Large-Scale Energy Storage Deployment in Ontario Utilizing Time-of-Use and Wholesale Electricity Prices: An Economic Analysis

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SUMMARY

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 (base-load generation). Additionally, wind generation typically is maximum at night, a time period when the demand is minimum. This raises the question whether energy storage systems (ESSs) should be deployed in Ontario to shift the excess energy from the nighttime to peak hours during the day (if and when there is surplus power in the system). In today’s competitive electricity markets, policy makers and regulators are encouraging private investors to build, own, and operate large-scale energy storage plants as merchant operators. In such a case, the main objective of an ESS owner would be to generate profit by exploiting energy price arbitrage opportunities. An optimal dispatching algorithm is required to command an ESS to maximize the profitability of the investment.

In this paper, a real-time optimal dispatching (RTOD) algorithm is developed by formulating a mixed integer linear programming problem to determine the ESS charging and discharging power set-points in the Ontario electricity market. The RTOD algorithm aims to utilize the same Compressed-air ESS technology optimally sized for two models as follows: 1) the model using wholesale electricity market prices and 2) the model using contract-based electricity prices. Compressed-air has been chosen due to its lower capital expenditure and its ability to be positively influenced by the availability of waste heat. In the first case, the hourly Ontario energy prices and pre-dispatch prices, issued by the Ontario independent electricity system operator, are employed to optimally dispatch the ESS where the ESS seeks to generate revenue by exploiting arbitrage opportunities in the day-ahead wholesale market. In the second case, the time-of-use (TOU) electricity prices, as an example of contract-based electricity prices, are used to optimally dispatch the ESS where the ESS seeks to generate revenue by exploiting arbitrage opportunities available in TOU rates. The economic benefits of both cases are presented and compared. The simulation results reveal that while both TOU and wholesale electricity rates do not make any ESS investments economically viable, the profitability of the investment in ESSs operating in the wholesale market is considerably higher as compared to the TOU rates.

KEYWORDS

Electricity market, energy storage system, optimal dispatch, time-of-use electricity prices, wholesale electricity prices.

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1. INTRODUCTION

Energy storage units have great potentials to enhance the flexibility of electric grids and are key elements which enable smart grid realization. Diffusion of large-scale ESSs is important to allow a higher penetration of wind energy to electric grids as the maximum wind generation usually occurs during the night in many geographical locations, a time period when the load demand is minimum. Accordingly, utility regulators and policy makers have become interested in promoting different energy storage technologies for various objectives [1]. ESSs in competitive electricity markets, especially large-scale ESSs, are preferred to be managed by private investors. Privately owned ESS owners seek to utilize energy price arbitrage, available due to market price volatility, by optimally storing inexpensive electricity during off-peak periods and releasing it back to the system when the electricity is expensive during on-peak periods [2].

The prior studies conducted on the relevant topic aim to investigate the economic viability and profitability of three types of storage technologies appropriate for large-scale applications (i.e., pumped-hydroelectric, compressed-air, and cryogenic ESSs) operating in a wholesale electricity market as a single entity to generate revenue [2]–[10]. These studies have estimated the ESS revenue of single or multiple applications using different dispatching algorithms and historical market prices. Recently, some studies have been conducted on peak-shaving ESS diffusion in Ontario using contract-based electricity prices, such as TOU rates [11]. These studies pre-assume that there are higher arbitrage potentials in TOU electricity prices compared to wholesale market prices and, thus, they assume the energy shifting based on TOU prices would be more profitable as compared to energy
chasing based on wholesale market prices. Comparison studies would be required to compare the value and benefit of the ESS optimized to utilize wholesale and TOU electricity prices.

