times S_{max}$	$C_{DhgO} = 40\% \times C_{Main}/P_{max}^{Dhg}$
$\eta_{Dsp} = 0.0063\% \times S_t$	$C_{EInc} = 150\% \times C_{Cap}$

border between economic and uneconomic operations of the ESS. The ESS extra revenue is defined as follows:

$$\text{Extra Revenue}: \sum_{t=1}^{N} \left(\left(P_t^{\text{Dhg}} - P_t^{\text{Chg}} \right) .(I) E_t - C_{\text{DhgO}} . P_t^{\text{Dhg}} - C_{\text{ChgO}} \, . \, P_t^{\text{Chg}} \right) . \, \Delta t - N \times \left(C_{\text{EInc}} + C_{\text{Cap}} \right) \tag{21}$$

in which the total revenue and expected revenue over the optimization horizon are defined as follows:

$$\text{Total Revenue}: \sum_{t=1}^{N} \left(\left(P_t^{\text{Dhg}} - P_t^{\text{Chg}} \right) .(I) E_t - C_{\text{DhgO}} . P_t^{\text{Dhg}} - C_{\text{ChgO}} \, . \, P_t^{\text{Chg}} \right) . \, \Delta t \tag{22}$$

$$\text{Expected Revenue: } N \times \left(C_{\text{EInc}} + C_{\text{Cap}} \right) \tag{23}$$

where, C_{Cap} is the hourly capital cost, defined by wasting the capital cost over the life of the plant, and C_{EInc} is the hourly expected income due to investment (see Table III). As expressed in (21), the summation of these constant parameters has been subtracted from the total revenue to express the ESS revenue excluding the capital cost and expected income over the optimization horizon, named extra revenue in this paper.

Theoretically, "$I_{\min}$" can be calculated as stated in the following where the extra revenue [see (21)] equals zero:

$$I_{\min} = \frac{\sum_{t=1}^{N} \left(C_{\text{DhgO}} \, . \, P_t^{\text{Dhg}} + C_{\text{ChgO}} \, . \, P_t^{\text{Chg}} \right)}{\sum_{t=1}^{N} \left(P_t^{\text{Dhg}} - P_t^{\text{Chg}} \right) . \, E_t} + \frac{N \times \left(C_{\text{EInc}} + C_{\text{Cap}} \right)}{\sum_{t=1}^{N} \left(P_t^{\text{Dhg}} - P_t^{\text{Chg}} \right) . \, E_t}. \tag{24}$$

"$I_{\min}$" in (24) is the minimum required modulation factor to meet the expected revenue in each optimization horizon. However, in practice, "$I_{\min}$" cannot be calculated simply by using (24) since electricity prices do not follow a constant pattern in each optimization horizon. In this case, the objective is not to make the ESS to operate economically in every single optimization horizon; instead, it is expected that the monthly or annual extra revenue of ESS operation at least reaches to zero. This will be investigated in Sections IV-C and V.

IV. PERFORMANCE EVALUATIONS

In this section, the performance of CES_1 and CES_2 sized for weekly and daily usages, respectively, is evaluated. The operating parameters of the CES are reported in Table III.

TABLE IV
DIFFERENT LEVELS OF THE GENERIC PRICE PROFILE SHOWN IN FIG. 4

Price Profiles	Price Levels ($/MWh)					
	For Weekdays			For Weekends		
	A	B	C	A	B	C
Profile 1	60	90	120	50	60	70
Profile 2	60	120	180			
Profile 3	60	150	240			

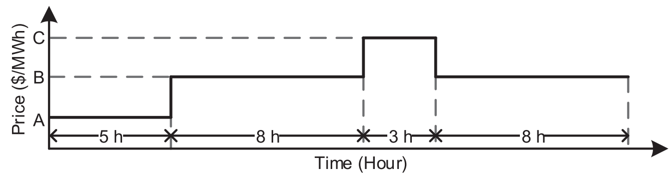

Fig. 4. Generic electricity price profile [4].

In this table, the hourly expected income due to investment (i.e., C_{EInc}) is defined as 150% of the capital cost. This way, the expected revenue (i.e., $C_{\text{EInc}} + C_{\text{Cap}}$) will be defined as 250% of the capital cost at the entire life of ESS (i.e., 30 years [28]) or 8.34% of the capital cost per year. For a $117 M investment, this corresponds to an annual expected revenue of $9.76 M. This means that if the plant is able to generate at least $9.76 M per year it would be profitable; otherwise, the plant can be subsidized using the appropriate value of modulation factor to become profitable.

