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Adaptive Real-Time Optimal Dispatch of Privately Owned Energy Storage Systems

Hadi Khani
The University of Western Ontario

Supervisor
Dr. Mohammad Reza Dadash Zadeh
The University of Western Ontario

Graduate Program in Electrical and Computer Engineering
A thesis submitted in partial fulfillment of the requirements for the degree in Master of Engineering Science

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(Thesis format: Monograph)

by

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The School of Graduate and Postdoctoral Studies
The University of Western Ontario
London, Ontario, Canada

Abstract

Large-Scale Energy Storage Systems (ESSs) have recently become matters of significant interest for the purpose of shifting surplus energy generation from off-peak to on-peak periods. This especially allows a higher penetration of wind energy to electrical girds as the maximum wind generation usually occurs during the night in many geographical locations, a time period when the electricity load demand is low. This is the main concept of electric energy shifting which results in peak shaving as well. In order to take advantage of energy shifting, utility regulators and policy-makers are attempting to encourage private investors to build, own, and operate large-scale ESSs in the near future. In such a case, the main objective of the ESS from private owner's perspective is to maximize financial benefits by exploiting arbitrage opportunities available due to inter-temporal variations of electricity prices in the day-ahead/week-ahead market. This is achieved mainly by optimally storing inexpensive energy during off-peak periods and releasing it when the electricity is expensive during on-peak periods. A private ESS requires a new optimal dispatch algorithm to achieve maximum profit. To utilize an ESS for such a purpose, an optimal dispatch algorithm is required to determine appropriate charging/discharging power set-points. For utility procured ESSs, the main objective would be to achieve some technical objectives for the grid/microgrid. However, in this thesis, a real-time optimal dispatching (RTOD) algorithm is developed by formulating a mixed integer linear programming problem to determine charging and discharging power set-points of a privately owned ESS in a competitive electricity market based on real-time and day-ahead forecasted electricity prices. The objective of the optimization problem is to generate revenue by exploiting price volatility in the day-ahead/week-ahead market. Moreover, this thesis aims to evaluate and improve the usefulness of publicly available electricity market prices for RTOD of a privately owned ESS in a competitive electricity market by developing a new adaptive technique as part of the optimization problem. 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 forecasted and the actual prices. As an example of large-scale ESSs, a compressed air ESS is optimally sized and modeled for evaluations. First, the conventional RTOD algorithm is developed, and its sensitivity to price forecast inaccuracy is evaluated. It is demonstrated that the forecast inaccuracy of publicly available market prices significantly reduces the revenue resulted from the ESS operation. 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 reduce the adverse impact of the price forecast inaccuracy on the ESS revenue by online calibration of the 24-h-ahead market prices using 24-h-behind market prices. Moreover, the concept of optimal weekly usage of cryogenic energy storage (CES) is introduced and compared with the common daily usage optimization. The results reveal significant benefits of weekly usage of the CES as compared to the daily usage.

Keywords

Adaptive real-time optimal dispatch, compressed air energy storage, cryogenic energy storage, energy shift, privately owned energy storage system, publicly available market prices

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Table of Contents

List of Tables

List of Figures

Abbreviations and Symbols

ARIMA	Autoregressive Integrated Moving Average
BESS	Battery Energy Storage System
CAES	Compressed Air Energy Storage
CAISO	California Independent System Operator
CES	Cryogenic Energy Storage
ESS	Energy Storage System
GLPK	Gnu Linear Programming Kit
HFE	Historical Forecast Error
HFME	Historical Forecast Mean Error
HFMPE	Historical Forecast Mean Percentage Error
HFPE	Historical Forecast Percentage Error
HOEP	Hourly Ontario Energy Price
IESO	Ontario Independent Electricity System Operator
MAE	Mean Absolute Error
MILP	Mixed Integer Linear Programming
PDP	Pre-dispatch price
ROA	Return On Asset
RTOD	Real-Time Optimal Dispatching
SOC	Stage of the Charge

Acronyms

P_t^{Chg}	Charging power (MW)
$P_{\min}^{Chg}$	Minimum allowed charging power (MW)
$P_{\max}^{Chg}$	Maximum allowed charging power (MW)
P_t^{Dhg}	Discharging power (MW)
$P_{\min}^{Dhg}$	Minimum allowed discharging power (MW)
$P_{\max}^{Dhg}$	Maximum allowed 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)
$S_{\min}$	Minimum state of the charge (MWh)
$S_{\max}$	Maximum state of the charge (MWh)
S_{Int}	Initial state of the charge (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)
$C_{E\,\mathrm{Re}\,v}$	Hourly expected revenue due to investment ($/h)
E_t	Electricity price (Cents/kWh) or ($/MWh)
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: $T_c/\Delta t$
τ	Set of time steps in the optimization horizon
τ_c	Set of time steps in the calibration horizon

Chapter 1

1 Introduction

In this chapter, an introduction to the problem and the proposed solution is presented. The previous studies related to the research topic are reviewed. Then, contributions of this study are summarized. Finally, the organization of the thesis is explained.

1.1 Power System

Electric power system is a network consisting of different electric components used to generate, transmit, and distribute electric energy. Generally speaking, a power system is composed of four main components including generation system, transmission system, distribution system, and loads. The generation system supplies electric power; the transmission system carries electric power over long distances; the distribution system distributes power between loads; the loads consume the electricity. The majority of power systems are based on three-phase alternative current (AC) systems.

1.1.1 Concept of Economic Dispatch in Power Systems

Economic dispatch is a process which determines the optimal outputs of the generation units to meet the load requirements at the lowest possible cost still providing the electric power to the consumers in a robust and reliable fashion. Usually, the economical dispatching problem is formulated mathematically as an optimization problem and then solved by computer software while considering the constraints of the power system.

1.1.2 Energy Storage Systems

Energy storage is made by physical devices to store energy at the present moment and use it for more useful operations at later time. Several forms of energy storage systems can be used to realize an energy storage system. For example, a battery converts electric energy to chemical energy and then converts it back to the electric energy when needed. In this thesis, the focus is on large scale ESSs to convert electric energy into compressed air/liquefied air, store it, and convert it back to the electricity form when needed.

The large-scale ESSs used in this thesis are compressed air energy storage (CAES) and cryogenic energy storage (CES) systems which are described with details in Chapter 2.

1.1.3 Storing Electricity by Grid-Scale Energy Storage Systems

In the close future, it is expected that large-scale ESSs to be used to shift considerable amount of electric energy in power systems. In this case, the electric energy is stored when there is excess generation while it is released when there is a need of electricity. This way, the generation system needs not tolerate drastic changes to meet the load requirement and maintain system stability. This feature is essential as the penetration of the renewable energy resources into the electrical grid is increasing while fossil fuel-based power plants are being closed across the world. In addition, energy storage systems (ESSs) are enabling technologies for new applications in the energy field such as power peak shaving [1].

Large-scale ESSs have recently become matters of significant interest for the purpose of shifting wind energy generation from off-peak to on-peak periods. This allows a higher penetration of wind energy to electrical girds as the maximum wind generation usually occurs during the night, a time period when it is not needed. In order to take advantage of energy shifting, utility regulators and policy makers are attempting to encourage private investors to build, own, and operate large-scale ESSs in the near future. In this case, the main objective of the ESS from private owner’s perspective is to maximize profit by exploiting arbitrage opportunities available due to energy price volatility in the day-ahead market. 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. Several studies of utility procured ESSs have shown that the utility’s optimal power flow can determine the contribution of the ESS to achieve optimal grid or microgrid operation. In contrast, a private ESS requires a new optimal dispatching algorithm to generate profit in a competitive electricity market for the private owner of the ESS.

1.2 Literature Survey

ESSs in a competitive electricity market, especially large-scale ESSs, are preferred to be managed by private investors. Additionally, due to the large price forecasting errors in real-world electricity markets, these optimal dispatching algorithms do not achieve maximum financial benefits; this is because the ESS charging and discharging power set-points are determined based on the imperfectly forecasted prices, whereas the electricity is purchased and sold based on the actual values of energy price. As demonstrated in this thesis, since the price forecast error in real-world markets is large, the profit loss of the privately owned ESS is considerable.

Several studies have investigated the idea of optimal energy shifting using different types of ESSs where energy is stored during lower price time periods mostly during night and discharged during peak time periods. Generally, the application of ESSs can be divided into the following main categories:

1.2.1 ESS as Part of a Microgrid

The ESS is employed in [2] to optimize the operation of a microgrid based on day-ahead power forecasting. A real-time control strategy based on load forecast and dynamic programming methods is presented in [3]. The proposed optimization model is solved by using a dynamic programming technique. The objective is peak shaving and prolonging the battery lifetime, and the constraints considered include battery state of charge (SOC), cycling times per day, converter capacity, and step power.

In [4], authors present a method to evaluate the impact of ESS specific costs on the net present value, i.e., the difference between the present value of cash inflows and the present value of cash outflows of ESS installations in distribution substations. Optimal bid schedules for a hybrid ESS participating in both energy and regulation service markets is proposed in [5]. An economically optimal operating schedule for a distributed hydrogen-electric system is presented in [6].

1.2.2 ESS Combined with Renewable Generation Sources

Water storage is utilized to improve wind park operational economic gains [7]. In this investigation, an algorithm is proposed to identify the optimum daily operational strategy to be followed by the wind turbines and the hydro generation pumping equipment. Optimal allocation and economic analysis of the ESS in microgrids on the basis of net present value are presented in [8]. In [9], an approach for security constrained unit commitment with integration of an ESS and wind generation is presented. The proposed approach allows optimization of the energy and the ancillary services using 24-h optimization horizon. An approach for planning and operating an energy storage system for a wind farm in the electricity market is proposed using 24-h price forecast in [10]. In [11], a linear programming-based algorithm for creating 24-h dispatching schedules for customer-owned renewable energy systems coupled with energy storage has been developed. An algorithm has been developed in [12] for creating 24-h dispatching schedules for customer-owned renewable energy systems coupled with an ESS. A double battery energy storage system (BESS) is used in [13] where the generated wind power charges one BESS while the second BESS is employed to discharge power into the grid. Based on the forecasted charging wind power and the monitored SOC of the two BESSs, the discharge power level from the generating station is determined and scheduled a few hours ahead.

1.2.3 ESS for Ancillary Services

Some of the studies also use ESSs to provide ancillary services to the grid, such as frequency regulation. The work in [14] demonstrates the use of ESSs as a solution to reduce the frequency variations. A simple dispatching strategy is provided for operation of a wind farm coupled with a utility-scale battery. In [15], the technical characteristics, modeling approach, methodologies, and results for providing regulation services in the California independent system operator (CAISO) market are presented.

As discussed above, the optimal dispatching algorithms proposed in most prior studies reported in the literature are not appropriate for privately owned ESSs since they do not consider the ESS as a single entity which can freely purchase/sell the electricity in the competitive electricity market. In this case, a new approach of optimal dispatching algorithm should be developed for a privately owned ESS to achieve maximum profit.

Moreover, in 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 [16]. 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 [17].

Although various techniques have been reported in the literature to improve price forecast accuracy, short-term operation scheduling in a competitive electricity market is still a very challenging task due to the uncertainty associated with future electricity prices [18].

In [7], this concern has been addressed by assuming that accurate forecasting of electricity price is possible in the optimization algorithm. However, accurate price forecast is not possible in practice [18]. In recent years, several approaches have been applied to short-term electricity price forecasting, such as [19]–[21]. A summary of some price forecasting approaches is presented in [22]. By reviewing these techniques, one can realize that different levels of error in price forecasting have been reported for the studied markets. For instance, forecast errors ranging from about 5% to 20% were reported for the Spanish [23], PJM [24], and Ontario [25], [26] electricity markets. Such large differences in price forecasting errors depend on the characteristics of the market under study and volatility of market prices [26], [27].

Increasing price forecast accuracy could always be considered as an approach to reduce the adverse impact of forecast error on the short-term optimal scheduling of an ESS in a competitive electricity market. Various techniques have been reported in the literature for improving the accuracy of electricity price forecasts. For instance, in [28], wavelet transforms were employed to improve the accuracy of an ARIMA model by about 2.7 percentage points. However, in most of the studies in the literature, several practical parameters affecting the forecast accuracy are not considered; in real-world applications, the amount of price forecasting errors are usually significantly higher than those mentioned in the literature, e.g., 20% or even 50% [18].

There are also some studies in the literature which deal with the economic impact of electricity price forecasting error on the operation scheduling. In [18], electricity market price forecasts with different levels of accuracy are used to optimally schedule the next-day operation of two industrial loads as follows: a process industry owning on-site generation facilities, and a municipal water plant with load-shifting capabilities. The main contribution of this work is to analyze the economic impact of electricity price forecasting error on the short-term operation scheduling of two types of demand-side market participants.

As reviewed, producing price forecasts with very low error levels is not always possible [18]. In this way, changing operating philosophy from preventive to corrective fashion is another approach to handle the problem.

In this thesis, a new adaptive real-time optimal dispatching (RTOD) algorithm is proposed for privately owned ESSs to considerably reduce the adverse impact of price forecast inaccuracy on the ESS revenue by adapting the objective function of the optimization problem online based on electricity market prices available before real time.

In the Ontario electricity market, several market participants employ publicly available pre-dispatch prices (PDPs) for short-term scheduling in the next several hours. However, their optimal operations suffer from forecast inaccuracy [29]. 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.

1.3 Research Objectives

- To develop an RTOD algorithm for privately owned ESSs by formulating a mixed integer linear programming (MILP) problem to determine ESS charging and discharging power set-points in a competitive electricity market based on real-time and forecasted electricity price. The RTOD aims to generate revenue by exploiting energy price arbitrage opportunities in the day-ahead/week-ahead electricity market.

- To study the adverse impacts of publicly available market price forecast error on financial benefits achieved from ESS operation.

- To propose a new approach to reduce the adverse impact of public-domain market price forecast error on the ESS operation; this way the financial benefits of ESS operation can be significantly increased.

- To investigate the idea of weekly usage of cryogenic energy storage (CES) technology by comparing the economical benefits of two equally-expensive CES systems which are sized optimally for their charging and discharging patterns.

1.4 Assumptions

- Based on the charging and discharging opportunities in the electricity market, the ESS is sized first. After that, the RTOD aims to determine the optimal charging/discharging power set-points for the ESS to utilize energy price arbitrage opportunities available due to price volatility. For this reason, optimal sizing would be different from ESS optimal operations.

- The type of ESS scheduling in this thesis will be short-term (i.e., daily or weekly), since the price forecast for longer-than-week periods would have considerable amount of error and, thus, it is not appropriate for ESS scheduling. Moreover, long-term scheduling of the ESS would not significantly increase the ESS revenue.

- The term “optimal” used in this thesis and related studies in the literature refers to optimal solution of the economic dispatch problem. Depending on the dispatch problem definition and the accuracy of the inputs to the problem such as forecasted values, the optimal solution may change. However, this type of algorithm in literature is called “optimal dispatch” as it provides the most optimal solution to the problem given the definition and the inputs of the problem.

- Since the ESS is assumed to be operated in a competitive electricity market, it can freely purchase/sell energy to generate maximum possible profit.

- The ESS is assumed to be a price-taker entity, which means it will not impact energy prices in the market. However, with a large number of ESS diffusion in the market, the ESS operation may impact market prices. In such a case, another parameter shall be included in the optimization process to account for price variations due to the ESS operation.

1.5 Main Contributions of this Thesis

- An RTOD is proposed in [30] for privately owned ESSs by formulating an MILP problem. The optimal charging/discharging power set-points are determined based on real-time actual and forecasted electricity prices in a competitive electricity market to generate profit.

- The impact of publicly available market price forecast error on the conventional RTOD is investigated. It is demonstrated that the price forecast error can significantly reduce the financial benefit of ESS operation.

- Based on publically available market prices, an adaptive mechanism is proposed to calibrate the price forecasts in order to reduce the adverse impact of price forecast error and increase the financial benefits of ESS operation. It is demonstrated that the proposed adaptive RTOD can significantly increase the financial benefits of ESS operation as compared to the conventional RTOD when publically available market prices are used for short-term scheduling of ESSs.

- The idea of weekly usage optimization of CES is introduced. It is revealed that weekly usage optimization of these types of ESSs can significantly increase the financial benefit of ESS operation as compared to common daily usage optimization [30].

1.6 Organization of the Present Work

In Chapter 2 of this thesis, two air-based large-scale ESSs (i.e., CAES and CES systems) are introduced and, then, they are optimally sized by using a simple method proposed in this thesis. By sizing of the CAES and CES, the ratings of charging, discharging, and storage tank plants are determined for them.

In Chapter 3 of this thesis, an RTOD algorithm is developed by formulating an MILP problem to determine private ESS charging and discharging power set-points in a competitive electricity market based on real-time and forecasted electricity prices. The publically available market prices published by the Ontario independent electricity system operator (IESO) are used for evaluations. Moreover, the economic impact of electricity market price forecasting errors on the proposed RTOD algorithm is evaluated.

In Chapter 4, 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 reduce the adverse impact of the price forecast inaccuracy on the ESS revenue by online calibration of the 24-h-ahead market prices using 24-h-behind market prices.

In Chapter 5, the concept of weekly usage of CES to shift the electric energy from lower prices during off-peak periods to higher prices during on-peak periods as compared to common daily usage is introduced. Two equally-expensive CES systems are optimally sized for daily and weekly usages. The RTOD algorithm, formulated in Chapter 3 of this thesis, is used for optimal weekly and daily usages of the CES, sized in Chapter 2. The economic benefits of both CES weekly and daily usages are presented and compared for different price profiles and round-trip efficiencies of the ESS.

Chapter 6 concludes this research. Achievements are listed and suggestions for future works are presented.

Chapter 2

2 Large-Scale Energy Storage Systems

In this chapter, two air-based large-scale ESSs are introduced and, then, they are sized by using a simple method proposed in this chapter [30].