In this paper, a comprehensive study is performed to analyze and compare the economic viability and profitability of the ESS deployment exploiting wholesale and TOU electricity prices. An RTOD algorithm is developed by formulating an MILP problem to determine economically optimal charging and discharging power set-points of an ESS. The same CAES technology has been employed in both cases of wholesale and TOU electricity prices to appropriately compare the economic benefits of ESS utilization in both cases. In the first case, IESO-generated HOEPs and PDPs are employed to optimally dispatch the ESS where the ESS seeks to generate revenue by exploiting arbitrage opportunities in the day-ahead wholesale market. In the second case, TOU electricity rates are used to optimally dispatch an ESS in which the ESS aims to generate revenue by exploiting arbitrage opportunities available in TOU prices. The ESS operation in both cases is presented and compared.

Due to the higher cost, relatively lower round-trip efficiencies, and smaller electricity price volatility in both wholesale and TOU rates, ESSs have not proven to be economical based on the expected revenue. To fill the gap between current and a stable expected ROR, utility regulators could provide subsidies to ESS owners in contract settings for the ESSs capital cost.

The rest of the paper is organized as follows: The optimization problem is formulated, and the proposed model is presented in Section II. As the case-ESS, a CAES unit is sized and modeled in Section III. The performance of ESS operation for both Ontario’s wholesale and TOU electricity prices are evaluated in Section IV. Finally, the main outcomes are summarized in Section V.

II. FORMULATION OF THE OPTIMIZATION PROBLEM

An MILP optimization problem is formulated in this section. Optimal decisions are updated by re-running the optimization calculations in every time step to account for the time-varying nature of the electricity price in the market. The optimization horizon (i.e., $T$) is selected as 24 h with 1-h time step (i.e., $\Delta t=1$). The time step is selected as 1 h since Ontario’s wholesale market prices are updated every hour. The optimal dispatch problem will be, therefore, a multi-interval optimization problem with $N=24$ h / 1 h = 24 time steps.

Equation (1) expresses the objective function of the optimal dispatching problem, as follows:

$$\text{Maximize } \sum_{t=0}^{N} \left\{ (P_{t}^{Dhg} - P_{t}^{Chg} \cdot E_{t} - C_{Dhg} \cdot P_{t}^{Dhg} - C_{Chg} \cdot P_{t}^{Chg}) \right\} \cdot \Delta t$$

subject to the following operational constraints for the ESS:

$$M_{t}^{Chg} \cdot P_{min}^{Chg} \leq P_{t}^{Chg} \leq M_{t}^{Chg} \cdot P_{max}^{Chg} \quad \forall t \in \tau$$

$$M_{t}^{Dhg} \cdot P_{min}^{Dhg} \leq P_{t}^{Dhg} \leq M_{t}^{Dhg} \cdot P_{max}^{Dhg} \quad \forall t \in \tau$$

$$S_{min} \leq S_{t} \leq S_{max} \quad \forall t \in \tau$$

$$S_{t+1} = S_{t} + \frac{(P_{t}^{Chg} - P_{t}^{Dhg})}{\eta_{Dhg} - \eta_{Chg}} \cdot \Delta t$$

The objective function, given in (1), includes the profit of selling electricity to the market, the ESS operating cost for charging and discharging (OPEX), and the cost of purchasing electricity from the market within the optimization horizon, i.e., 24 h. In (1), $E_{t}$ is the electricity price forecast at the time step $t$. In real-time (i.e., $t=1$), $E_{t}$ would be equal to the actual market price since the actual price is available in real-time. Equations (2)–(4) express charging and discharging powers and the SOC constraints of the ESS where $M_{t}^{Chg}$ and $M_{t}^{Dhg}$ are binary variables and $P_{t}^{Chg}$, $P_{t}^{Dhg}$, and $S_{t}$ are positive real variables. The energy balance equation of the ESS is given by (5) defining the relation of ESS SOC at time steps $t$ and $t+1$. This equation is based on the physics of the ESS stating that at the time step $t+1$, the SOC must be equal to the SOC at the time step $t$ plus the net charged energy minus the net discharged energy and the net dissipated energy between time steps $t$ and $t+1$.
The framework of the proposed model in this study which aims to employ an ESS as a single entity to utilize energy price arbitrage, available in the wholesale/TOU electricity prices, has been depicted in Figure 1. In this model, it is assumed that the large-scale ESS can be either scheduled based on TOU prices or wholesale prices. The model will be described in details throughout the paper. The model represented in Figure 1 is implemented in MATLAB. The operating parameters of the case-ESS are adopted from [10]. The optimization problem including variables, parameters, the objective function, and the constraints are defined in a file, called problem file developed using GNU MathProg modeling language. Then, the optimization problem is solved by GLPK package to find the objective values and the values of the optimization problem variables such as charging and discharging powers. The charging and discharging power set-points at the present time will provide the required commands to the ESS. It should be noted that in this study, for the sake of simplicity, it is assumed that the ESS bidding in the market is always successful.