In CES technology, to maintain rated efficiency, it is required to operate the liquefaction plant close to its rated value [4]. Thus, $P_{\text{min}}^{\text{Chg}}$ is set to 80% of $P_{\text{max}}^{\text{Chg}}$. However, the cryogenic turbine and its supplying pump can efficiently operate at very lower power set-points [4]. Energy dissipation in the reservoir is assumed 0.15% per day thus 0.0063% = 0.15%/24 per hour [4]. Using parameters defined in Table III, the optimization problem is solved by GLPK package and the results are obtained for two types of daily and weekly usages of CES. Real-time charging and discharging powers of the CES and actual market prices are used to calculate the financial benefit of selling electricity to the market minus the cost for purchasing electricity from the market, minus the OPEX, and minus the expected revenue, resulting in annual extra revenue.

Three different price profiles each with different modulation factors are used for evaluations. The generic price profile is shown in Fig. 4 while price levels (A–C) are defined in Table IV for three cases (typical price levels in the Ontario market [37]). The CES round-trip efficiency is assumed to be 60%, a typical value for a highly efficient CES unit [4].

A. Concept of Real-Time Daily Usage

In this section, by using price Profile 1, the optimization is executed considering the optimization horizon of 24 h. Real-time daily optimal dispatch is performed for seven days individually including two weekends and five weekdays. Since the ESS has a constraint on the minimum allowed SoC [see (13)], the SoC at the end of the optimization horizon must be equal to or larger than S_{min}, i.e., $10\% \times S_{\text{max}}$. The result of all seven days can be combined to obtain the CES

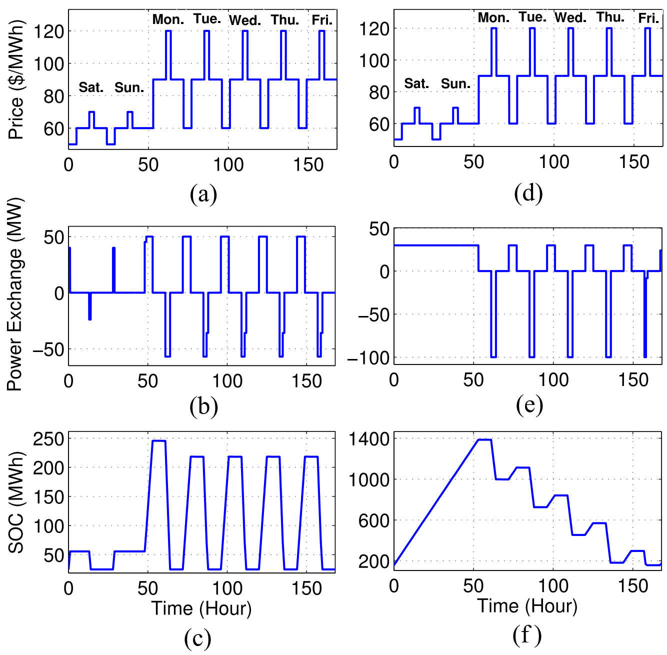

Fig. 5. (a) and (d) Price profile 1. (b) and (e) CES power exchange. (c) and (f) SoC. (a)–(c) Daily usage. (d)–(f) Weekly usage.

performance for a week in case of daily usage. Fig. 5(a)–(c) shows the evaluation results for a complete week. In Fig. 5, positive and negative power exchanges indicate charging and discharging, respectively. In each weekday, the CES is charging at low energy prices and discharging at high prices. Since the RTOD aims to make the maximum possible benefit, the entire allowed energy is discharged by the end of the optimization horizon causing the SoC at the end of the day equal to $S_{\min}$. The same pattern repeats for the next weekdays. As it was expected, CES is mostly off in weekends and does not store energy for future use in weekdays. In weekends, CES operates only to compensate the energy dissipation to maintain the minimum allowed SoC by the end of the day.

B. Concept of Real-Time Weekly Usage

In this section, using the same conditions as Section IV-A, the weekly optimal dispatch is performed considering the optimization horizon of one week, i.e., 168 h. In this case, the RTOD considers energy price of a week ahead to determine optimal dispatch quantities. Fig. 5(d)–(f) represents the simulation results. It can be observed that during weekends and low energy price periods of weekdays, CES is charging while it is discharging during high energy price periods of weekdays. The RTOD in weekly usage is utilizing low energy prices in the weekend by charging in the entire weekend.