2.1 Compressed Air Energy Storage (CAES)

The CAES technology has been in use for 30 years [32]. A CAES plant stores electricity in the form of compressed air, then recovers it when needed to generate power. As shown in Figure 2-1, CAES plants can be divided into the following components:

- Power system: turbine(s), generator and the recuperator.
- Compression system.
- Depleted gas reservoir.
- Control equipment: switchgear, substation, cooling system, etc.

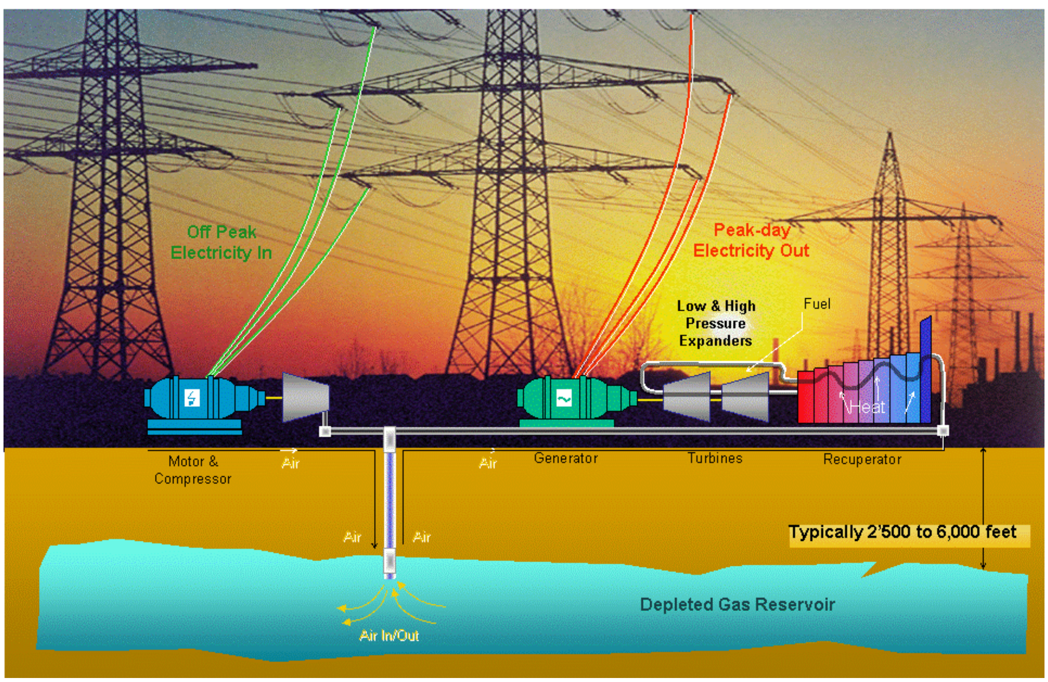

Figure 2-1: Schematic for underground CAES

Basically, off-peak or inexpensive electricity is used for pre-compressing the air, which is then stored typically in an underground cavern. When the CAES plant works to regenerate power, the compressed air is released and heated by a recuperator; then, it is being mixed with fuel and expanded to make a turbine to turn to generate electricity.

2.1.1 Daily Sizing of CAES

A generic price profile is considered in this study for ESS sizing for the sake of simplicity. Since the ESS makes financial benefits only based on the arbitrage of electricity price, i.e., the difference between the high and low levels of price profile, a smooth price profile with different levels is a good tool even though more complex price profiles could be used. This generic electricity price profile is represented in Figure 2-2. One can see in this figure, that there are there different levels, i.e., low, medium, and high levels. The low level is in accordance with the hours in which the electricity price is low, i.e. mostly from midnight till early in the morning. The medium level is showing most of the hours when the price is medium. The high level is in accordance with the peak hours when the prices are high. This profile is adopted from electricity prices at distribution level in Ontario, and it is used in this thesis. By considering the above-mentioned price profile, the optimal dispatch of the ESS is willing to set the charging power set-points in the low (and medium level) and to set the discharging power set-points in the high level to generate the highest possible revenue. Considering typical operating parameters for the CASE unit, the charging hours is approximately 5 h (in the lowest level of price), and the discharging hours is 3 h (in the highest level of price). During weekends and holidays, since the prices are low in most of the hours, and there is not a big difference between the price levels, there is no charging/discharging, and the ESS will not operate.

Since usually the electricity price is inexpensive during weekends, there is a potential to store the energy in weekends and release it during peak periods in weekdays when the electricity price is high. However, to make this possible, very large storage size and low energy dissipation rate are required. Only if the storage is based on aquifers, the "bubble" underground can be enlarged via extra compression energy to allow larger storage size for weekly usage [31]. This technique is only viable in specific geographical locations [31]. Thus, generally, weekly usage optimization of CAES is not economical.

The round-trip efficiency of the CAES unit can vary from 30% to about 65% depending on the size, use of thermal energy recovered during the compression cycle, and use of waste heat [32]. If minimum round-trip efficiency is used in sizing process, this results in smaller storage tank size not allowing to utilize CAES in case of higher efficiencies. Instead, maximum round-trip efficiency is used for sizing to provide enough storage tank size in case of high efficiencies.

In addition, in this study, the round-trip efficiency is assumed to be equally split between charging and discharging plants which is fair consumption. In practice, the charging and discharging efficiencies are dependent on the technology of the charging and discharging plants and is provided by the manufacturer.

The ESS price per kWh will vary depending on several parameters. According to some typical projects reported in [32], \$1000/kW is considered for the CAES cost in this study. Table 2-1 represents the parameters which are used to size the CAES.

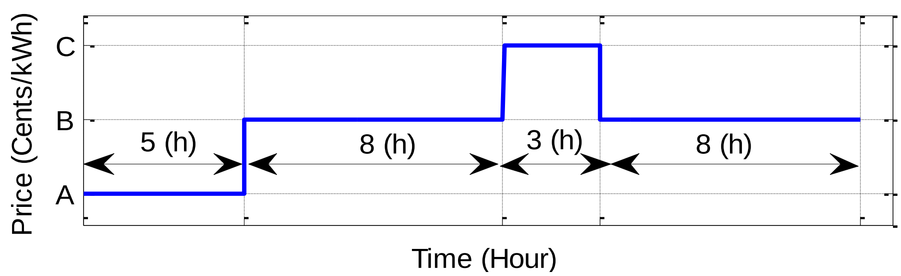

Figure 2-2: The generic electricity price profile used in this thesis

Table 2-1: Parameters used for CAES sizing

Charging Period in Weekend	0 Hours
Discharging Period in Weekend	0 Hours
Charging Period in Weekday	5 Hours per day
Discharging Period in Weekday	3 Hours per day
Max Charging Efficiency (η_{Chg})	80%
Max Discharging Efficiency (η_{Dhg})	80%
Capital Cost of CAES Discharging Plant	\$1000/kW

The maximum discharging power for the CAES is assumed to be 100 MW. Based on the CAES maximum efficiency and desired hours of charging and discharging in daily usage, maximum charging power, i.e., compression plant rating and the storage tank size are obtained. In this case, the total charging period is 5 h, while the discharging period is 3 h. Hence, based on the fact that the maximum discharging power is 100 MW, the total required charging energy and the rating of the compression plant can be calculated as below.

$$\text{Discharging energy} = 3\ (\text{h}) \times P_{\max}^{Dhg} = 3\ (\text{h}) \times 100\ (\text{MW}) = 300\ (\text{MWh}) \tag{2-1}$$

$$\text{Charging energy} = \frac{\text{Discharging energy}}{\eta_{Chg} \times \eta_{Dhg}} = \frac{300\ (\text{MWh})}{0.8 \times 0.8} = 468.75\ (\text{MWh}) \tag{2-2}$$

$$P_{\max}^{Chg} = \frac{\text{Charging energy}}{\text{Charging period}} = \frac{468.75\ (\text{MWh})}{5\ (\text{h})} = 93.75 \approx 94\ (\text{MW}) \tag{2-3}$$

$$S_{\max} = 5\ (\text{h}) \times 94 \times 0.8 \times 1.25 = 470\ (\text{MWh}) \tag{2-4}$$

25% extra size in storage tank (S_{max}) is considered to first maintain minimum 10% charge in the tank and 15% to take benefit in cases where the electricity price suddenly increases or if the CAES is also utilized for ancillary services to the grid. As given by (2-4), in S_{max} calculation, the maximum capacity should be determined based on off-peak charging on a weekday; this is generally the maximum storable energy. The total capital cost of CAES will be \$1000/kW ×100 (MW) = \$100 Million.

The compression and generation power ratings, storage tank capacity, and the capital cost of the CAES are as shown in Table 2-2.

Table 2-2: Ratings of the CAES sized for daily usage

Capital Cost	**CAES: Daily Usage**		
	$P_{\max}^{Chg}$	$P_{\max}^{Dhg}$	$S_{\max}$
\$100 Million	94 (MW)	100 (MW)	470 (MWh)

2.2 Cryogenic Energy Storage (CES)

Figure 2-3 shows the block diagram of a CES unit. The CES compromises of three major components: liquefaction plant, liquefied and cold air storage units, and power recovery. In this technology, cryogen (liquid air) is produced using electrical energy in liquefaction plant. The resultant cryogen which is around -190° C is stored at low pressure in liquefied air storage tank which is an insulated tank. Due to some natural heat gain from the ambient environment, a small fraction of liquid air boils and converts into gaseous phase commonly referred to as the “boil-off”. This causes an increase in the tank pressure. In order to maintain constant pressure inside the tank, this gaseous air has to be vented out. This process causes a continuous reduction in the amount of liquid air inside the tank with time. However, the tanks used to store cryogenics are typically vacuum insulated and hence the boil-off rate is usually very small (around 0.1-0.2% of the tank capacity per day). The boil-off air can be further used in storage plant for various purposes such as purging the liquefier heat exchanger and high grade cold storage and powering the valves. In power recovery, auxiliary heat, i.e. waste heat from any source or even from ambient conditions, is added to the cryogen converting liquid cryogen into superheated vapor (gaseous phase) at high pressure. This high-pressure gas then expands in a series of expansion turbines which drives 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 used with a low-grade cold store. Using auxiliary waste heat could increase the round-trip efficiency level to 70% range.

In this technology, storage tank is significantly inexpensive as compared to the Liquefaction and Power recovery parts and does not occupy large space as compared to the CEAS technology. This is especially important to allow economical weekly usage of CES as compared to daily usage. Further, it makes this technology superior to other ESS technology for long-term energy shift.

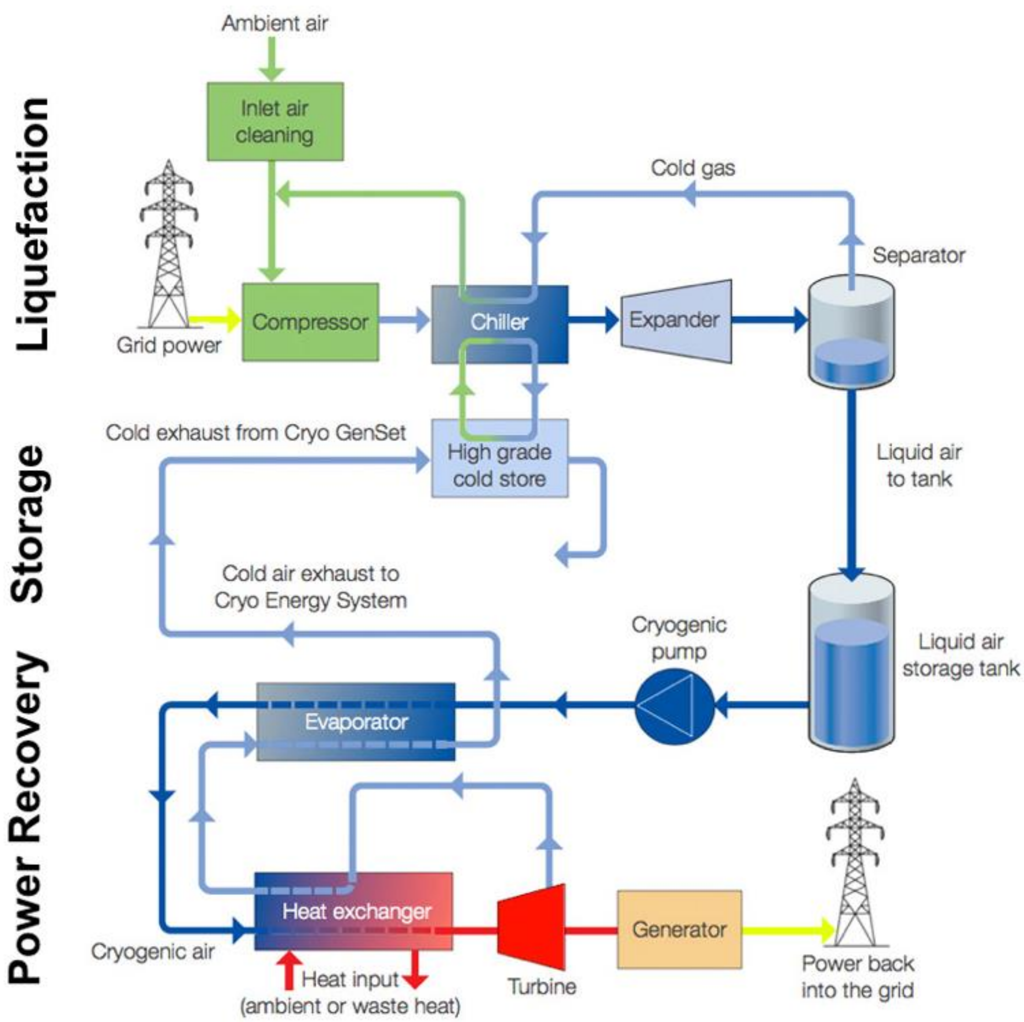

Figure 2-3: The block diagram of a CES unit [37]

2.2.1 Weekly and Daily Sizing of the CES

In this section, using the same price profile (shown in Figure 2-2), the CES is sized for weekly and daily usages.

In order to fairly compare the economical benefits of weekly usage of CES over daily usage, two equally-expensive CES systems are sized in this section with a simple method. Several parameters 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 [37] for this study. Table 2-3 presents the parameters which are used to size CES. The efficiency of the CES unit can vary from 30% up to 70% depending on the size, use of low-grade cold storage tank, and use of waste heat. If minimum round-trip efficiency is used in sizing process, this results in smaller storage tank size not allowing to utilize CES in case of higher efficiencies. Since in this study, it is desired to evaluate and compare the performance of both CES systems for various efficiencies and electricity price profiles, maximum round-trip efficiency is used for sizing of both CES systems to allow performance comparison in case of high and low efficiencies. In addition, the round-trip efficiency is equally split between charging and discharging plants. As the main purpose of this study is to compare the weekly and daily usage, any insignificant error in the assumptions will not considerably impact the final objective of the comparison study.

Table 2-3: Parameters Used for CES Sizing

Charging Period in Weekend for Weekly Usage	48 Hours
Charging Period in Weekend for Daily Usage	0 Hours
Discharging Period in Weekend for Weekly and Daily Usages	0 Hours
Charging Period in Weekday for Weekly and Daily Usages	5 Hours per day
Discharging Period in Weekday for Weekly and Daily Usages	3 Hours per day
Max Charging Efficiency (η_{Chg})	83 %
Max Discharging Efficiency (η_{Dhg})	83 %
Capital Cost of CES Charging Plant	$1.68 Million/MW
Capital Cost of CES Discharging Plant	$0.56 Million/MW
Capital Cost of CES Tank Plant	$0.007 Million/MWh

Either weekly or daily usage can be used as the base case. In this study, however, weekly usage is employed as the base for sizing two equally-expensive CES systems, i.e., CES_1 and CES_2: weekly and daily, respectively. The maximum discharging power for CES_1 is assumed 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 storage tank size are obtained. Then, the total cost of CES_1 is calculated. For CES_2, the maximum discharging power is unknown; instead the total 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 total cost, three equations and three unknowns including maximum charging and discharging power ratings and storage tank size can be written and solved.

In weekly design, i.e. CES_1, the total charging period is 73 h, (2 full weekends plus 5 weekdays each day with 5 h of charging opportunity) = 2×24+5×5, while the discharging period is 15 h, (5 weekdays each with 3 h of discharging opportunity) = 5×3. Hence, based on the fact that the maximum discharging power is 100 MW in weekly usage, the total required charging energy and the rating of the liquefaction plant can be calculated as follows:

$$\text{Discharging energy} = 15\,(\text{h}) \times P_{\max}^{Dhg} = 15\,(\text{h}) \times 100\,(\text{MW}) = 1500\,(\text{MWh}) \tag{2-5}$$

$$\text{Charging energy} = \frac{\text{Discharging energy}}{\eta_{Chg} \times \eta_{Dhg}} = \frac{1500\,(\text{MWh})}{0.83 \times 0.83} \approx 2177\,(\text{MWh}) \tag{2-6}$$

$$P_{\max}^{Chg} = \frac{\text{Charging energy}}{\text{Charging period}} = \frac{2177\,(\text{MWh})}{73\,(\text{h})} \approx 30\,(\text{MW}) \tag{2-7}$$

$$S_{\max} = (2 \times 24 + 5)\,(\text{h}) \times P_{\max}^{Chg} \times \eta_{Chg} \times 1.2 \approx 1575\,(\text{MWh}) \tag{2-8}$$

$$\begin{aligned} &1.68\,P_{\max}^{Chg} + 0.56\,P_{\max}^{Dhg} + 0.007\,S_{\max} = \\ &1.68 \times 30 + 0.56 \times 100 + 0.007 \times 1575 \approx \$117\ \text{Million} \end{aligned} \tag{2-9}$$

20% extra size in storage tank (S_{max}) is considered to first maintain minimum 10% charge in the tank and 10% to take benefit in cases where electricity price suddenly increases or if CES is also utilized to operate for ancillary services. As given by (2-8), in S_{max} calculation, the maximum capacity should be determined based on full charging on weekends (Saturday and Sunday) and off-peak charging on the following Monday; this is generally the maximum storable energy. Using the cost coefficients mentioned in Table 2-3, the total capital cost of CES_1 can be calculated as (2-9).