III. SIZING AND MODELING OF A CAES UNIT

The CAES technology has been in use for 30 years [12]. A CAES plant stores electricity in the form of compressed air, then recovers it when needed to generate power. A CAES unit can be divided into the following main components: Power system (including turbine(s), generator, and recuperator), Compression system, Depleted gas reservoir, and Control equipment: (including switchgear, substation, and cooling system).

In this study, the maximum charging and discharging power set-points of the ESS have been selected as 100 MW, and the round-trip efficiency has been considered 70% [10]. If the ESS is going to be sized based on a 12-h charging period, which is the case for TOU rates, 1 GWh capacity would be appropriate. Additionally, for the wholesale market prices, when the price forecast is assumed to be perfect, the aforementioned capacity (i.e., 1 GWh) would be appropriate to exploit the maximum arbitrage potential in the wholesale market. However, when the price forecast in not perfect, increasing hours of storage would increase the revenue capture. The reason is explained as follows: When the ESS is scheduled based on an imperfect price forecast, it is not perfectly prepared to take advantage of low prices (by charging) and high prices (by discharging). In such a case, when the actual price is issued in real-time, the ESS might not have enough space for charging or enough energy for discharging since it has not been perfectly prepared for it. With higher capacities, however, the probability that the ESS has enough space for charging or enough energy for discharging in real-time would be higher. Accordingly, the ESS might be able to take advantage of lower and higher prices in real-time even if it is not prepared for them and, therefore, higher values of revenue could be captured when an ESS with a higher capacity is used.

Subsequently, considering that the cost of incremental capacity ($/MWh) is quite low for a CAES unit, the reservoir could be enlarged via extra compression energy to allow a larger storage capacity for higher charging/discharging periods. In order to determine the appropriate capacity for the CAES unit, the ideal revenue of the ESS under six different ESS capacities has been calculated. According to the results, the higher the capacity is (from 0.5 to 2 GWh), the higher the revenue capture would be. However, there would be no more potential for increasing revenue capture by increasing the capacity larger than 2 GWh. Even the revenue could be slightly less at capacities larger than 2 GWh due to a higher energy dissipation rate for larger capacities [10]. The optimal capacity is, therefore, selected as 2 GWh in this paper, and the analyses have been carried out based on this optimal sizing. Considering the low cost of the CAES reservoir plant, different capacities in the above-mentioned range will not

Figure 1. The framework of the developed model for setting up an ESS to exploit arbitrage opportunities available in the Ontario’s wholesale and TOU electricity prices.
considerably impact the capital cost of the plant even though increasing the ESS capacity might be limited in practice due to geographical constrain. Nevertheless, a 2-GWh capacity for a CAES unit falls in the ranges proposed in some prior studies, such as [10], [13]. The capital cost of the plant has been selected as $1 Million/MW of discharging power [10], thereby $100 Million for the selected case-ESS.