C. Comparison Study

In the following, three different price profiles defined in Fig. 4 and Table IV and different round-trip efficiencies of the CES between 30% and 70% are employed. The CES extra revenue for both weekly and daily usages are calculated and compared.

The RTOD is simulated for a one-year time period considering three different modulation factors and different round-trip efficiencies of CES. Annual extra revenue is calculated for the three predefined price profiles and plotted in Fig. 6 in terms of million dollar. As represented in Fig. 6(g), for price profile 3, a numerical example is given in Table V to reveal how to use the curves and to quantitatively compare the extra revenue of CES weekly and daily usages. As reported in Table V, for the efficiency of 67% and price modulation of one (i.e., no price change), the extra revenue is \$48 Million for weekly usage while for daily usage it is −\$93 Million at the entire life of ESS. This example reveals the significant financial benefit of CES weekly usage as compared to common daily usage.

As represented in Fig. 6, in all cases and for all efficiencies, the annual extra revenue of weekly usage is higher than that of daily usage. This is because in weekly usage, the RTOD algorithm considers a week ahead electricity price and stores considerable amount of energy in weekends and weekday nights when the electricity is inexpensive and sells it back during on-peak periods of weekdays. In addition, as CES efficiency increases, the revenue of both weekly and daily usages increases linearly since by increasing the efficiency, the energy loss in ESS system decreases. As the technology grows, the efficiency of these types of ESSs, i.e., CES will increase and, thus, utilizing such ESSs will become more economical.

Moreover, as represented in Fig. 6 (the left-hand and middle columns), the curves at the left side of breakpoints are approximately flat for both weekly and daily usages. In this area, the ESS stops operating since it cannot overcome the OPEX. As expressed in the following, at the left side of the breakpoint efficiency, the arbitrage benefit is less than the OPEX:

$$\sum_{t=1}^{N}\left(P_t^{\mathrm{Dhg}}-P_t^{\mathrm{Chg}}\right).\,E_t\,.\,\Delta t < \sum_{t=1}^{N}\left(C_{\mathrm{DhgO}}\,.\,P_t^{\mathrm{Dhg}}+C_{\mathrm{ChgO}}\,.\,P_t^{\mathrm{Chg}}\right).\,\Delta t. \qquad (25)$$

As represented in Fig. 6, there are different breakpoints for profile 1 (left-hand column) and profile 2 (middle column), and there is no such a point for profile 3 (right-hand column) considering CES efficiencies from 30% to 70%. As reported in Table IV, each price profile has a different high to low price ratio (HLPR) (i.e., C/A ratio) in weekdays. The larger the HLPR is, the smaller the efficiency breakpoint will be. Since the efficiency at the breakpoint depends on the value of HLPR, and HLPR does not change by price modulation, the breakpoint efficiency will not change for different modulations.

The minimum allowed SoC constraint [see (13)] forces the ESS with weekly usage regime to operate once a week while with daily usage once a day to compensate the energy dissipation to maintain the SoC above or equal to the $S_{\min}$. Since any ESS operation at efficiencies smaller than the breakpoint causes financial loss, as shown in Fig. 6 (left-hand column), higher operations of ESS with daily usage results in lower extra revenue which means higher financial loss as compared to the ESS with weekly usage.