In daily design, i.e. CES_2, the total charging period is 5-h while the discharging period is 3-h. The maximum discharging power is unknown in this case. The total charging energy and the rating of the liquefaction plant can be calculated as given by (2-10) and (2-11). To maintain the same cost as weekly CES, three equations (2-10), (2-12), and (2-13) can be solved and three unknowns P^{Chg}_{max}, P^{Dhg}_{max}, and S_{max} can be found as shown in Table 2-4. This table presents the capital cost, charging, discharging and storage tank plant sizes for the CES_1 and CES_2.

Table 2-4: Weekly and Daily Ratings of CES

Capital Cost	CES$_1$: Weekly Usage			CES$_2$: Daily Usage		
	$P_{\max}^{Chg}$	$P_{\max}^{Dhg}$	$S_{\max}$	$P_{\max}^{Chg}$	$P_{\max}^{Dhg}$	$S_{\max}$
\$117 M	30 (MW)	100 (MW)	1575 (MWh)	50 (MW)	57 (MW)	247 (MWh)

$$1.68\,P_{\max}^{Chg} + 0.56\,P_{\max}^{Dhg} + 0.007\,S_{\max} \approx \$117\ \text{Million} \tag{2-10}$$

$$\text{Charging energy} = \frac{3\times P_{\max}^{Dhg}}{\eta_{Chg}\times\eta_{Dhg}} = 4.35\,P_{\max}^{Dhg}\ \text{(MWh)} \tag{2-11}$$

$$P_{\max}^{Chg} = \frac{\text{Charging energy}}{\text{Charging period}} = \frac{4.35\times P_{\max}^{Dhg}}{5\text{(h)}} = 0.87\,P_{\max}^{Dhg}\ \text{(MW)} \tag{2-12}$$

$$S_{\max} = 5\times P_{\max}^{Chg}\times\eta_{Chg}\times 1.2 \approx 4.33\,P_{\max}^{Dhg}\ \text{(MWh)} \tag{2-13}$$

2.3 Summery

In this chapter, two large-scale ESSs, i.e. CAES and CES systems, are introduced; then, a simple method is proposed and used for determining the appropriate ratings of the ESSs, i.e., charging, storage tank, and discharging plants.

Chapter 3

3 Real-Time Optimal Dispatch (RTOD)

In this chapter, an RTOD algorithm is developed by formulating a mixed integer linear programming (MILP) problem to determine private energy storage system (ESS) charging and discharging power set-points in a competitive electricity market based on real-time and forecasted electricity prices. The CAES sized in Section 2.1.1 is used as an example to demonstrate and evaluate the performance of the proposed algorithm. The performance of the proposed RTOD is evaluated for different possible forecast errors using a generic price profile and also the real-world price data of the Ontario electricity market; then, the results are discussed. It is demonstrated that the considerable error of electricity price forecast significantly reduces the financial benefit of the ESS.

3.1 Formulation of the RTOD for a Privately Owned ESS

In this thesis, the ESS is considered as a single entity which freely purchases/sells electricity from/to the electricity market. An optimization problem is developed to determine the proper periods and dispatch quantities for the ESS charging and discharging to maximize the ESS revenue for the private investor in the ESS.

To develop an RTOD algorithm for a privately owned ESS, an MILP optimization problem is formulated as explained in this section. 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 time step to account for the time-varying nature of the electricity price in the market. In this chapter, 24-h optimization horizon with 1-h time step is considered to determine optimal dispatch quantities including charging and discharging power set-points. 1-h time step is selected since electricity market price is updated every hour in the case study of this study, i.e., the Ontario electricity market. In this case, the optimal dispatch problem will be a multi-interval optimization problem with $T/\Delta t$ = 24 h /1 h = 24 time steps, each of which represents one hour time interval. In this case, all of the main optimization variables will be arrays with

24 elements that are 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 [33], [34].

Equations (3-1) to (3-5) express charging and discharging powers and the state of the charge (SOC) constraints of the ESS. In the following equations, M_t^{Chg} and M_t^{Dhg} are binary variables while P_t^{Chg}, P_t^{Dhg}, *and* S_t are positive real variables.

$$P_t^{Chg} = 0 \qquad \forall t \in \tau \wedge M_t^{Chg} = 0 \tag{3-1}$$

$$P_{\min}^{Chg} \le P_t^{Chg} \le P_{\max}^{Chg} \qquad \forall t \in \tau \wedge M_t^{Chg} = 1 \tag{3-2}$$

$$P_t^{Dhg} = 0 \qquad \forall t \in \tau \wedge M_t^{Dhg} = 0 \tag{3-3}$$

$$P_{\min}^{Dhg} \le P_t^{Dhg} \le P_{\max}^{Dhg} \qquad \forall t \in \tau \wedge M_t^{Dhg} = 1 \tag{3-4}$$

$$S_{\min} \le S_t \le S_{\max} \qquad \forall t \in \tau \tag{3-5}$$

where τ is the set of time steps, i.e., {1, …, N} in which $N=T/\Delta t$ is the length of the optimization horizon. The energy balance equation of the ESS is given by (3-6) defining the relation of ESS state of charge (SOC) at time steps t and t+1. This equation is based on the physics of the ESS showing that at the time step (t+1), the SOC is 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. As it is given by this equation, the variable S_t is an array with one more element as compared to other optimization variables.

$$S_{t+1} = S_t + (\eta_{Chg} P_t^{Chg} - \frac{P_t^{Dhg}}{\eta_{Dhg}} - \eta_{Dsp} S_t)\,\Delta t \qquad \forall t \in \tau \tag{3-6}$$

Equation (3-7) shows the objective function of the optimal dispatch problem which is to be maximized. The objective function, given in (3-7), includes the profit of selling electricity to the market, the ESS operating cost for charging and discharging, and the cost of purchasing electricity from the market within the optimization horizon, i.e., 24 h. In this equation, E_t is the forecasted electricity price at the time step t. It should be noted that at the present time step, i.e., t=1, E_t is equal to the actual electricity price.

$$\text{Obj. Function : Revenue} = \sum_{t=0}^{N} \left\{ (P_t^{Dhg} - P_t^{Chg})E_t - C_{DhgO}P_t^{Dhg} - C_{ChgO}P_t^{Chg} \right\}.\Delta t \qquad (3\text{-}7)$$

A positive value of (3-7) means that the ESS is making profit; a zero objective value indicates that the ESS can only return operating cost; a negative value means that ESS is not even able to return the operating cost.

The framework of the proposed model in the thesis which aims to employ an ESS as a single entity to utilize energy price arbitrage in the day-ahead/week-ahead electricity market has been depicted in Figure 3-1. The model will be described in details throughout the thesis.

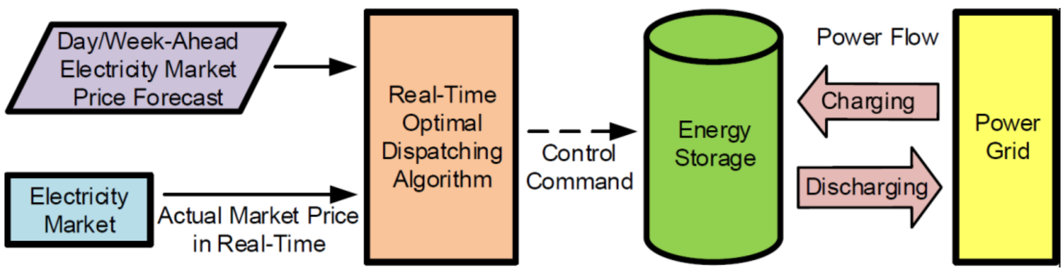

Figure 3-1: The framework of the proposed model in this thesis

Figure 3-2 shows how the proposed RTOD is implemented in this study. The RTOD and ESS are simulated in Matlab. The optimization problem including variables, parameters, the objective function, and the constraints are defined in a file which is called hereafter problem file developed using GNU MathProg modeling language. The values for the problem parameters are generated at each time step by a Matlab code in another file which is called hereafter data/parameter file. The data file includes ESS parameters such as $P^{Chg}{}_{min}$ and $P^{Chg}{}_{max}$, ESS SOC at the present time step, i.e., S_{Int}, and the electricity price forecast for the optimization horizon, i.e., E_t. If a more accurate price forecast is available for the first few hours (e.g., m hours), it could substitute the first few hours of the 24-h-ahead forecast. For instance, in the Ontario market, 24-h-ahead and 3-h-ahead price forecasts are issued [35].

Both files are inputted to the GNU linear programming kit (GLPK) [36]. Then, the optimization problem is solved by GLPK to find the objective values as well as the values of optimization problem variables such as charging/discharging powers. The charging and discharging power set-points at the present time will provide the required commands to the ESS. In the next time step, the SOC of the ESS 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 till the end of the simulation.

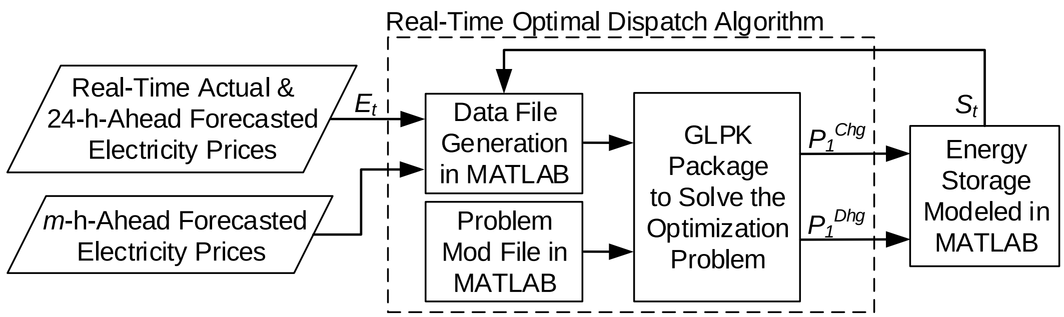

Figure 3-2: The flowchart for implementation of the proposed RTOD

3.2 Performance Evaluation of the Conventional RTOD

In this section, a CAES unit, an example of large-scale ESSs, is used as the case ESS. As mentioned in Chapter 2 of this thesis, CAES is basically composed of three main plants as follows: Charging plant, compressed air tank plant, and discharging plant (one can refer to Chapter 2 of this thesis for more information about CAES). Based on its application, CAES 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 [32]. In this chapter, the CAES, sized in Chapter 2, is used for simulation studies.

Operating parameters of the CAES are shown in Table 3-1. In this table, the amount of expected revenue due to investment (C_{ERev}) is considered the same as the one considered for solar power plant projects; it is also in the range of some CAES projects analyzed by EPRI-DOE handbook [32]. This way, after the life of ESS (30 years [32]), the total revenue should be at least 250% of the total capital cost (150% of the capital cost plus initial capital cost). As a result, C_{ERev} per year is considered as 8.34% = (250/30)% of the capital cost. A typical value of return on assets (ROA) is expected to be above 8% of the capital cost per year for a private entity investing in a risky asset. In this study, the ROA results in 250/30%=8.34% of the capital cost per year. Nevertheless, changing the expected revenue will not affect the results since the total revenue obtained from the ESS operation is calculated and evaluated throughout the study; it should be emphasized that the total revenue consists of the expected revenue plus the extra revenue (if there is any). Changing the expected revenue will change the extra revenue; the total revenue, however, will not be affected by changing the expected revenue.

In large-scale ESSs including CAES technology, to maintain rated efficiency, it is required to operate the compression plant close to its rated value. Therefore, P^{Chg}_{min} is set to 80% of P^{Chg}_{max}. However, the generating turbine and its supplying pump can efficiently operate even at lower power set-points. Energy storage dissipation is assumed to be 1% per day thus 0.0416%=1%/24 per hour. The parameter values shown in Table 3-1 are typical values and can be changed according to different types of CAES units as well as different technologies. Nevertheless, the values of these parameters will not affect the ultimate outcomes of the present work.

Table 3-1: The operating parameters of the CAES Unit Sized in this thesis

P^{Chg}_{min}	80% × P^{Chg}_{max}	C_{Cap}	Total Capital Cost/(Life of ESS (=30) ×365×24)
P^{Dhg}_{min}	3% × P^{Dhg}_{max}	C_{Main}	5% × C_{Cap}
S_{min}	10% × S_{max}	C_{ChgO}	60% × C_{Main} / P^{Chg}_{max}
S_{Int}	10% × S_{max}	C_{DhgO}	40% × C_{Main} / P^{Dhg}_{max}
η_{Dsp}	0.0416% ×S_t	C_{ERev}	250% × Total Capital Cost/(30×365×24)

3.2.1 Sensitivity Analyses of the RTOD to Price Forecast Error

In this section, first, a generic price profile is used for sensitivity analysis of the proposed RTOD. Then, the real electricity price profiles from the Ontario market are used to verify the findings of this section. The generic electricity price profile is shown in Figure 2-2. Price levels *A*, *B*, and *C* are assumed to be 6, 15, and 24 Cents/kWh (typical values in the Ontario market [35]), respectively. Using the pre-defined price profile (see Figure 2-2) and round-trip efficiency of 60% (a typical value for a high-efficient unit [32]), the real-time optimization is performed considering 24-h optimization horizon. To perform sensitivity analysis in case of price forecasting error, different levels of under-forecasting and over-forecasting (from 0 to 100% with 10% steps) are simulated and studied. In all cases, the actual electricity prices are identical, while they are scaled differently to generate imperfectly forecasted ones. The under-forecasting and over-forecasting levels are applied uniformly to the 24-h electricity price. For the purpose of result comparison, this approach ensures that the ESS pays/obtains the same rate for purchasing/selling electricity from/to the market in all cases.

Further, the real-time optimization is performed considering 24-h optimization horizon. The optimizer will consider the electricity price of the next 24 h to make dispatch decisions. Daily optimal dispatch is executed for 24 consecutive hours with resolution of one hour. Figure 3-3 shows the simulation results with the assumption that there is no price forecast error. In this case, the forecasted price is exactly equal to the actual one. Figure 3-3 (a) shows the actual and forecasted prices which are equal. Figure 3-3 (b) shows the power exchange between the CAES and the grid. Positive values of the exchange power mean that the CAES is charging and negative values mean that it is discharging. One can see that the CAES is charging during low energy prices and discharging the energy when the prices are high. This way it can make financial benefit. Figure 3-3 (c) shows the state of the charge (SOC) or the amount of energy stored in the CAES tank. Figure 3-3 (d) shows the values of extra revenue for each hour. As shown in Figure 3-3 (d), the extra revenue is negative when the CAES is charging since it is paying to buy the electricity from the grid; it is positive when the CAES is selling electricity to the grid. Since the selling prices are higher than buying prices, it will make financial benefit. It is also clear that the extra revenue has negative offset all the times. This offset is due to the constant parameters added to the objective function including expected revenue (C_{ERev}) and capital cost per hour (C_{Cap}) as define in Table 3-1. The total revenue per week that the CAES can make is the integral of the curve in Figure 3-3 (d) which is \$202.91 k (thousand dollars).

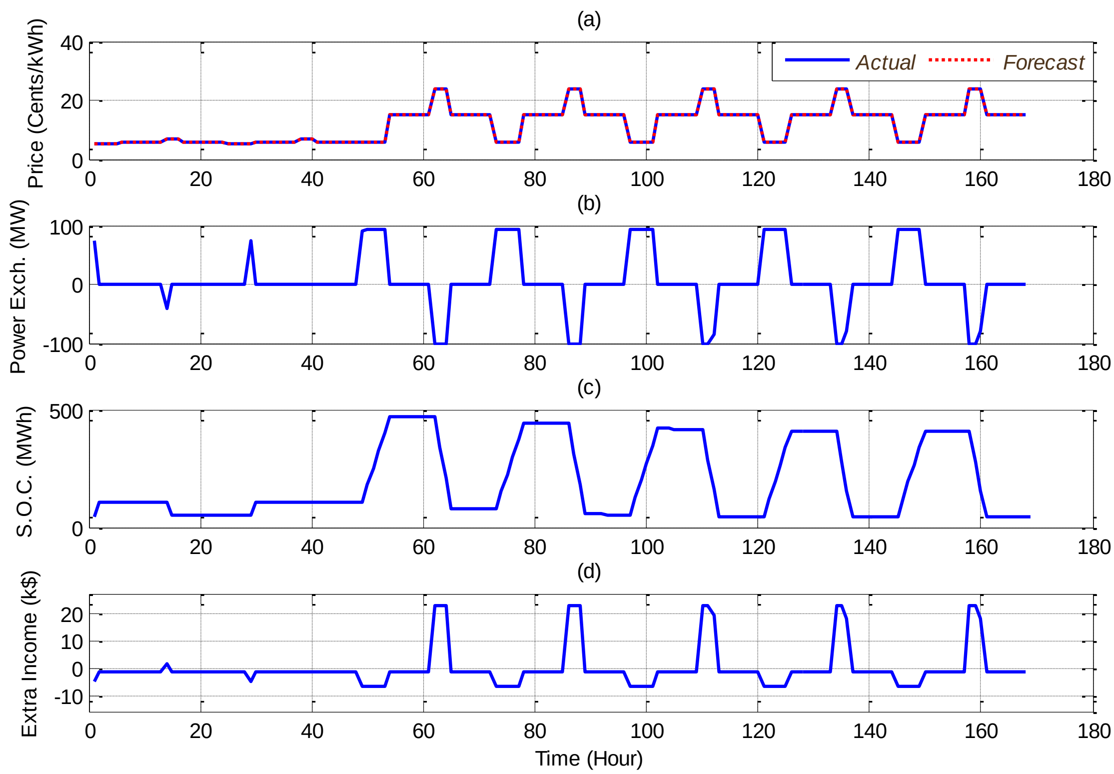

Figure 3-3: (a): Actual and forecasted prices, (b): Power exchange, (c): SOC, (d): Extra income (revenue): all for exact forecast of price

Figure 3-4 shows the simulation results for the case in which there is 30% price under-forecast. This will cause 30% price forecast error. As shown in Figure 3-4, although there is significant amount of price forecast error, the simulation results are the same as the case in which there is no price forecast error (see Figure 3-3). According to observations in this thesis, the performance of the RTOD will not be affected by price forecast error until a certain level of error. In the next paragraphs, this will be evaluated with more details. In this case, the total revenue per week that the CAES can make is $201.3 k, which is approximately the same as the first case in which there is no price forecast error.