IV. ESS OPERATION USING ONTARIO’S WHOLESALE/RESIDENTIAL PRICES

In this section, the proposed model in Figure 1 is developed for economic analyses of ESS operation utilizing Ontario’s wholesale and TOU prices. The RTOD algorithm aims to utilize the same ESS in order to generate revenue in two cases. In the first case, HOPEs and PDPs, issued by the Ontario’s IESO, are employed to optimally dispatch the case-ESS. The Ontario’s IESO publishes two sets of PDPs as follows: 24-h-ahead and 3-h-ahead PDPs both with 1-h time resolutions (i.e., $\Delta t = 1$) [13]. The first set is the next day PDPs (starting from 1am) published at 3:30pm 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 1am to 3pm of each day. To mitigate this issue, PDPs at the same hours of the last day are duplicated for the missing hours. Accordingly, the real-time simulation has been executed using Ontario’s wholesale market prices from 2006 to 2009 and 2011, and the annual revenue of ESS has been calculated for three cases as follows:

1) Optimal dispatch using a perfect price forecast: The price forecasts are substituted with the actual prices. The resulted revenue would be, therefore, equal to the ideal revenue, as reported in Table I.

2) Optimal dispatch by PDPs: This approach is called conventional algorithm in this study. In this case, IESO-generated PDPs are used (imperfect forecasting). Table I reports the annual revenue capture in percent of the ideal revenue by the conventional algorithm.

3) Optimal dispatch using back-casting method: In this approach, the ESS scheduling for the next 24 h is performed using the actual prices in the last 24 h. Table I reports the annual revenue capture in percent of the ideal revenue by this approach.

In the second case, Ontario’s TOU prices are used to optimally dispatch the ESS. TOU pricing is a rate structure that reflects the costs associated with electricity production throughout the day. Prices rise and fall over the course of the day and tend to drop overnight and on weekends, depending on the demand and the availability of supply. Currently in Ontario, TOU rates and periods are defined as follows [14], [15]:

- Off-peak is when demand is low and less expensive sources of electricity are used ($75/MWh from 7pm to 7am in summer and winter as well as the entire weekends and holidays).

### Table I: Annual Revenue of ESS (in Million $ and % of the Ideal Revenue Capture) Using Ontario’s Wholesale Market Prices from 2006 to 2009 and 2011 under Different Optimization Methods

<table>
<thead>
<tr>
<th>Year</th>
<th>Ideal Revenue</th>
<th>Conventional Algorithm</th>
<th>Back-Casting Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>$6.03 M</td>
<td>$3.25 M (53.99%)</td>
<td>$4.11 M (68.28%)</td>
</tr>
<tr>
<td>2007</td>
<td>$7.21 M</td>
<td>$3.68 M (51.11%)</td>
<td>$4.76 M (66.03%)</td>
</tr>
<tr>
<td>2008</td>
<td>$8.86 M</td>
<td>$3.51 M (39.61%)</td>
<td>$6.14 M (69.28%)</td>
</tr>
<tr>
<td>2009</td>
<td>$5.26 M</td>
<td>$2.70 M (51.36%)</td>
<td>$3.85 M (73.22%)</td>
</tr>
<tr>
<td>2011</td>
<td>$4.62 M</td>
<td>$2.00 M (43.25%)</td>
<td>$3.31 M (71.69%)</td>
</tr>
<tr>
<td>Average</td>
<td>$6.39 M</td>
<td>$3.03 M (47.37%)</td>
<td>$4.43 M (69.35%)</td>
</tr>
</tbody>
</table>

### Table II: Five-Year Average Revenue of ESS (in Million $) for Ontario’s Wholesale Electricity Market Prices (Under Different Optimization Methods) and for Ontario’s TOU Prices

<table>
<thead>
<tr>
<th>Annual Expected Revenue</th>
<th>For Wholesale Electricity Market Prices</th>
<th>For TOU Electricity Prices</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ideal Revenue</td>
<td>Conventional Algorithm</td>
</tr>
<tr>
<td>$8.34 M</td>
<td>$6.39 M</td>
<td>$3.03 M</td>
</tr>
</tbody>
</table>
Ontario’s Wholesale Market Price ($/MWh)

- Actual Price (HOEP)
- Price Forecast (PDP)

Figure 2: Actual HOEPs and PDPs publically available in the Ontario’s wholesale market (in April 2011).