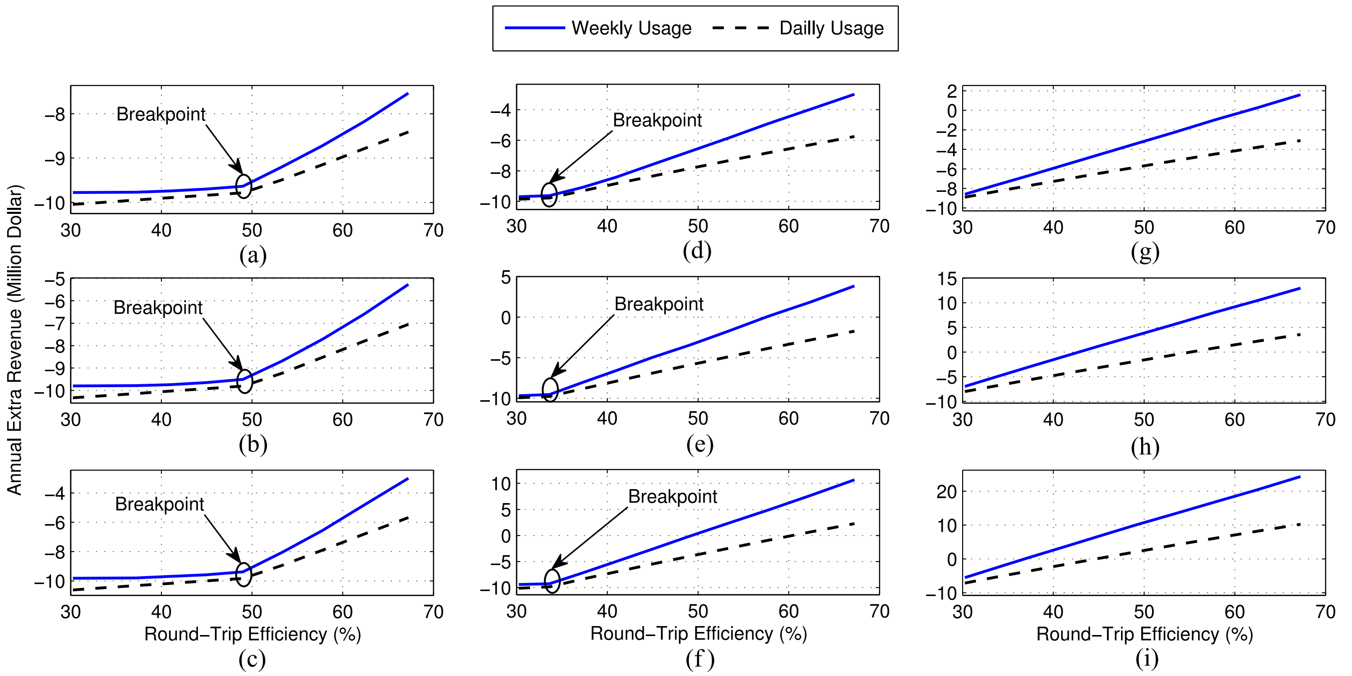

Fig. 6. Annual extra revenue of CES operation versus round-trip efficiency for three different price profiles (see Table IV) each with three different price modulation factors. For price (a)–(c) profile 1, (d)–(f) profile 2, and (g)–(i) profile 3.

TABLE V
CES EXTRA REVENUE FOR THE THIRD PROFILE SHOWN IN FIG. 6(G)

Round-Trip Efficiency	CES_1: Weekly Usage		CES_2: Daily Usage	
	Annual	At Life of ESS	Annual	At Life of ESS
67%	\$1.6 M	\$48 M	–\$3.1 M	–\$93 M

As the curves of Fig. 6(a), (d), and (g) represent, in the case of un-modulated prices (i.e., at $I = 1$), the annual extra revenue is negative for most of the operating points; negative extra revenue in one operating point means that using the ESS is no longer economical. However, by modulating the price profiles, the obtained annual extra revenue increases for the operating points with efficiencies larger than the breakpoint efficiency. If the ESS operating point is smaller than the breakpoint efficiency, the price modulation does not have considerable effect on the ESS benefit since the ESS is not operating.

Moreover, comparing the HLPR value of price profiles, it can be observed that the larger the HLPR is, the more extra revenue is obtained for both cases of daily and weekly usages [compare Fig. 6 (left-hand, middle, and right-hand columns)]. By increasing the HLPR in profile 2 compared to profile 1 and profile 3 compared to profile 2, the extra revenue increases.

V. NUMERICAL RESULTS FOR REAL CASE-MARKET

In this section, wholesale electricity prices publicly available in the Ontario market are used for evaluations. The day-ahead predispatch prices (PDPs) published by the Ontario independent electricity system operator (IESO) are employed as the price forecast; the corresponding ex-post hourly Ontario energy prices (HOEPs) are employed as the actual prices. Since week-ahead market prices are not available in the Ontario market, the price forecast of the same day in the last week can be duplicated to generate a forecast for the entire week ahead, or a separate forecasting algorithm can be used to forecast week-ahead market prices. The price forecasts are updated every 1 h, and accordingly, the RTOD is executed every 1 h to account for the time-varying nature of the prices.