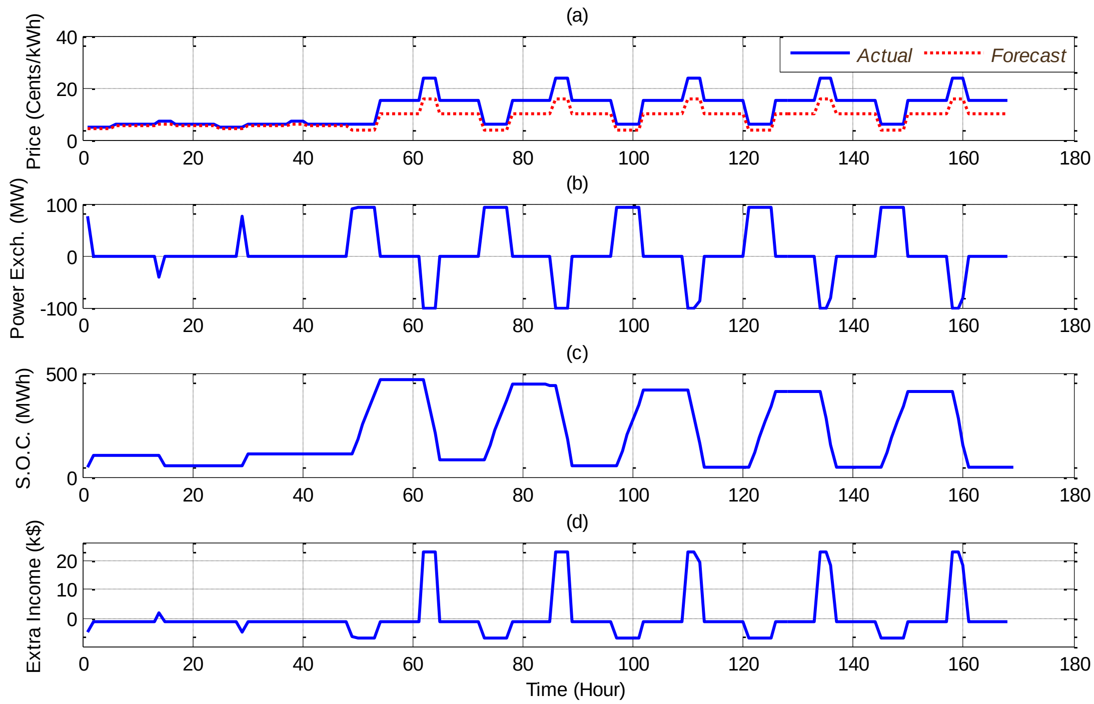

Figure 3-4: (a): Actual and forecasted prices, (b): Power exchange, (c): SOC, (d): Extra income (revenue): all for under-forecast of price

Figure 3-5 shows the simulation results for the case in which there is 40% price under-forecast. This will cause 40% price forecast error. As shown in Figure 3-5 , the curves are now significantly deviated from two cases above and the CAES is no longer working in the optimal fashion since the energy is being discharged in the medium level of price not in the peak level. In the next paragraphs, the reason of this will be evaluated with more details. The total revenue per week that the CAES can make is \$69.5 k in this case, which is significantly smaller than the expected revenue (i.e., \$159.8 k).Thus, the operation of the CAES is no longer acceptable since it is not working economically.

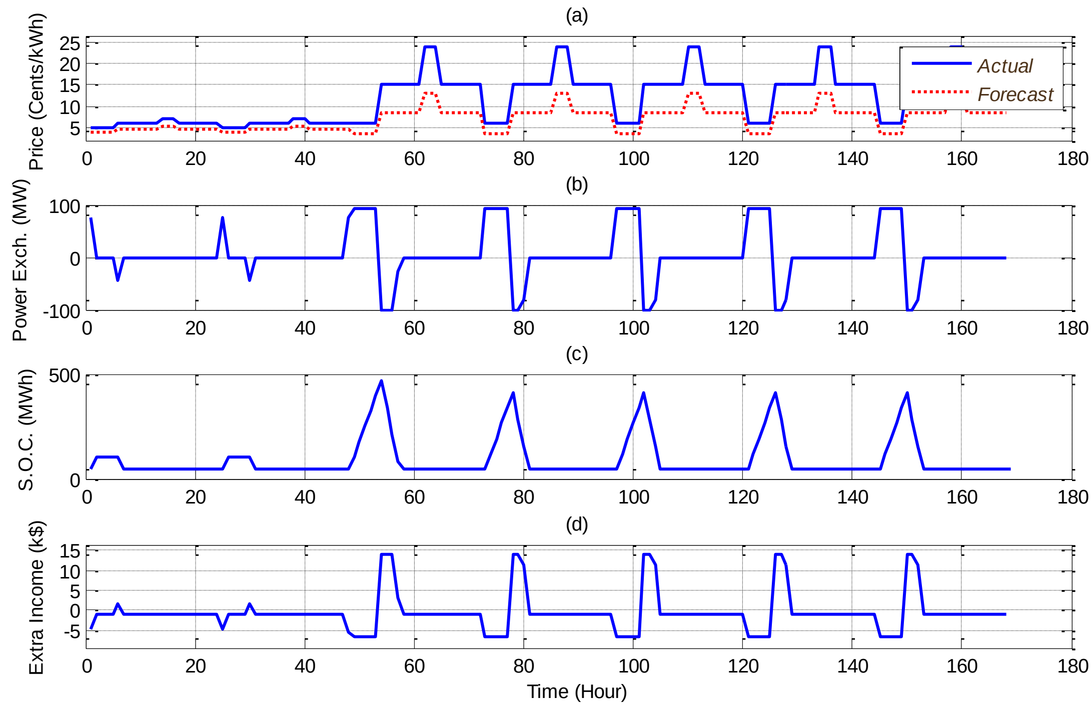

Figure 3-5: Actual and forecasted prices, (b): Power exchange, (c): SOC, (d): Extra income (revenue): all for too under-forecast of price

Figure 3-6 shows the simulation results for the case in which there is 60% price over-forecast. This will cause 60% price forecast error. As shown in Figure 3-6, although there is significant amount of price forecast error, the simulation results are approximately the same as the case in which there is no price forecast error (see Figure 3-3). The total revenue per week that the CAES can make is \$201.1 k in this case, which is approximately the same as the first case in which there is no price forecast error.

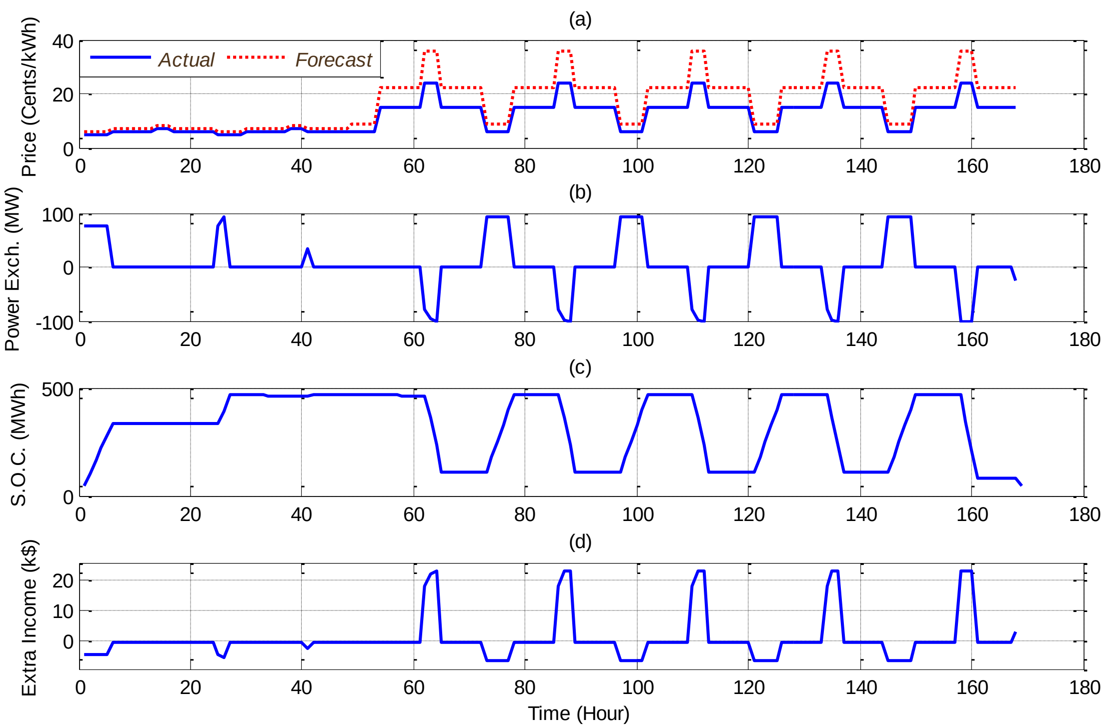

Figure 3-6: Actual and forecasted prices, (b): Power exchange, (c): SOC, (d): Extra income (revenue): all for over-forecast of price

Figure 3-7 shows the simulation results for the case in which there is 70% price over-forecast. This will cause 70% price forecast error. As shown in Figure 3-7, the curves are now significantly changed compared to the above case in which there is 60% of price over-forecast error, and the CAES is no longer working. Only small charging and discharging occurs to compensate the energy dissipation. In the next paragraphs, the reason of this will be evaluated with more details. The total revenue per week that the CAES can make is -$10.9 k in this case, which is equal to $10.9 k of financial loss. Thus, the operation of the CAES is no longer acceptable since it is not working economically.

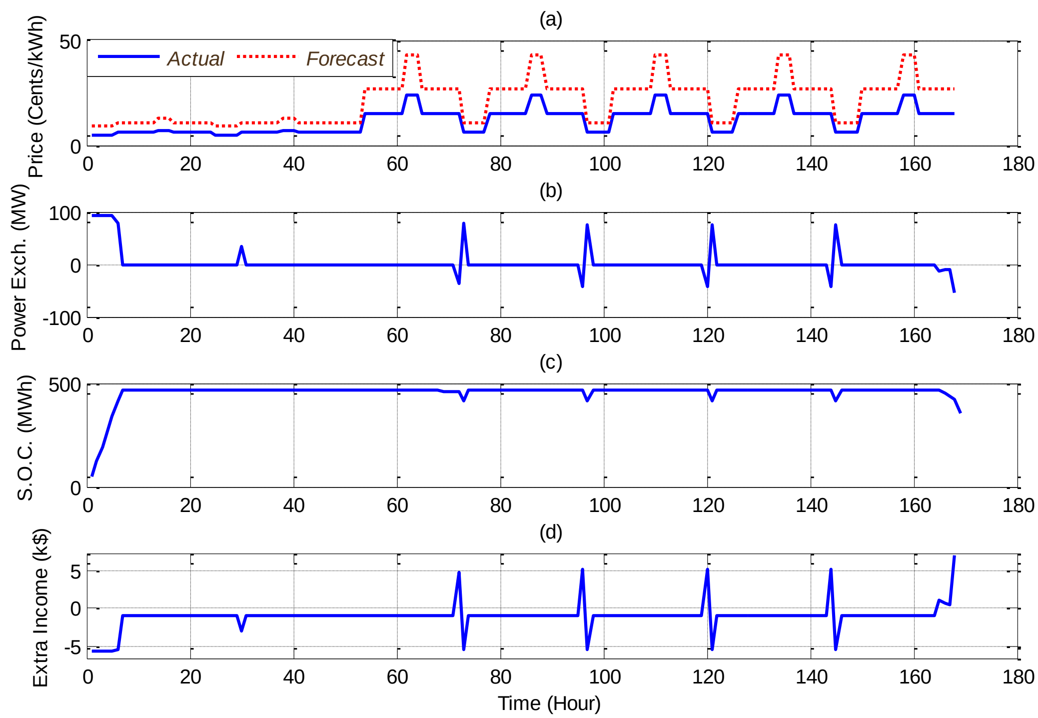

Figure 3-7: (a): Actual and forecasted prices, (b): Power exchange, (c): SOC, (d): Extra income (revenue): all for too over-forecast of price

Further, three important cases, Cases 1 to 3, are selected to discuss the results of this investigation with details. In Case 1, the price forecast is identical to the actual forecast. In Case 2, the electricity price is 40% under-forecasted, while in Case 3, it is 70% over-forecasted.

Table 3-2 shows the values of obtained revenue in the first 24 h of ESS utilization, for Case 1 to Case 3 plus two other cases with 10% less under-forecasting and over-forecasting, respectively. As shown in this table, a certain level of under-forecasting/over-forecasting does not affect the profit of the ESS. This is because the ESS takes advantage of the electricity price arbitrage to make profit and, thus, the uniform forecast error does not affect the ESS profit until it reaches to a certain level which is 40% in case of under-forecasting and 70% in case of over-forecasting.

Table 3-2: Comparison of the obtained revenue for the first 24-h of ESS utilization under different price forecasting conditions

Forecasting Conditions	Revenue (Thousand $)	Acceptability
Ideal Forecast	39	Acceptable
30% Under-Forecast	39	Acceptable
40% Under-Forecast	13.9	Unacceptable
60% Over-Forecast	32.4	Acceptable
70% Over-Forecast	-39.8	Unacceptable

The presumed actual and forecasted electricity price profiles within 24-h time period are shown in Figure 3-8 (a, d, and g) for Cases 1, 2, and 3, respectively. ESS power exchange for the three cases is shown in Figure 3-8 (b, e, and h), respectively. The positive power exchange indicates that the CAES is charging; whereas, the negative one indicates that the CAES is discharging. Figure 3-8 (c, f, and i) shows SOC values for the three studied cases. One can see the SOC increases when the ESS is charging; the SOC slowly drops with ESS dissipation rate when the power exchange is zero; finally, the SOC decreases when the ESS is discharging. As shown in the first column, ESS makes profit by charging at low electricity prices and discharging at high electricity prices in case of ideal forecasting.

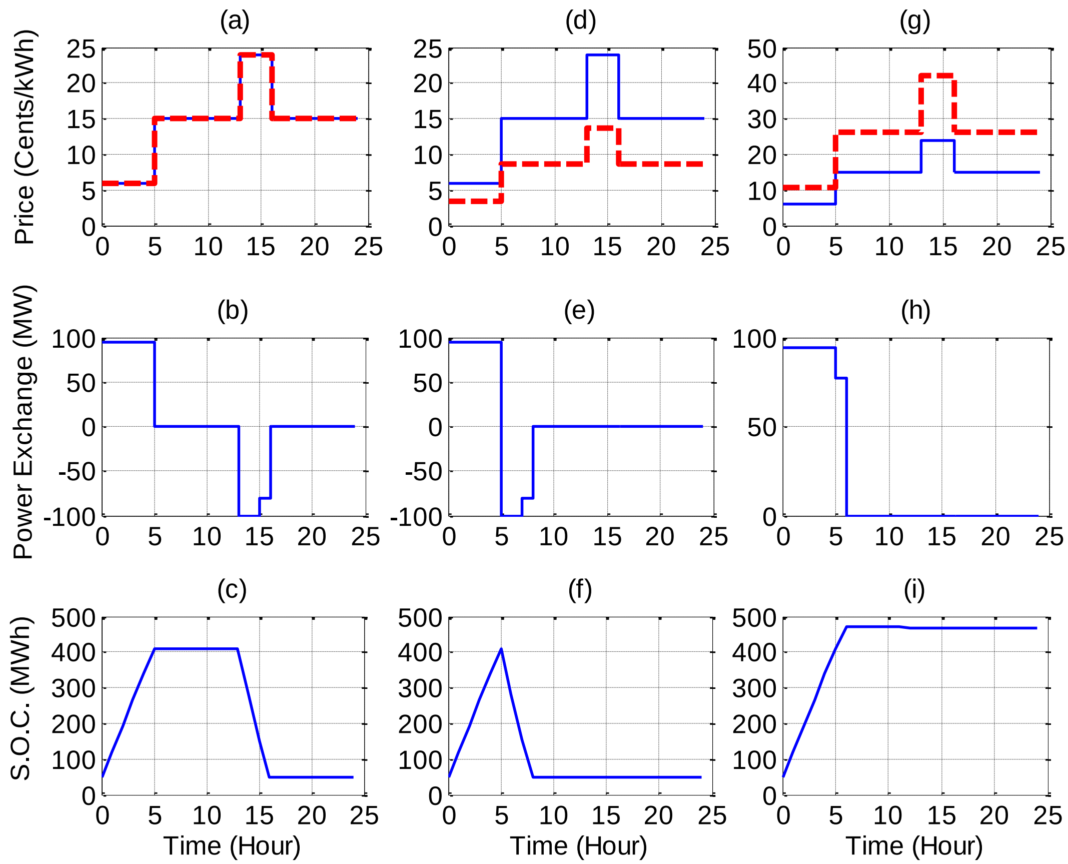

Figure 3-8: (a), (d), and (g): Actual (bold line) and forecasted (dotted line) price profiles- (b), (e), and (h): Power exchange- (c), (f), and (i): SOC- (a), (b), and (c): Ideal forecasting- (d), (e), and (f): Under-forecasting- (g), (h), and (i): Over-forecasting.