### Table III: The Average Cost for the Daily Energy Purchase, the Average Benefit Achieved by the Daily Energy Sale, and the Average Revenue Generated through the Daily Energy Trade for the TOU Rates as well as for the Ontario’s Wholesale Market Prices in 2011

<table>
<thead>
<tr>
<th></th>
<th>Wholesale Prices</th>
<th>TOU Rates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Cost for Daily Energy Purchase</td>
<td>$8.7 k</td>
<td>$74 k</td>
</tr>
<tr>
<td>Average Cost for Daily Energy Sale</td>
<td>$17.2 k</td>
<td>$78 k</td>
</tr>
<tr>
<td>Average Revenue for Daily Energy Trade</td>
<td>$8.5 k</td>
<td>$4 k</td>
</tr>
</tbody>
</table>

- Mid-peak is when the cost of energy and demand are moderate ($112/MWh from 7am to 11am and from 5pm to 7pm in summer as well as from 11am to 5pm in winter).
- On-peak is when demand is highest and more expensive forms of electricity generation are required ($135/MWh from 11am to 5pm in summer as well as from 7am to 11am and from 5pm to 7pm in winter).

Based on the above-mentioned TOU rates in specific time periods, the optimal dispatch has been executed for one year, and the ESS revenue has been calculated. In this study, the generated revenue at the entire life of ESS (i.e., 30 years [12]) is expected to be 250% of the total capital cost. The expected annual revenue would be, therefore, equal to (250/30)% = 8.34% of the capital cost in order for the plant to be profitable [10].

For the purpose of comparison, the five-year average revenue of ESS using the Ontario’s wholesale market prices for three different optimization methods as well as the ESS annual revenue using summer and winter TOU prices in Ontario have been calculated and reported in Table II. As it is demonstrated in Table II, a significant portion of the ideal revenue in the wholesale market is lost due to price forecast inaccuracy in each year for the conventional and back-casting methods. However, back-casting method has been more effective than the conventional method in capturing a higher percent of ideal revenue. This would reveal that PDPs issued by the IESO are not an appropriate price forecast for ESS scheduling due to the significant forecast uncertainty. As a result, ESS scheduling using the simple back-casting method is preferred over the publically available PDPs.

Moreover, as reported in Table II, the profitability of the investment in the ESS, operating in the wholesale electricity market using different optimization methods, is significantly higher as compared to the TOU electricity prices. As an illustration, actual HOEPs and PDPs publically available in the Ontario’s wholesale electricity market (in April, 2011) has been plotted in Figure 2. One can observe in this figure that there are considerably higher on-peak prices (up to $560/MWh) as well as significantly lower and even negative off-peak prices (down to −$140/MWh) in wholesale prices which can be utilized by the ESS. Specifically, in the wholesale electricity market, when the energy...
price is very low or even negative, ESS charging would be a great advantage since in this way, the average cost for the energy purchase will significantly decrease. For the TOU prices, however, this opportunity will not exist since there is a constant value for off-peak prices. For instance, the average cost for the daily energy purchase and the average benefit generated by the daily energy sale are calculated for TOU rates as well as for the Ontario’s wholesale market prices in 2011 as a sample year and reported in Table III. It can be observed in Table III that although the energy is being sold by the ESS more expensive for TOU rates compared to wholesale prices, it is being purchased significantly inexpensive for wholesale prices as compared to TOU rates. As reported in Table III, the average revenue generated for daily energy trading in wholesale market is $8.5 k, which is more than two times higher than the revenue generated using TOU rates.

Consequently, although TOU prices have been recently increased and, thus, the ESS scheduling models based on contracted electricity prices have been more interesting, the models based on wholesale market prices are still more appropriate for investing in large-scale peak-shaving ESSs due to a higher profitability level of the ESS investment in this market as compared to the TOU rates.