The RTOD algorithm as shown in Fig. 3 has been executed in a simulation environment for the Ontario market from 2006 to 2009 and 2011. Two studies have been conducted as follows. In one study, the price forecast is assumed to be perfect; this means the price forecast is substituted with the actual prices. In the second study, IESO-generated PDPs [37] are employed as an imperfect price forecast in a real-world market, i.e., the Ontario electricity market. To decrease the adverse impact of the public-domain market price forecast error on the ESS revenue, PDPs are calibrated using the proposed adaptive algorithm in [1] (Method 1) and then applied as the market price forecast. Consequently, the performance of weekly and daily usages is investigated using both cases of perfect and imperfect price forecasts in a real-world electricity market to reveal the impact of price forecast inaccuracy on the outcomes.

The simulation results for daily and weekly usages of the CES in the Ontario market for one complete week in case of the imperfect price forecast has been plotted in Fig. 7. As shown in Fig. 7(a) and (d), market prices in the weekend (Saturday and Sunday) is generally lower than that in weekdays. One can observe that charging and discharging patterns in Fig. 7 are similar to those in Fig. 5 obtained using the generic price profile. It can be observed in Fig. 7(e) and (f) that

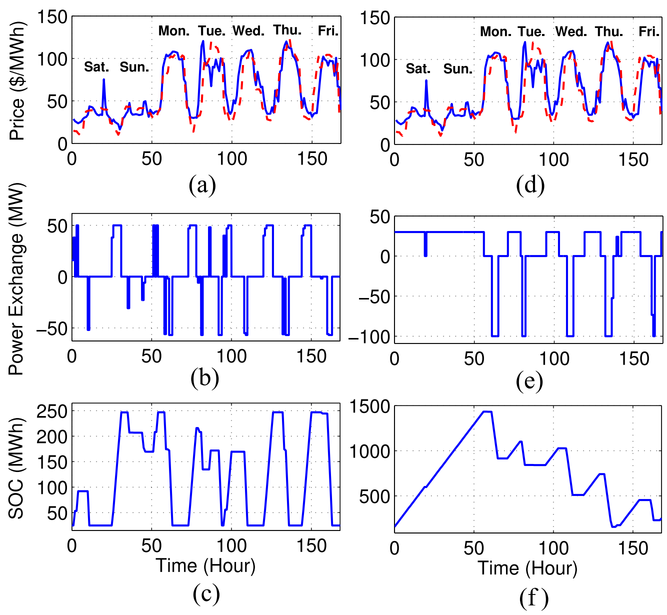

Fig. 7. (a) and (d) Sample price profiles of one week in the Ontario market (bold: actual and red dotted: forecast). (b) and (e) CES power exchange. (c) and (f) SoC. (a)–(c) Daily usage. (d)–(f) Weekly usage.

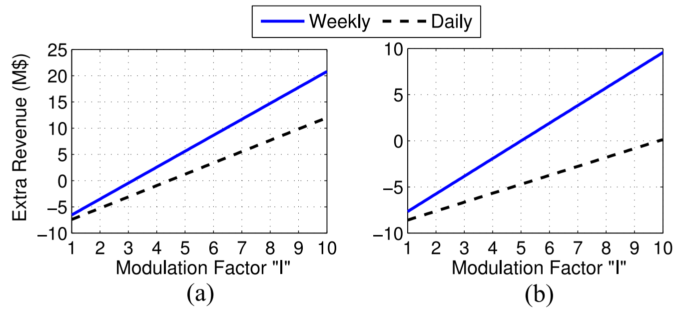

Fig. 8. Five-year average of CES extra revenue versus modulation factor "I." (a) For the perfect price forecast. (b) For an imperfect price forecast in the Ontario electricity market from 2006 to 2009 and 2011.

TABLE VI
FIVE-YEAR AVERAGE OF CES EXTRA REVENUE FOR PERFECT AND IMPERFECT PRICE FORECASTS IN THE ONTARIO MARKET (FIG. 8)

	Perfect Forecast (Fig. 8(a))			Imperfect Forecast (Fig. 8(b))		
	$I = 1$	$I = 3.2$	$I = 4.4$	$I = 1$	$I = 5$	$I = 9.9$
Weekly	–\$6.55 M	\$0.00 M	\$3.79 M	–\$7.67 M	\$0.00 M	\$9.38 M
Daily	–\$7.41 M	–\$2.66 M	\$0.00 M	–\$8.59 M	–\$4.71 M	\$0.00 M

in weekly usage, the CES is charging in the entire weekend, thereby taking an advantage of low energy prices in weekends. However, in daily usage, this opportunity does not exist since the optimization is performed only for the next day in each time step.