As shown in Figure 3-8 (d), at 40% or more under-forecasting levels, similar to the Case 1, the RTOD first charges the ESS at time periods when the electricity price is low. However, as the peak of the forecasted price is lower than the medium level of the actual price, RTOD commands discharging at the medium level of the actual price which is equal to or higher than the expected peak of the forecasted price. Hence, RTOD decides to discharge the energy of the ESS sooner than the appropriate time, i.e., the peak of the actual price. This causes the ESS to lose significant amount of financial benefit. As shown in Table 3-2, the obtained revenue for 24-h operation of the ESS with 40% under-forecasting is \$13.9k which is significantly less than the one obtained by the ideal forecasting, i.e., \$39k. In this case, the ESS operation is no longer economical since the obtained revenue is significantly less than the expected revenue due to investment, i.e.,

$22.8k in total. In under-forecasting condition, the ESS considerably operates every weekday but loses significant financial benefit. As shown in Table 3-2, the revenue for 30% price under-forecasting is the same as the revenue obtained by applying the ideal forecasting, i.e., $39k. Hence, until a certain level between 30% and 40% under-forecasting levels, the ESS profit is not affected.

In case of over-forecasting, as shown in Figure 3-8 (g), at 70% or more over-forecasting levels, similar to the Case 1, the RTOD first charges the ESS at time periods when the electricity price is low. Since RTOD expects to sell at time periods when the electricity price is very high, it charges the ESS even more than the Case 1 (see Figure 3-8 (c and i)). As the peak of the actual price is lower than the medium level of the forecasted price, RTOD incorrectly assumes that the price values will be higher in the future within the next 24 h. Hence, it waits for this opportunity. As the time elapses, the actual price never reaches to the expected forecasted one, thus the RTOD never issues a discharge command. This causes the ESS to lose significant amount of financial benefit. As shown in Table 3-2, in case of 70% over-forecasting, the revenue significantly decreases to -$39.8k. This negative revenue is because of the fact that the ESS pays to buy electricity, but does not discharge in the first 24 h to make any profit. In this case, the ESS operation is obviously not acceptable.

If the price is 70% or more over-forecasted in the following days, the RTOD is willing to keep the SOC to the maximum value in order to prepare the ESS to make maximum profit by selling expensive electricity in the future. However, since the ESS has been fully charged in the first 24 h, the RTOD cannot further charge the ESS in the following days unless the SOC drops considerably due to the natural dissipation.

As shown in Table 3-2, the revenue obtained for 24-h operation of the ESS in case of 60% price over-forecasting is close but less than the revenue obtained by applying the ideal forecasting, i.e., Case 1. The difference is caused because similar to 70% over-forecasting, the ESS charges a little more as compared to the case of ideal forecasting to obtain more profit in the future. However, in contrast to 70% over-forecasting, the ESS will have the opportunity to discharge energy but not as equivalent as of the energy absorbed during the last charging stage. Small part of the charged energy will be left which results in additional financial loss within the first 24 h as compared to the Case 1.

In practice, the electricity price profile is not as smooth as the one shown in Figure 2-2. To evaluate the performance of the RTOD in case of real-world electricity price profiles and verify the prior findings, the ESS operation is investigated by using the actual and forecasted electricity price profiles selected from the Ontario electricity market. This market has been considered as the case study in some of the previous research studies such as [26], [27]. The combination of 3-h-ahead and 24-h-ahead pre-dispatch prices (PDPs) issued by the Ontario independent electricity system operator (IESO) [35] and the corresponding ex-post hourly Ontario energy prices (HOEPs) are used as the forecast and actual electricity prices in this research study.

In this study, the RTOD is executed in a real-time simulation based on Ontario real-world price data within 2006 to 2011. In this period, the prices of a few months were not available. Using the available data, in one study, it is assumed that there is no price forecast error. This means that the forecasted price data are substituted with the actual price data. In the second study, the actual and the forecasted electricity price data issued by Ontario IESO are used. Table 3-3 shows the values of annual revenue obtained by the ESS sized in Section 2.1.1 for 2006, 2007, …, 2011, and total (2006 to 2011). The second column of Table 3-3 shows the values of annual revenue of the study in which there is no price forecast error. The third column shows the values of annual revenue obtained by applying price forecast issued by the IESO; the fourth column shows the percent of the annual revenue loss due to price forecast error. As it is shown, there is a significant difference between the revenue obtained by applying the ideal forecast and the revenue achieved using the real forecast of electricity price. For instance, in 2011, 64% of the revenue is lost due to the price forecast error. This study also verifies the considerable sensitivity of privately owned ESSs to the electricity price forecast error.

Table 3-3: Impact of price forecast error on the annual revenue for the Ontario market

Year	Revenue (Million $)		Revenue Loss (%)
	Ideal Forecast	*Regular Forecast*	
2006	1.6615	0.6262	62.311
2007	3.6580	1.4288	60.940
2008	4.8472	1.6726	65.493
2009	3.2926	1.2409	62.312
2010	1.9407	0.2162	88.860
2011	2.4201	0.8571	64.584
Total	17.8201	6.0418	66.095

3.2.2 Impact of Price Forecast Error on Charging/Discharging of the ESS

In this section, the impact of price forecast error on charging/discharging hours of the CAES which is controlled by the conventional RTOD algorithm is investigated. The RTOD has been executed in real-time for the Ontario electricity market with two assumptions as follows.

- There is no price forecast error (the forecasted price data are substituted with the actual price data); the simulation results for this case are shown in Figure 3-9.
- The actual and the regular forecasted price data are used; the simulation results for this case are as shown in Figure 3-10.

In these figures, (a) shows the actual and forecast of price for the year of 2011; (b) shows the mean absolute error (MAE) of price forecast; (c) shows the power exchange; (d) shows the SOC; (e) shows the revenue in terms of (k$).

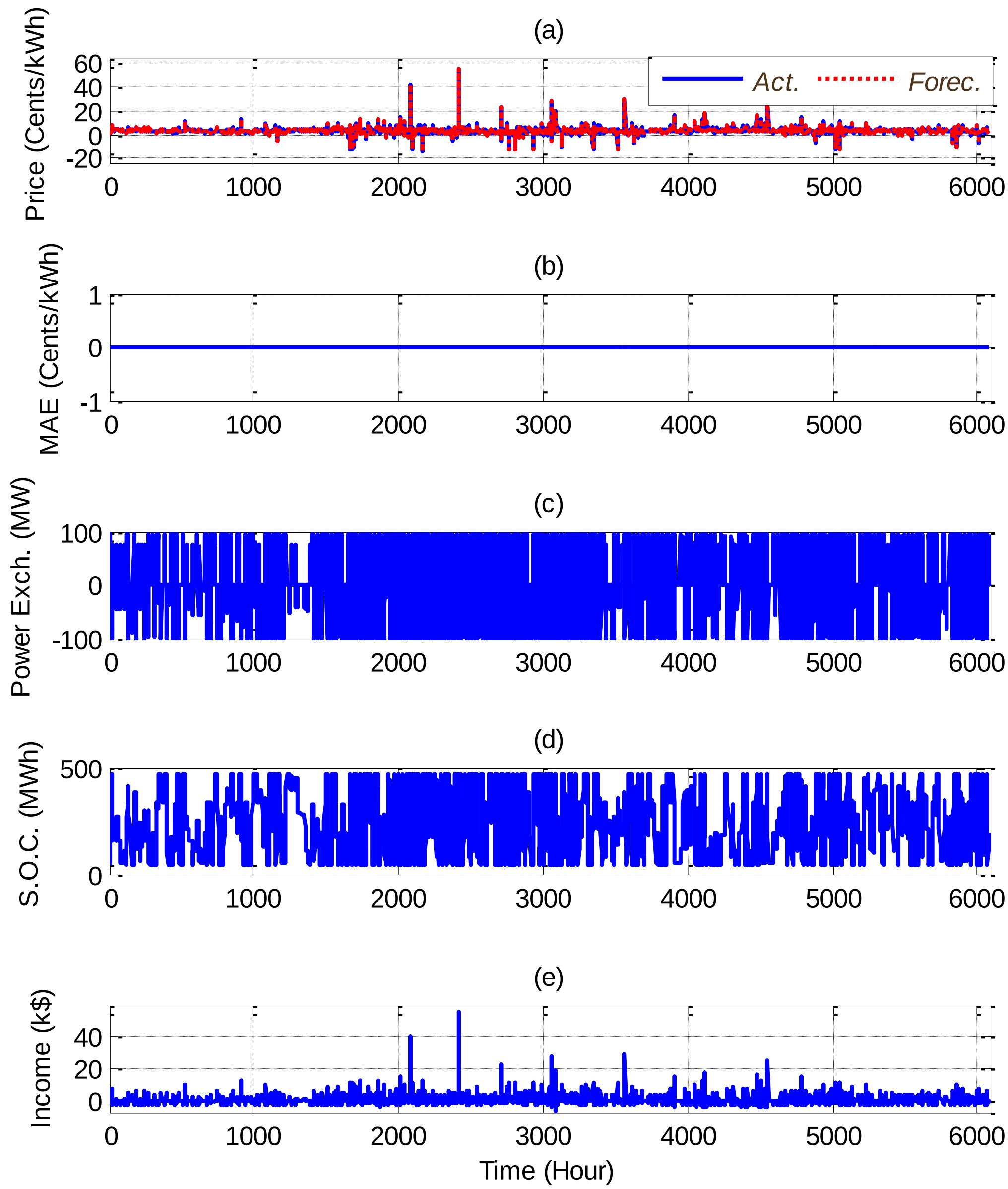

Figure 3-9: (a): Actual and forecasted electricity prices of Ontario in 2011, (b): MAE, (c): Power exchange, (d): SOC, (e): Income (revenue): all for the ideal price forecast

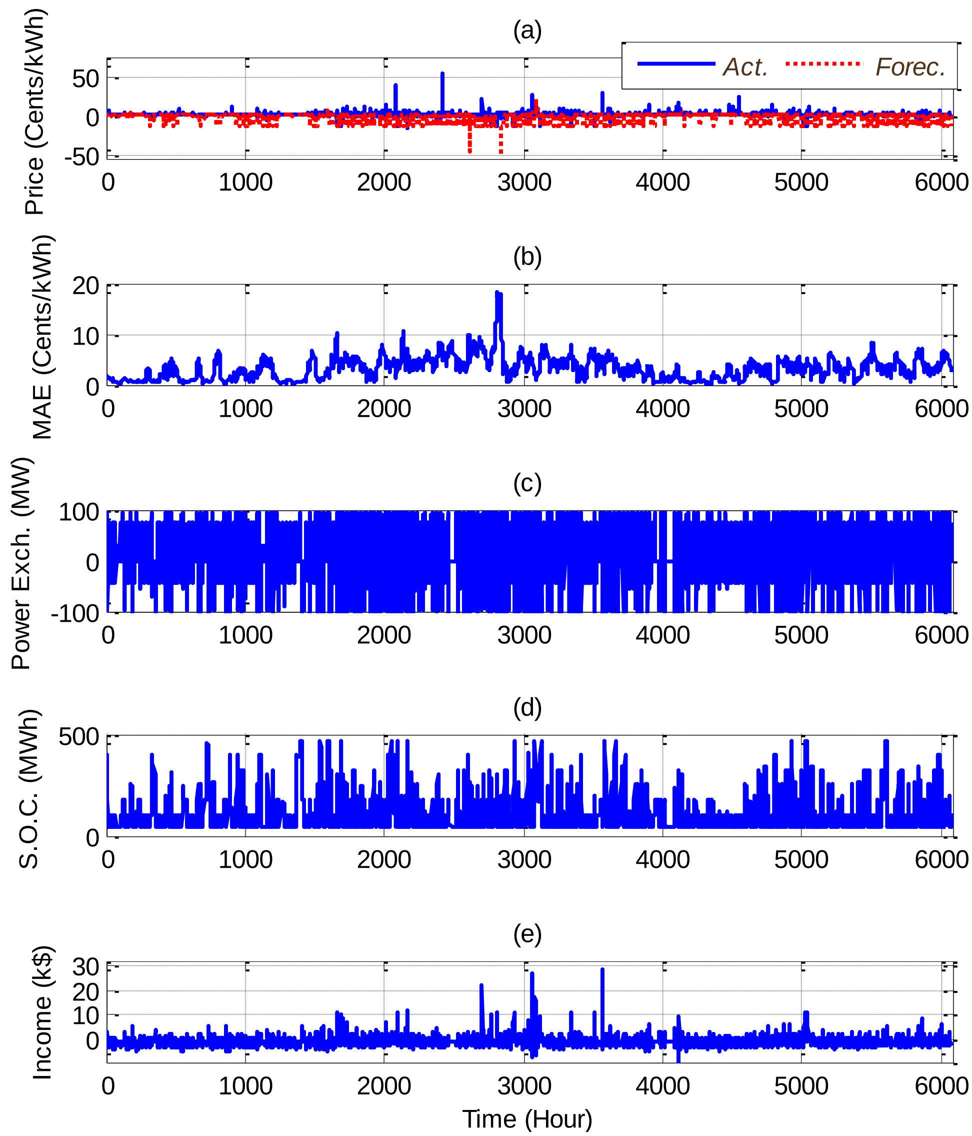

Figure 3-10: (a): Actual and forecasted electricity prices of Ontario in 2011, (b): MAE, (c): Power exchange, (d): SOC, (e): Income (revenue): all for the regular price forecast

In order to evaluate the situation with more details, the charging/discharging hours and charged/discharged energy of the ESS for the Ontario market from 2006 to 2011 are calculated and shown in Table 3-4 to Table 3-6.

Table 3-4: Charging/discharging hours and charged/discharged energy for ideal/regular price forecast for Ontario market (in 2006, 2007, and 2008)

	2006		2007		2008	
Type of Forecast for each year	**Ideal Forecast**	**Regular Forecast**	**Ideal Forecast**	**Regular Forecast**	**Ideal Forecast**	**Regular Forecast**
Total hours of operation	1732	1133	3393	2275	3250	2647
Total hours of charging	1020	655	2004	1338	1869	1534
Total charged Energy (MWh)	90309	53412	176437	111177	164512	121873
Total hours of discharging	712	478	1389	937	1381	1113
Total discharged Energy (MWh)	53843	31494	105162	65849	97759	71808
Weekly hours of charging	40.11	25.76	42.51	28.38	40.01	32.84
Weekly charged Energy (MWh)	3551	2100	3743	2358	3522	2609
Weekly hours of discharging	28	18.80	29.46	19.87	29.56	23.82
Weekly discharged Energy (MWh)	2117	1238	2231	1397	2092	1537

Table 3-5: Charging/discharging hours and charged/discharged energy for ideal/regular price forecast for Ontario market (in 2009, 2010, and 2011)

	2009		2010		2011	
Type of Forecast for each year	**Ideal Forecast**	**Regular Forecast**	**Ideal Forecast**	**Regular Forecast**	**Ideal Forecast**	**Regular Forecast**
Total hours of operation	3584	3082	2206	2044	1894	1889
Total hours of charging	2030	1823	1253	1082	1082	1019
Total charged Energy (MWh)	178750	146378	111641	81255	94823	76023
Total hours of discharging	1554	1259	953	962	812	870
Total discharged Energy (MWh)	105366	82125	66294	45857	56220	42559
Weekly hours of charging	42.67	38.32	26.66	23.02	29.94	28.19
Weekly charged Energy (MWh)	3757	3077	2375	1729	2624	2103
Weekly hours of discharging	32.67	26.46	20.28	20.47	22.47	24.07
Weekly discharged Energy (MWh)	2215	1726	1410	976	1555	1177

Table 3-6: Charging/discharging hours and charged/discharged energy for ideal/regular price forecast for Ontario market (in total 2006 to 2011)

	Total (2006-2011)	
Type of Forecast for total years	**Ideal Forecast**	**Regular Forecast**
Total hours of operation	16059	13070
Total hours of charging	9258	7451
Total charged Energy (MWh)	816471	590117
Total hours of discharging	6801	5619
Total discharged Energy (MWh)	484644	339692
Weekly hour of charging	36.98	29.42
Weekly charged Energy (MWh)	3262	2329
Weekly hour of discharging	27.07	22.25
Weekly discharged Energy (MWh)	1937	1342

In in Table 3-4 to Table 3-6, for each year, the left column shows the parameters obtained by applying the actual and ideal forecast of price (the forecast error is zero) while the right column shows the parameters obtained by applying the actual and regular forecast of price. One can see that for all years, the charging/discharging hours and charged/discharged energy of the ESS are reduced when there is price forecast error. The forecast error will cause the ESS not to be 100% ready for charge/discharge opportunities and, thus, the ESS does not have sufficient space for appropriate charging of energy or sufficient energy for appropriate discharging at the required time.

3.3 Summery

In this chapter, an RTOD algorithm is developed by formulating an MILP problem to determine the optimal charging and discharging power set-points for a privately owned ESS in a competitive electricity market based on real-time and forecasted electricity prices. The performance of the RTOD is evaluated for different possible forecast errors using a generic price profile and also real-world price data of the Ontario electricity market. It is shown that the considerable error of electricity price forecast (e.g., 40% under forecasting and 70% over forecasting of the generic price profile) significantly reduces the financial benefits of the ESS. In the next chapter, the adaptive RTOD is proposed to calibrate the price forecast in order to decrease the adverse impact of price forecast error on the revenue resulted from ESS operation.