Nevertheless, for both TOU and wholesale electricity prices, the price arbitrage is not enough to convince investors to invest in peak-shaving ESSs since the current revenue is significantly below the expected one, i.e., 8.34% of the capital cost per year equal to $8.34 M in this study. As reported in Table II, while $8.34 M would be required to reach to 100% profitability level, the ideal profitability level obtained using perfect price forecast, which is not practically possible, would be 77%. In this case, the profitability level obtained by utilizing wholesale prices (using back-casting method) and TOU prices are 53% and 23%, respectively. The revenue shortfall in the back-casting method compared to the ideal revenue is due to inconsistency of inter-day wholesale market prices. Additionally, the significant revenue shortfall in the convention algorithm is due to sizable forecast error of public-domain PDPs. To deal with price forecast uncertainty to some extent, authors have proposed a new optimization algorithm which increases the profitability level of the ESS investment up to 60% [10]. To fill the gap between current and a stable expected ROR, utility regulators could provide subsidies to ESS owners in contract setting for the ESSs capital cost. The subsidy provision to these green technologies can be justified due to several potential environmental and technical benefits of ESS diffusion in power systems. In the following, a brief analysis has been conducted to reveal how much energy price arbitrage would be required in contract-based electricity prices in order for the ESS to be profitable: According to the simulation studies, if the ESS is being scheduled using contract-based electricity prices with the same periods as the TOU prices, the desired off-peak rates need to be 76% of the current off-peak rates (i.e., 0.76 × 75 = $57/MWh) in order for the plant to return the expected revenue. From another point of view, the desired on-peak rates need to be 130% of the current on-peak rates (i.e., 1.3 × 135 = $176/MWh) for the plant to return the expected revenue.

V. CONCLUSION

In this paper, an RTOD algorithm was developed by formulating an MILP optimization problem to determine ESS charging and discharging power set-points in the Ontario electricity market. The RTOD algorithm aimed to utilize a large-scale peak-shaving ESS using 1) wholesale and 2) TOU electricity prices. A CAES unit with 2 GWh storage capacity was selected for the case study. In the first study, IESO-generated HOEPs and PDPs were employed as the day-ahead market prices to optimally dispatch the ESS. In the second study, TOU prices were used to optimally dispatch the ESS. The economic benefits resulted from ESS operation in both studies were presented and compared. As it was demonstrated, while both TOU and wholesale electricity market rates do not offer attractive ROR to make any ESS investments viable today, the profitability of the investment in ESSs operating in the wholesale market is significantly higher as compared to the TOU rates. Using the simple back-casting optimization method, the five-year average revenue of ESS for Ontario’s wholesale market prices equals $4.43 M, whereas the annual revenue of ESS for the TOU rates equals $1.92 M. This was mainly due to the existence of very low and even negative electricity prices in the wholesale market in several hours during the year which can be utilized for the ESS charging. However, for the TOU prices, this opportunity does not exist since there is a constant value for off-peak prices. For instance, the average revenue generated for daily energy trading in wholesale market was $8.5 k which was three times higher than the revenue generated using TOU rates. Price forecast inaccuracy in
public-domain PDPs significantly reduced the financial benefits of ESS. Simple back-casting method, in which 24-h-behind market prices is used for ESS scheduling, proved to be significantly more effective than the conventional method in which PDPs are used for ESS scheduling. Although the ideal revenue could not be captured in practice due to an imperfect price forecast, studies are required to decrease the adverse impact of market price forecast inaccuracy on the ESS operation. As it was presented, the ideal profitability level obtained using the perfect price forecast, which is not practically possible, was 77%. The profitability level obtained by utilizing wholesale and TOU prices were 53% and 23%, respectively. The ESS revenue capture could be increased and become closer to the ideal revenue if price forecast error is decreased.

BIBLIOGRAPHY