The annual extra revenue of CES operation in the Ontario market from 2006 to 2009 and 2011 has been calculated and plotted in Fig. 8(a) and (b) for perfect and imperfect price forecasts, respectively, at different price modulation factors. Different modulation factors are employed to evaluate the impact of electricity price modulation on ESS revenue in case of a real-world market. The CES round-trip efficiency is considered as 60%. The five-year average of extra revenue has been reported in Table VI for three important values of modulation factors: $I = 1$ (pertaining no subsidy), "$I_{\min}$" for weekly usage, and "$I_{\min}$" for daily usage. In this paper, "$I_{\min}$" is considered as the modulation factor in which the annual extra revenue of ESS operation reaches to zero.

As represented in Fig. 8 and Table VI, at $I = 1$, the annual extra revenue is negative revealing that the CES is not able to return the expected revenue plus OPEX; however, the annual extra revenue of weekly usage is higher than that of daily usage (i.e., 11.6% and 10.7% higher for perfect and imperfect price forecasts, respectively, as reported in Table VI). Moreover, the annual extra revenue of both weekly and daily usages increases linearly by increasing the price modulation factor revealing the efficacy and feasibility of the proposed method to subsidize ESS owners. In all modulation factors, the weekly usage outperforms daily usage to capture higher values of revenue. For instance, as reported in Table VI for the perfect forecast, when the extra revenue for weekly usage reaches to zero at $I = 3.2$, it is $-\$2.66$ Million for daily usage; and when it reaches to zero for daily usage at $I = 4.4$, it is \$3.79 Million for weekly usage. For the imperfect price forecast, since the forecast error reduces the ESS revenue, larger modulation factors are required to fill the gap between current and a stable expected ROR. The extra revenue of weekly usage compared to daily usage of CES is based on the fact that the CES determines more appropriate charging/discharging power set-points when the optimization horizon is one week.

As demonstrated in this paper, historical price data of an electricity market can be used to investigate the impact of price modulation on the ESS operation; then, the level of the price modulation can be offered by the utility regulator.

As presented in Section III, the expected income (C_{EInc}) offsets, and the life of ESS approximately offsets the objective values of the RTOD. If C_{EInc} is increased to gain more revenue, the extra revenue decreases and vice-versa. Considering C_{EInc} as a percentage of C_{Cap}, for 1% increase/decrease of C_{EInc}, the curves plotted in Figs. 6 and 8 will be shifted downward/upward by the following factor:

$$0.01 \times \frac{\text{Capital cost}}{\text{Life of ESS}} = 0.01 \times \frac{\$117\,\text{M}}{30} = \$0.039\,\text{Million}. \quad (26)$$

If the life of ESS is considered lower, C_{EInc} and C_{Cap} shall be returned in less time and, thus, the extra revenue decreases and vice versa. In general, if the life of ESS is changed from 30 to x years, the curves shown in Figs. 6 and 8 will be shifted approximately by the following factor:

$$(1 + C_{\mathrm{EInc}}) \times \text{Capital cost} \times \left(\frac{1}{30} - \frac{1}{x}\right) = \$292.5 \times \left(\frac{1}{30} - \frac{1}{x}\right) \text{Million} \quad (27)$$

in upward/downward for positive/negative sign of the factor.

VI. Conclusion

In this paper, the CES technology was introduced. Due to the significant lower footprint and inexpensive reservoir compared to other components of CES, it was proposed to increase the reservoir size to enable weekly energy shifting. An RTOD algorithm was developed by formulating an MILP problem to determine ESS charging and discharging powers in the day-ahead/week-ahead market. A comprehensive economic study was performed revealing that the weekly usage of CES outperforms the common daily usage to gain more profit. Using Ontario's wholesale market prices, it was demonstrated that CES with 60% round-trip efficiency actively operates in the market, but it cannot return the expected revenue. In this case, the five-year average of annual extra revenue of weekly usage in the Ontario market was 11.6% and 10.7% higher than that of daily usage for perfect and imperfect price forecasts, respectively. The price modulation was proposed as a new approach to provide uniform and at the same time competitive subsidy to privately owned ESSs by utility regulators. For the perfect price forecast in the Ontario market, it was required to modulate electricity prices by 3.2 and 4.4 for weekly and daily usages, respectively, to meet the expected revenue for CES owners. It was demonstrated that the price forecast inaccuracy reduces the ESS revenue and, thus, higher price modulation factors (i.e., 5 and 9.9 for weekly and daily usages, respectively) would be required to fill the gap between current and a stable expected ROR.

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