Chapter 4

4 Adaptive RTOD of Privately Owned ESS

In Chapter 3, it was shown that the price forecast error of public-domain market data (i.e., the Ontario market) can significantly reduce the financial benefits of the ESS operation. Since it is not possible to forecast the actual price without any error, it is impossible to achieve the revenue with ideal forecast. Therefore, it is important to investigate various methods to decrease the adverse impacts of price forecast error on the performance of the RTOD algorithm. This way, a portion of the financial loss can be saved even if the forecast error is still considerable. In this chapter, an adaptive RTOD algorithm is proposed to decrease the adverse impact of forecast error of publicly available price forecast on the ESS operation. In the proposed algorithm, the objective function of the RTOD algorithm is adapted online based on publicly available market prices available before real-time to reduce the financial loss of the ESS. The CAES sized in Section 2.1.1 is used as an example to demonstrate and evaluate the performance of the proposed algorithm. The adaptive RTOD is presented, and the hourly electricity price of the Ontario market and its forecast is used as the real-world case-market to test its performance. The investigation results reveal that the proposed adaptive RTOD outperforms the conventional RTOD to gain more financial benefits for the ESS owner when public-domain market prices are used for optimal dispatching of the privately owned ESS.

4.1 Formulation of the Proposed Adaptive RTOD

As mentioned in Chapter 1, in real-world markets, the electricity price forecasting error (mean absolute percentage error) can even reach up to 40% [18]. As shown in the Chapter 3, this amount of forecast error can significantly reduce the financial benefits of a privately owned ESS operating in that market. Studying the actual and forecasted electricity prices issued by different markets especially the Ontario market, the author has realized that the average error of electricity price forecast does not change over several hours or days drastically in the market. For instance, if the price in a typical day is under/over-forecasted, the next day price will also be under/over-forecasted with a high probability.

As an illustration, actual and forecasted electricity prices publically available in the Ontario market (for two weeks in 2011) has been shown in Figure 4-1.

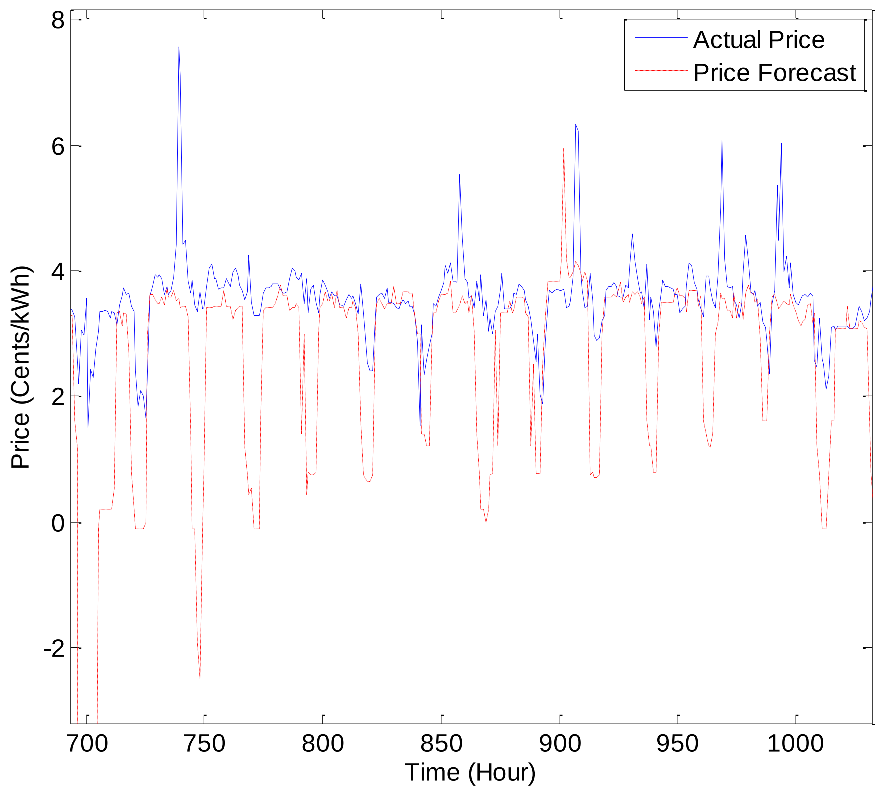

Figure 4-1: (a): Actual and forecasted electricity prices publically available in the Ontario market (in 2011)

It can be observed in Figure 4-1 that in most days the price has been under-forecasted for consecutive days. This will raise the idea of taking an advantage of historical market price forecast error in the day-behind, for instance, to calibrate the day-ahead price forecast to decrease the adverse impact of price forecast error on the ESS optimal operation. It is worth mentioning that the mean value of forecast error for the prices in 2011 equals 2.44 Cents/kWh, which indicates that in most days of the year the price is under-forecasted. According to the observations, the same outcomes can be obtained for the electricity prices in other years (from 2006 to 2010). Therefore, the price forecast, publically available in the Ontario market, has a negative offset in most days. Since the amount of offset is time-variant, it cannot be compensated using a constant value, but rather it might be dynamically predicted and compensated. As the ESS is more sensitive to the electricity price arbitrage than the absolute price value, it is proposed to adapt the objective of the RTOD as stated in (4-1) by linearly calibrating the electricity price forecast based on how much the market has been under-forecasted or over-forecasted in the past several hours or days.

$$\text{AdaptiveObj.} := \sum_{t=0}^{N} \left\{ (P_t^{Dhg} - P_t^{Chg})((1+A_t)E_t + B_t) - C_{DhgO}P_t^{Dhg} - C_{ChgO}P_t^{Chg} \right\} . \Delta\text{t} \quad (4\text{-}1)$$

where A_t and B_t are scaling and offset calibrating coefficients at time step t, respectively. Several historical data lengths such as 1, 2, 7, and 30 days have been considered to estimate the level of expected under-forecasting or over-forecasting for the next 24 h based on which A_t and B_t are determined. According to the investigation results performed in this study for the Ontario market, increasing the length of the historical data beyond 24 h does not improve the ESS profit for the studied years. Therefore, in this study, the results of different methods to estimate calibrating coefficients are only presented for one-day historical data length. However, changing the length of historical data to track the behavior of the electricity price forecast error can be considered as an option which may help to improve the results in the 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 values of forecasted price is available. Additionally, since the calibration variable length is M, the forecasted data for the past M time steps should be stored in an $M \times N$ data buffer. Figure 4-2 shows how the proposed adaptive RTOD is implemented. As shown in this figure, the next N forecasted electricity prices are inputted to the data buffer as well as the data file generation. In this research, the 2-D data buffer is represented with $E^h_{i,t}$ where i is the time index and t points to future time steps within the prediction horizon. Time index i is equal to the present time in 24-h time notation divided by Δt. For instance, at 3pm, i=15/1=15 if Δt is considered 1h. Therefore, $E^h_{15,t}$ represents historical electricity price forecast for the last 3 pm.

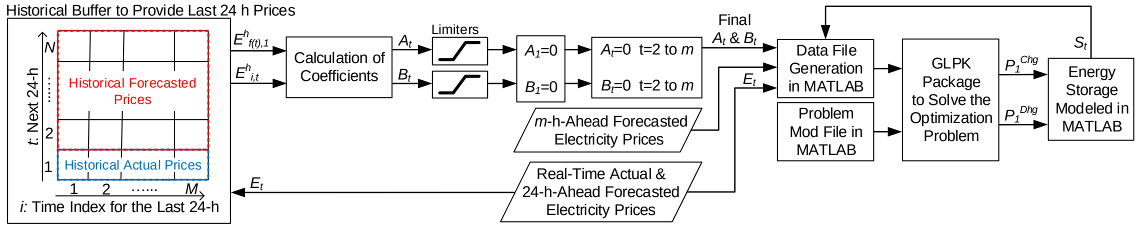

Figure 4-2: (a): The flowchart for implementation of the proposed adaptive RTOD

The scaling and offset calibrating coefficients, i.e., A_t and B_t are calculated using historical actual and forecasted prices as discussed later in this section. Once calibrating coefficients are calculated, a limiter is applied to each coefficient to avoid undesired calibration in case of spurious market behavior. In general, the lower and upper limits can be different. 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, where actual electricity price is available. The values of A_t and B_t for t=2 to m can be forced to zero if more accurate price forecast is available up to the first few hours (e.g., m hours). For instance, in Ontario, 3-h electricity price forecast is issued hourly. Hence, the calibration can be performed on the remaining hours. Then, the coefficients A_t and B_t are used in the objective function of the proposed adaptive RTOD as per (4-1) to calibrate the forecasted electricity price. Four different definitions for error calculations are presented in the next paragraph which are assigned to A_t and B_t for price calibrations. Other steps of the proposed adaptive RTOD are the same as the conventional RTOD in Chapter 3.

In general, two different categories of definitions can be considered for measuring price forecast error. The first one presents the price forecast error in terms of Cents/kWh, 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 at every time instance or as a single value which is the average of the error vector. The definitions for price forecast error, proposed in this work, are given by (4-2) to (4-5) for every time index i. In HFME (Historical Forecast Mean Error) and HFE$_t$ (Historical Forecast Error) definitions, the forecast error is in terms of Cents/kWh. 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 (4-3) and (4-5) result in 1-D arrays with the length of prediction horizon, while (4-2) and (4-4) result in single numbers which are the average of (4-3) and (4-5), respectively.

$$HFME = \frac{1}{M}\sum_{t=1}^{M}(E^h_{f(t),1} - E^h_{i,1}) \tag{4-2}$$

$$HFE_t = E^h_{f(t),1} - E^h_{i,1} \tag{4-3}$$

$$HFMPE = \frac{\sum_{t=1}^{M}(E^h_{f(t),1} - E^h_{i,1})}{\sum_{t=1}^{M}(E^h_{f(t),1})} \times 100 \tag{4-4}$$

$$HFPE = \frac{E^h_{f(t),1} - E^h_{i,1}}{\frac{1}{M}\sum_{t=1}^{M}(E^h_{f(t),1})} \times 100 \tag{4-5}$$

where $E^h{}_{f(t),1}$ is an array which represents historical actual price in the calibration horizon stored in the first row of the data buffer (see Figure 4-2) in which *f(t)* is an array with *M* elements as given by (4-6). *i* is the time index as defined earlier.

$$f(t) = \{i,\ldots,M \; \& \, 1,\ldots,i-1\} \qquad \forall i \in \tau_c \tag{4-6}$$

In the following, four calibration methods are proposed based on the four above-mentioned definitions for historical price forecast error. In Method 1, HFME is calculated based on the definition presented in (4-2). Then, the calculated HFME, which is in Cents/kWh is assigned to B_t for the entire prediction horizon, while A_t is assumed to be zero. As shown in Figure 4-2, B_t can be limited to a certain value such as ±1 Cents/kWh or ±2 Cents/kWh; depending on the average electricity market price.

The second calibration method is the same as Method 1, but rather than using the average of forecast error, the forecast error of historical price data based on the definition presented in (4-2) is calculated. In this method, the length of calibration horizon shall be selected the same as the prediction horizon, 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 by using the forecast error at the *t* of the day before. For example, the price forecast at 1:00pm in the next day is calibrated using the forecast error at 1:00pm of the day before and so on for the other time steps.

In Method 3, HFMPE is calculated based on the definition presented in (4-3). 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 ±30% or ±50%.

The fourth calibration method is the same as Method 3, but rather than using the average of forecast error, the forecast error of historical price data based on the definition presented in (4-4) is calculated. Similar to Method 2, the length of the calibration horizon shall be selected the same as the prediction horizon. Then, the calculated HFPE_t is assigned to A_t for every t, while B_t is assumed to be zero.

4.2 Performance Analysis of the Proposed Adaptive RTOD

In this section, the performance of the proposed Adaptive RTOD algorithm is evaluated for the CAES sized in Section 2.1.1 using the public-domain actual and forecasted electricity price data provided by the Ontario electricity market. The Ontario independent electricity system operator (IESO) publishes two sets of price forecasts: day-ahead and 3-h-ahead pre-dispatch prices (PDPs). The first set of data is the forecast of the next day (starting from 1am) which is published at 3:30pm eastern time every day, while the second set of data is the forecast of next 3 h which is published every hour. The challenge of using the IESO forecast is that the complete next 24-h forecast is not available for each time step within 1am to 3pm of each day. For instance, at 10am, only the next 15 h, i.e., 10 am to 12 midnight is available. To mitigate this problem, as it is given by (4-7) and (4-8), it is proposed to duplicate the forecasted prices at the same hours of the last day. Since the price forecast accuracy is not inherently high, this duplication will not considerably increase the forecast error.

When the day-ahead pre-dispatch prices are issued from 1am to the next 24 h, it is stored in a 1-D temporary data buffer represented by E_t^{Tmp}. If the time index i is equal to 1, the issued forecast in E_t^{Tmp} is used for the next 24 h without change; if i is within 2 to 15, the issued forecast in E_t^{Tmp} is circulated to generate forecast for missing hours (see (4-7)). When i reaches to 16, the pre-dispatch prices are issued for the next day. In this case, the forecasted price for the next 24 h is created by using historical price data for the period of i to 24 and newly issued prices saved in E_t^{Tmp} for the rest of hours (see (4-7)).

In every time index i, after creating the next 24 h price forecast, the first 3h of that is updated by using the second type of issued prices, i.e., Ontario 3-h price forecast.

$$E_t = \left\{ \begin{array}{lll} E_t^{Tmp} & 1 \le t \le 24 & i = 1 \\ E_{g(t)}^{Tmp} & 1 \le t \le 24 & 2 \le i \le 15 \\ & & \\ \left(\begin{array}{ll} E_{i-1,g(t)}^{h} & 1 \le t \le 25 - i \\ E_{t-(25-i)}^{Tmp} & 26 - i \le t \le 24 \end{array} \right) & & 16 \le i \le 24 \end{array} \right\} \tag{4-7}$$

where $g(t)$ is defined as follow.

$$g(t) = \left\{ \begin{array}{ll} \{i, ..., 24 \,\&\, 1, ..., i-1\} & 2 \le i \le 15 \\ \{2, ..., 26 - i\} & 16 \le i \le 24 \end{array} \right\} \tag{4-8}$$

The error of the 3-h-ahead price forecast is considerably smaller as compared to day-ahead forecast. Thus, there is no need of RTOD calibration for this span of time. This can be simply implemented by considering m=3 in the flowchart depicted in Figure 4-2. As mentioned earlier, the lower and upper limits can be different, but they are considered identical for the sake of simplicity in this study.

The ESS sized in Section 2.1.1 and the proposed adaptive RTOD are simulated in Matlab. The simulation is executed at time steps of 1 h. The optimal dispatch problem is formulated and solved by combined Matlab and GLPK package. Then, the values of ESS revenue are computed using both RTOD and adaptive RTOD for Ontario electricity market from 2006 to 2011. According to the analysis performed on the historical price data for Ontario, the HFME is calculated as 2 (Cents/kWh) for the time period between 2006 and 2011, while HFMPE is calculated as 50% for the same time period. Based on this fact, 112 cases have been selected and studied including different time periods: {2006, 2007, …, 2011 and total (2006 to 2011)}, different calibration methods: {Method 1, …, Method 4} and different calibration coefficient limits: {±30%, …, ±70%, ±∞%}

for A_t and {±1 Cents/kWh, ±3 Cents/kWh, …, ±∞ Cents/kWh} for B_t. ±∞ indicates here that there is not any limitation on the values of A_t and B_t.

To better analyze and compare the results of adaptive RTOD and RTOD for the 112 case studies, the percentage of the annual revenue increase using adaptive RTOD as compared to the annual revenue obtained by RTOD is reported in Table 4-1 to Table 4-4.

Table 4-1: Annual revenue increase (%) by using price calibration method 1

Year	*Calibration limit*			
	±1 ¢	*±2 ¢*	*±3 ¢*	*±∞ ¢*
2006	20.92	26.94	27.77	27.19
2007	25.01	33.87	31.47	31.12
2008	41.76	62.11	71.11	67.43
2009	23.31	36.34	54.83	49.09
2010	190.79	274.10	249.77	211.89
2011	42.41	48.64	42.39	43.98
Total	37.28	52.17	<u>56.22</u>	52.76

Table 4-2: Annual revenue increase (%) by using price calibration method 2

Year	*Calibration limit*			
	±1 ¢	*±2 ¢*	*±3 ¢*	*±∞ ¢*
2006	17.10	28.14	30.88	25.10
2007	20.10	28.03	32.23	30.06
2008	34.98	56.81	71.24	65.59
2009	20.41	27.20	42.79	40.65
2010	146.44	221.46	245.93	259.90
2011	25.88	41.11	42.78	40.82
Total	29.40	44.62	<u>54.20</u>	51.31

Table 4-3: Annual revenue increase (%) by using price calibration method 3

Year	*Calibration limit*			
	±30%	*±50%*	*±70%*	*±∞%*
2006	17.47	18.16	18.48	18.46
2007	19.93	25.83	25.80	26.14
2008	36.70	49.66	52.40	52.96
2009	7.86	8.30	8.67	16.52
2010	151.62	178.21	161.61	145.33
2011	25.31	23.31	17.49	10.84
Total	27.31	<u>33.13</u>	32.57	32.89

Table 4-4: Annual revenue increase (%) by using price calibration method 4

Year	Calibration limit			
	±30%	±50%	±70%	±∞%
2006	17.41	24.42	21.65	21.80
2007	16.80	21.32	19.85	23.90
2008	31.19	43.97	52.35	58.25
2009	7.38	8.16	9.03	10.36
2010	116.23	131.87	122.66	126.73
2011	15.41	18.48	20.49	16.54
Total	22.27	28.76	30.58	33.05

As shown in Table 4-1 to Table 4-4, in all years, the annual revenue is increased considerably by using the proposed adaptive RTOD as compared to the conventional RTOD. However, for different calibration methods, the level of the improvement in gaining financial benefits is different. As shown in this table, for the Ontario electricity market, the largest values of annual revenue for each method can be obtained by using specific values of calibration limit. These values of calibration limit are shown in the following for each method.

- Method 1 with ±3Cents/kWh calibration limit.
- Method 2 with ±3Cents/kWh calibration limit.
- Method 3 with ±50% calibration limit.
- Method 4 with ±∞% calibration limit.

Figure 4-3 shows the plotted values of annual revenue increase (in terms of %) for the methods with the above-mentioned calibration limits. According to Figure 4-3, Methods 1 and 2 are more or less the same; it is also shown that Methods 3 and 4 are approximately the same. Moreover, it is clear that Methods 1 and 2 return significantly more revenue than Methods 3 and 4.

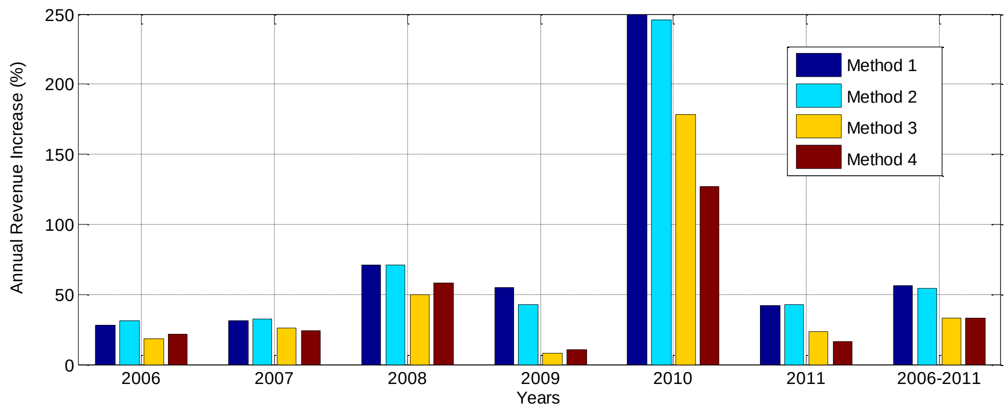

Figure 4-3: Annual revenue increase (%) at the most optimal value of calibration limit for each calibration method (Method 1 and 2 with ±3Cents/kWh limit; Method 3 with ±50% limit; Method 4 with ±∞ limit)

As shown in Figure 4-3, the annual revenue increase of the year of 2010 is larger than that of the other years. This is because the price forecast error of the year 2010 is significantly more than that of other years. Thus, the proposed methods for price calibration in the year of 2010 are significantly more effective than the other years.

Other values of calibration limit have been tried for the studied market. It was observed that these values do not help to increase the amount of revenue in this study. However, for the other electricity markets, the values of calibration limit used in this thesis may not be the best ones and should be determined by analyses of the price data in that market.

4.3 Impact of Price Forecast Calibration on Charging/ Discharging of the ESS

In the following, the impact of price forecast calibration on the charging/discharging of the ESS will be investigated. Figure 4-4 represents the simulation results of the CAES when the forecasted price of the Ontario market in 2011 is applied to the RTOD algorithm after calibration by Method 1 with 3 (Cents/kWh) of calibration limit.

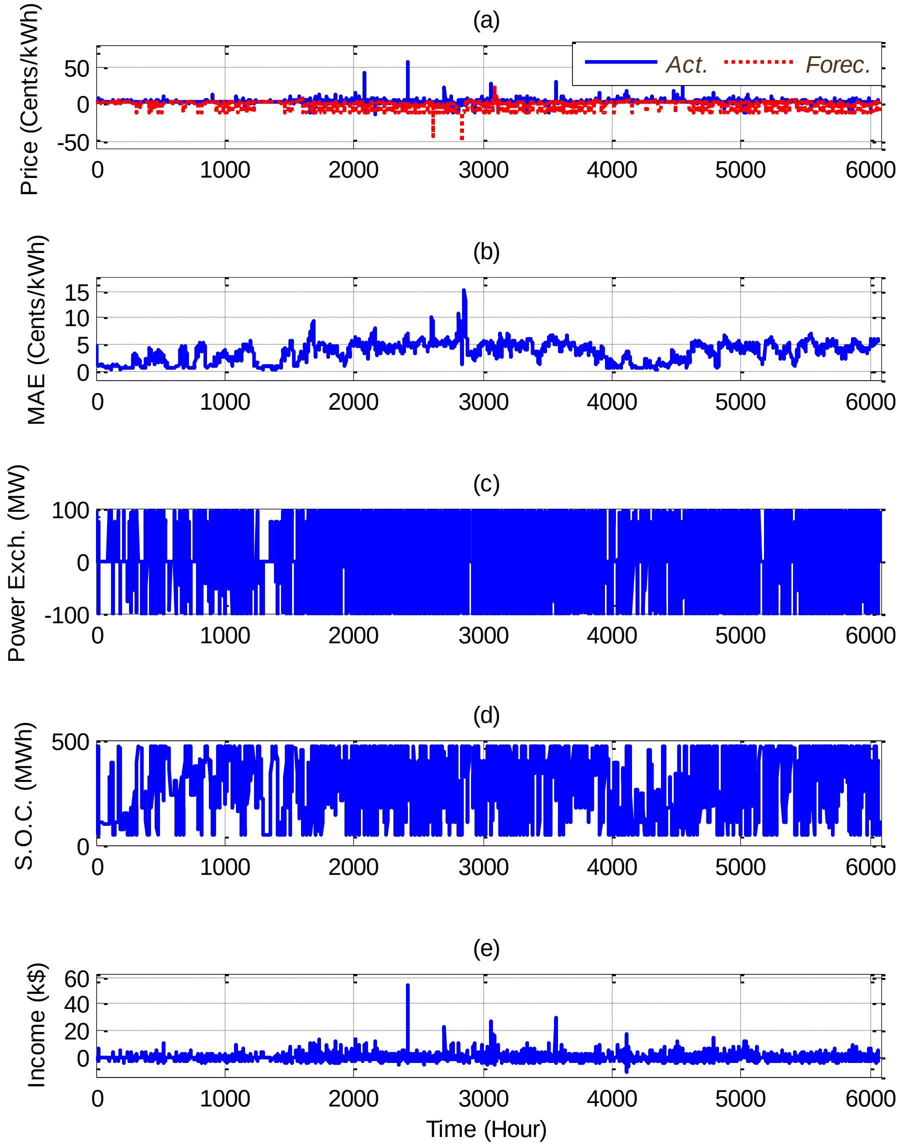

Figure 4-4: (a): Actual and forecasted electricity prices of Ontario in 2011, (b): MAE, (c): Power exchange, (d): SOC, (d): Income (revenue): all for calibrated price forecast by Method 1 with 3 Cents/kWh of calibration limit

In order to evaluate the situation with more details, the charging/discharging hours and charged/discharged energy of the ESS for the Ontario price from 2006 to 2011 are calculated and shown in Table 4-5 to Table 4-7. In this table, the results of regular (uncalibrated) price are compared with the results of the case in which the price is calibrated using Method 1 with 3 (Cents/kWh) calibration limit.

Table 4-5: Charging/discharging hours and charged/discharged energy for the regular/calibrated price forecast by Method 1 with 3 Cents/kWh of calibration limit for the Ontario market (in 2006, 2007, and 2008)

	2006		2007		2008	
Type of Forecast for each year	**Regular Forecast**	**Calibrated by Method 1**	**Regular Forecast**	**Calibrated by Method 1**	**Regular Forecast**	**Calibrated by Method 1**
Total hours of operation	1133	1223	2275	2491	2647	2698
Total hours of charging	655	711	1338	1449	1534	1581
Total charged energy	53412	62506	111177	124593	121873	137078
Total hours of discharging	478	512	937	1042	1113	1117
Total discharged energy	31494	36933	65849	73565	71808	80696
Weekly hours of charging	25.76	27.96	28.38	30.74	32.84	33.84
Weekly charged energy	2100	2458	2358	2642	2609	2934
Weekly hours of discharging	18.80	20.13	19.87	22.10	23.82	23.91
Weekly discharged energy	1238	1452.42	1397	1560.49	1537	1727.44

Table 4-6: Charging/discharging hours and charged/discharged energy for the regular/calibrated price forecast by Method 1 with 3 Cents/kWh of calibration limit for the Ontario market (in 2009, 2010, and 2011)

	2009		2010		2011	
Type of Forecast for each year	**Regular Forecast**	**Calibrated by Method 1**	**Regular Forecast**	**Calibrated by Method 1**	**Regular Forecast**	**Calibrated by Method 1**
Total hours of operation	3082	2927	2044	2218	1889	2095
Total hours of charging	1823	1754	1082	1238	1019	1184
Total charged energy	146378	147079	81255	107885	76023	103013
Total hours of discharging	1259	1173	962	980	870	911
Total discharged energy	82125	82464	45857	63341	42559	60293
Weekly hours of charging	38.32	36.87	23.02	26.34	28.19	32.76
Weekly charged energy	3077	3091	1729	2295	2103	2850
Weekly hours of discharging	26.46	24.65	20.47	20.85	24.07	25.20
Weekly discharged energy	1726	1733	976	1347	1177	1668

Table 4-7: Charging/discharging hours and charged/discharged energy for the regular/calibrated price forecast by Method 1 with 3 Cents/kWh of calibration limit for the Ontario market (in total 2006 to 2011)

	Total (2006-2011)	
Type of Forecast for total years	**Regular Forecast**	**Calibrated by Method 1**
Total hours of operation	13070	13652
Total hours of charging	7451	7917
Total charged energy	590117	682160
Total hours of discharging	5619	5735
Total discharged energy	339692	397290
Weekly hours of charging	29.42	31.42
Weekly charged energy	2329	2712
Weekly hours of discharging	22.251	22.811
Weekly discharged energy	1342	1581.6

In Table 4-5 to Table 4-7, for each year, the left column shows the parameters obtained by applying the regular forecast of price while the right column shows the parameters obtained by applying the calibrated forecast of price by Method 1. One can observe that the charging/discharging hours and charged/discharged energy of the CAES are increased for each year and for the total years when the proposed adaptive RTOD is applied. This is why the CAES can make more financial benefits when there is price calibration in comparison with the case in which the uncalibrated price forecast is used.

4.4 Summery

In this chapter, an adaptive RTOD algorithm was developed by formulating an MILP problem. The problem was modeled and solved using MATLAB and GLPK to determine optimal ESS charging and discharging power set-points in a competitive electricity market based on real-time and forecasted electricity prices. As a case study, the CAES sized in Section 2.1.1 is used. Using a smooth price profile, it is shown that the price forecast error will not impact the ESS revenue until it reaches a certain level. This is because the ESS revenue is more sensitive to the price arbitrage that the absolute values of price. This fact is used to linearly calibrate the public-domain market prices. Then, based on historical market price information, a new mechanism was proposed and implemented to calibrate the price forecast making the proposed RTOD adaptive to the forecast error. The performance of the proposed adaptive RTOD was evaluated through comparing economic benefits of the ESS operation for four proposed calibration methods, and the results were discussed. The simulation results revealed that the proposed adaptive RTOD significantly increases the financial benefits of the ESS as compared to the conventional RTOD in which the forecasted price is not calibrated.

Chapter 5

5 Optimal Weekly and Daily Usages of the Cryogenic Energy Storage (CES)

In this chapter, the concept of weekly usage of CES to shift the electrical energy from lower prices during off-peak periods to higher prices during peak periods as compared to common daily usage is introduced. Two equally-expensive CES systems are optimally sized for daily and weekly usages. The RTOD algorithm, formulated in Chapter 3 of this thesis, is used for optimal weekly and daily usages of the CES. The economic benefits of both CES weekly and daily usages are presented and compared for different price profiles and round-trip efficiencies of the storage. The results show significant benefits of weekly usage of the CES as compared to daily usage [30].

5.1 Comparison of CES with Other Types of ESS

Since electricity price is inexpensive during weekends, there is a potential to store the energy in weekends and release it during on-peak periods in weekdays when the electricity price is high. However, to make this possible, very large storage size and low energy dissipation rate are required. Batteries and CAES systems are the common technologies for long-term energy storage. However, the cost of battery energy storage system (BESS) approximately increases linearly with the storage size [38]. Therefore, it would be costly to store the energy during weekends and release during weekday peak periods. Furthermore, some battery technologies do not provide low dissipation rate which make them unsuitable for weekly usage. In case of CAES, only if the ESS is based on aquifers, the "bubble" underground can be enlarged via extra compression energy to allow larger storage size for weekly usage [31]. This technique is only viable in specific geographical locations [31].

As explained in Chapter 2 of this thesis, in CES technology, storage tank is significantly inexpensive as compared to liquefaction and power recovery parts and does not occupy large space as compared to CEAS technology. This is especially important to allow economical weekly usage of CES as compared to daily usage. Therefore, it is significantly inexpensive to increase the storage capacity as compared to other storage technologies. This is especially important to allow economical weekly usage of CES as compared to daily usage. Further, it makes this technology comparable or superior to other ESS technologies for long-term energy shift.

5.2 Performance Evaluation

In this section, the CES is considered as a single entity which freely buys/sells electricity from/to the electricity market. The optimization problem, developed in Chapter 3 of this thesis, is used here to determine the proper periods and dispatch quantities for storage charging and discharging to maximize the economic benefit for a private investor. Even though CES can be employed to provide additional financial and operational benefits through peak shaving, congestion relief, frequency regulation, and deferred transmission and distribution (T&D) investments, in this chapter, only the financial benefit due to energy shift of electricity with different prices is considered. The storage sizing method and formulation of optimal dispatch algorithm are explained in Chapter 2 and Chapter 3, respectively.

The performance of the two CES systems, CES_1 and CES_2 sized for weekly and daily usage regimes in Chapter 2 is evaluated. Operating parameters are shown in Table 5-1. In this table, the amount of expected revenue due to investment (C_{ERev}) is considered the same as the one considered for some ESS projects. This way, after the life of storage (=30 years), total revenue should be at least 250% of the total capital cost. As a result, C_{EInc} is considered as 8% = 250%/30 of the capital cost per year. In CES technology, to maintain rated efficiently, it is required to operate the liquefaction plant close to its rate value. Therefore, P^{Chg}_{min} is set to 80% of P^{Chg}_{max}. However, the cryogenic turbine and its supplying pump can efficiently operate even at lower power set-points. Energy storage dissipation per hour is assumed 0.15% per day thus 0.0063%=0.15%/24 per hour. Other parameters are calculated according to the assumptions made in Table 2-4. Using the parameters defined in Table 5-1, optimization problem is solved by GLPK package and results are obtained for two types of daily and weekly usages. Three different price profiles are used for evaluation purposes. General shape of the electricity price profile is shown in Figure 2-2, while price levels (*A*, *B*, and *C*) are defined in Table 5-2.

Table 5-1: Operating Parameters of the CES

$\boldsymbol{P^{Chg}_{min}}$	$80\% \times P^{Chg}_{max}$	$\boldsymbol{C_{Cap}}$	Total Capital Cost/(Life of ESS (=30) ×365×24)
$\boldsymbol{P^{Dhg}_{min}}$	$3\% \times P^{Dhg}_{max}$	$\boldsymbol{C_{Main}}$	$5\% \times C_{Cap}$
$\boldsymbol{S_{min}}$	$10\% \times S_{max}$	$\boldsymbol{C_{ChgO}}$	$60\% \times C_{Main} / P^{Chg}_{max}$
$\boldsymbol{S_{Int}}$	$20\% \times S_{max}$	$\boldsymbol{C_{DhgO}}$	$40\% \times C_{Main} / P^{Dhg}_{max}$
$\boldsymbol{\eta_{Dsp}}$	$0.0063\% \times S_t$	$\boldsymbol{C_{ERev}}$	250% × Total Capital Cost/(30×365×24)

Table 5-2: Different Levels of Price Profiles Shown in Figure 2-2

Price Levels (Cents/kWh)	**Weekday**			**Weekend**		
	A	***B***	***C***	***A***	***B***	***C***
Profile 1	6	9	12	5	6	7
Profile 2	6	12	18			
Profile 3	6	15	24			

5.2.1 Concept of Daily Usage Optimization

In this section, by using price Profile 1 and round-trip efficiency of 60%, the optimization is performed considering 24-h optimization horizon. In this case, the optimizer will consider the energy price of a day ahead to make dispatch decisions. Daily optimal dispatch is performed for seven days individually including two weekends and five weekdays. Since the CES has a sustainability constraint, the state of the charge (SOC) at the end of a day will be the same as the initial value. Therefore, the result of all seven days can be combined to obtain the CES performance for a week in case of daily usage. Figure 5-1 (a, b, and c) shows the evaluation results for a complete week. In this figure, the positive power exchanges indicate that the CES is charging while the negative ones indicate that CES is discharging. By looking at the charging power and the SOC, one can realize that at each weekday the storage is charging at low energy prices and discharging at high energy prices. At the end of the day, the storage capacity comes back to the initial value (10%) and 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 so that SOC remains equal or above the S_{min}.

5.2.2 Concept of Weekly Usage Optimization

In this section, using the same conditions as Section 5.2.1, the optimal dispatch is performed considering optimization horizon as one week. In this case, the optimal dispatch considers energy price of a week ahead to determine optimal dispatch quantities. Figure 5-1 (d, e, and f) shows the results for this case. One can realize during the weekends and low energy price hours of weekdays, CES is charging with full capacity while it is discharging in high price periods of the weekdays.

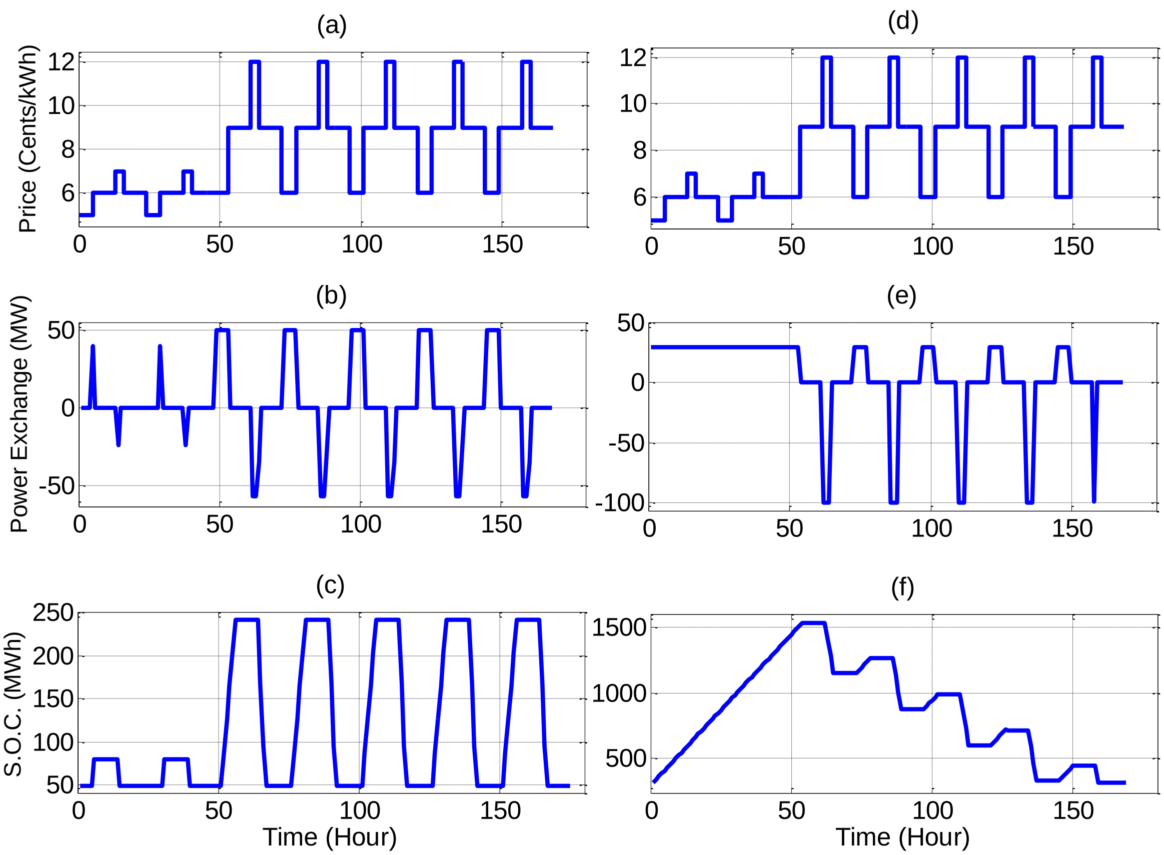

Figure 5-1: (a) & (d): Price profile 1, (b) & (e): ESS power exchange, and (c) & (f): SOC- (a), (b), and (c): Daily & (d), (e), and (f): Weekly usage optimization

5.2.3 Comparison of Weekly and Daily Usage Optimization

In this section, the economic benefits of ESS operation for both weekly and daily usages are investigated and compared first for the generic price profile (see Figure 2-2) and then for the real price data of Ontario electricity market.

5.2.3.1 Using the Generic Price Profile

In this section, a comparison is made between daily and weekly usages by employing three different price profiles defined in Table 5-2 and different efficiencies between 30% and 70%. As defined in Chapter 3, the revenue is the objective value which is the total benefit of ESS operation. If the expected revenue (C_{ERev}) which is a time invariant parameter is subtracted from the objective function, the objective value is the extra revenue which is the benefit excess from the normal expected revenue, i.e. totally 250 percent of the capital cost. Extra revenue values are plotted in million dollars per year for three price profiles versus different round-trip storage efficiencies in Figure 5-2.

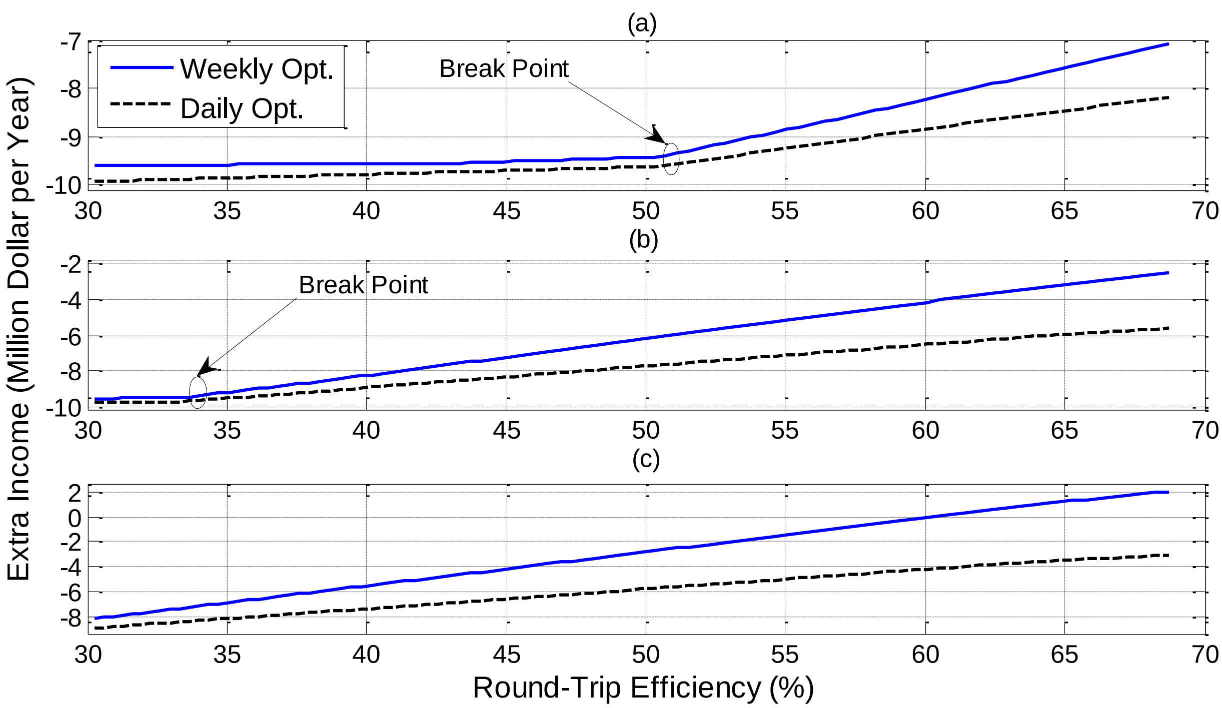

Figure 5-2: The extra income (revenue) vs. efficiency; (a): Profile 1, (b): Profile 2, (c): Profile 3

Table 5-3: Extra Revenue for the Third Profile, Shown in Figure 5-2 (c)

Round-Trip Efficiency	**CES_1: Weekly Usage at:**		**CES_2: Daily Usage at:**	
	one year	***life of storage***	***one year***	***life of storage***
60.5%	0 (M$)	0 (M$)	-4.1 (M$)	-123 (M$)
68.7%	2 (M$)	60 (M$)	-3 (M$)	-90 (M$)

The following outcomes can be obtained from Figure 5-2 and Table 5-3:

- As shown in Figure 5-2 (c), for price Profile 3, two numerical examples are given in Table 5-3 to reveal how to use the curves and to quantitatively compare the extra revenue of CES weekly and daily usages. Table 5-3 shows that for the efficiency of 60.5%, the extra revenue is $0 for the weekly usage while for daily usage it is -$4.1M×30=-$123M at the entire life of storage. This negative extra revenue means a significant financial loss for CES daily usage. Moreover, for the efficiency of 68.7%, the extra revenue is $2M×30=$60M for weekly usage while for daily usage it is -$3M×30=-$90M at the entire life of storage. Consequently, there is huge amount of financial loss in daily usage as compared to weekly usage optimization.

- As shown in Figure 5-2, for all efficiencies, the extra revenue of weekly optimization is higher than the daily one. This is because in weekly optimization, optimal dispatch algorithm considers a week a head electricity price and stores considerable amount of energy in weekends and weekday nights when electricity is cheaper and sells it during peak periods of weekdays. In addition, as CES efficiency increases the financial benefit of weekly usage as compared to daily usage increases linearly.

- As shown in Figure 5-2 (a and b), the left side of the break point is approximately flat for both daily and weekly usages; the flat part shows that by changing the round-trip efficiency, there is no significant changes in the amount of extra revenue. This occurs because CES operation is not economical and, therefore, the ESS stops working in the market. The break point, shown in Figure 5-2 (a and b), is therefore defined as the minimum efficiency in which the ESS can work in the market economically. As Figure 5-2 shows, there is different break points for Figure 5-2 (a and b), and there is no such a point for Figure 5-2 (c).

- As shown in Figure 5-2 (a), the weekly usage curve at the left side of the break point seems more flat than the daily usage one. For efficiencies less than the break point efficiency, the negative extra revenue, e.g. financial loss, is approximately constant in weekly usage while the case is worse in daily usage as the negative extra revenue increases with decreasing the efficiency. The reason of this phenomenon is explained as follows. Although the flat part of the curves shows that the ESS is not seriously working due to very low efficiencies, it must always work to compensate the energy dissipation to maintain the SOC above or equal to the minimum allowed stored energy. In order to do so, the ESS must charge at least for one time interval, i.e., one hour and with the minimum charging power, i.e., 40 MW in daily usage; the stored energy is therefore 40 MWh times charging efficiency. This energy is significantly more than what is needed for the compensation of the dissipation in one day; the extra energy should be discharged somewhere during the day to make profit; based on the fact that the output efficiency is very low, a lot of energy is lost during discharging; this process is going to be repeated in each day of the week causing considerable financial losses at the end of the week due to extra charging and discharging in uneconomical conditions. Consequently, although the ESS is not working in the market for operating points at the left side of the break point, due to its extra charging and discharging to compensate the dissipation, the objective function becomes dependent to the efficiency and the curve is not completely flat in daily usage. In weekly usage on the other hand, the ESS charges in one time interval during the weekend when the energy price is low, but does not have to discharge the extra energy at the end of that day as the optimization horizon is one week. Instead, it will keep the energy to compensate the dissipation in the entire week; this way, only a very small portion of energy is discharged in the high level of energy price during a weekday. This way, uneconomical charging and discharging in low efficiencies is less in ESS weekly usage as compared to daily usage causing to limit financial losses in low efficiencies. Consequently, for the operating points at the left side of the break point, charging and discharging is very small and the dependency of the objective function to the efficiency is minimal; thus, the curve of weekly usage is more flat than that of the daily usage as clearly illustrated in Figure 5-2 (a).

- The more efficiency the ESS has, the more extra revenues are obtained by both daily and weekly usages. This is because by increasing efficiency, the amount of energy lost in ESS system decreases. As the technology grows, the efficiencies of these types of ESSs will increase and, thus, utilizing such ESSs becomes more economical.

- As the curves show, for most of the cases, the extra revenue is negative; negative extra revenue in one operating point means that using the ESS is no longer economical in that operating point. Since these ESSs have a lot of benefit not only through the environmental point of view, but also due to their significant contribution in supporting the utility, these ESSs should receive governmental support in order for the ESSs to be able to work in the liberalized energy market. The government is recommended to provide this support for the investor to encourage them to invest on these technologies; the amount of this support should be so that the extra revenue will at least reach to zero; the zero value of the extra revenue is the border between economical and uneconomical situations.

- By comparing the effect of price difference between peak hours and off-peak hours (see Figure 5-2 (a, b, and c), it can be realized that the larger the difference exists between the higher and lower levels, i.e. arbitrage, of the energy price, the more extra revenue is obtained for both cases of daily and weekly usages. By increasing the arbitrage in Profile 2 compared to Profile 1 and Profile 3 compared to Profile 2, the revenue obtained by purchasing and selling the electricity from/to the market increases.

- As mentioned in Chapter 2, the expected revenue (C_{ERev}) offsets and the life of storage approximately offsets the objective of the optimization problem, i.e., the Extra Revenue vertically. If C_{ERev} increases, i.e., for more expected revenue, the Extra Revenue will decrease. Considering C_{ERev} as a percentage of C_{Cap}, for 1% increase of C_{ERev}, the curves shown in Figure 5-2 should be shifted in negative direction by 0.01 × (total capital cost/life of storage) = 0.01 × (\$117M/30) = \$0.039M. On the other hand, if the life of storage is considered lower, C_{EInc} and

C_{Cap} should be returned in less time and thus the Extra Revenue decreases. In general, if the life of storage is changed from 30 to x years, the curves shown in Fig. 4 will be shifted approximately by C_{ERev} × total capital cost × (1/30-1/x)=$292.5 × (1/30-1/$x$) M.

5.2.3.2 Using the Real Data of the Ontario Electricity Market

In this section, the economic benefit of ESS operation, i.e., extra revenue is calculated for weekly and daily usage optimization of CES by applying the electricity price profiles of Ontario market. In this study, the forecast error is considered zero as the objective is only comparing of weekly and daily usages of CES (the forecasted prices are substituted with the actual ones). Table 5-4 shows the extra revenue obtained by applying prices of Ontario market to RTOD for weekly and daily usages. The ESS round-trip efficiency is considered 60% in this study.

Table 5-4: Extra revenue of ESS operation for the Ontario electricity market

Year	Weekly Optimization	Daily Optimization
2006	-3.2988	-3.7200
2007	-5.7053	-6.7006
2008	-4.8151	-6.0024
2009	-6.4558	-6.9781
2010	-7.1493	-7.5942
2011	-5.0016	-5.3043
Total	**-32.4259**	**-36.2996**

As shown in Table 5-4, the extra revenue for all years are negative; this means that the ESS is not able to return the expected revenue. However, the values of extra revenue are less negative for weekly usage optimization, e.g., 10%. This reveals the advantage of weekly usage optimization as compared to common common daily usage optimization for CES.

5.3 Summery

In this chapter, the concept of weekly usage of CES to shift the electric energy from lower prices during off-peak periods to higher prices during on-peak periods as compared to common daily usage was introduced. Two equally-expensive CES systems optimally sized in Chapter 2 for daily and weekly usages were used in this chapter. The RTOD algorithm, formulated in Chapter 3 of this thesis, was used for optimal weekly and daily usages of the CES. The economic benefits of both CES weekly and daily usages were presented and compared for different price profiles and round-trip efficiencies of the ESS. The results revealed significant benefits of weekly usage of the CES as compared to daily usage.

Chapter 6

6 Conclusions and Suggestions

This chapter concludes the results of the present thesis and provides some suggestions for future works in the relevant area.

6.1 Summary of this Thesis

- In Chapter 1 of this thesis, the concept of privately ESSs was presented. The previous research studies related to this area were reviewed; then, the contributions of the present work were summarized. Finally, the organization of the thesis was explained.

- In Chapter 2 of this thesis, two air-based large-scale ESSs, i.e., the CAES and the CES systems were introduced and, then, they were sized by using a method proposed in this thesis. By sizing of the ESSs, the ratings of charging, discharging, and storage tank plants were determined for each ESS.

- In Chapter 3, an RTOD algorithm was proposed by formulating an MILP problem to determine ESS charging and discharging power set-points in a competitive electricity market based on real-time and forecasted electricity prices. Moreover, the economic impact of electricity market price forecasting errors using a generic price profile and public-domain market prices on the proposed RTOD algorithm was evaluated. It was demonstrated that the considerable price forecast error can significantly decrease the revenue resulted from the ESS operation.

- In Chapter 4, based on the historical market price information using public-domain prices in the Ontario market, a new approach was proposed and implemented to calibrate the price forecast making the RTOD adaptive to price forecast error. The performance of the proposed adaptive RTOD was evaluated through comparing economic benefits of the ESS operation for different possible calibration methods, and the results were discussed. The investigation results revealed that the proposed adaptive RTOD outperforms the conventional RTOD, presented in Chapter 3, by increasing the ESS financial benefits when the public-domain market prices are used for short-term scheduling of the ESSs.

- In Chapter 5, the concept of weekly usage of CES to shift the electric energy from lower prices during off-peak periods to higher prices during on-peak periods as compared to common daily usage was introduced. Two equally-expensive CES systems were optimally sized for daily and weekly usages. The RTOD algorithm, formulated in Chapter 3 of this thesis, is used for optimal weekly and daily usages of the CES, sized in Chapter 2. The economic benefits of both CES weekly and daily usages were presented and compared for different price profiles and round-trip efficiencies of the CES. The results revealed significant benefits of weekly usage of the CES as compared to common daily usage. The Ontario market was used as a real-world case study to validate the findings. It was demanstrated that for the wholesale market prices in the Ontario market, the weekly usage significantly outperforms the conventional daily usage of CESs.

6.2 Achievements of the Thesis

In this work, the concept of privately owned large-scale ESS was introduced. An RTOD algorithm was proposed to determine ESS charging and discharging power set-points in a competitive electricity market based on real-time and forecasted electricity prices. Sensitivity analysis was performed to evaluate the impact of energy price forecasting error on the performance of the proposed RTOD using a generic and actual electricity price profiles selected from the Ontario electricity market.

To mitigate the adverse impact of the price forecast error on the proposed RTOD, an adaptive RTOD was proposed and evaluated through comparing economic benefits of the ESS operation for different cases. The investigation results revealed that the proposed adaptive RTOD algorithm outperforms the RTOD by achieving higher financial benefits for the ESS private owner.

The CES technology was introduced. Due to the significant lower price of storage tank compared to other components of the CES, it was proposed to increase the storage tank size to enable weekly energy shift. Two equally-expensive CES systems were optimally sized for daily and weekly usages. The proposed RTOD was employed to determine CES dispatch quantities including time periods and amounts of charging and discharging power set-points. The daily and weekly usages were compared using three pre-defined price profiles and different round-trip efficiencies between 30% and 70%. The performance evaluation results showed that weekly usage is significantly more economical and effective than the daily usage for this energy storage technology.

6.3 Suggestions for Future Works

- In the present work, a simple method was used for ESS sizing since the main objective was not the ESS sizing. However, more complex methods for ESS sizing, introduced in the literature, can also be tried.

- The Ontario electricity market was used as the real-world case-market for simulation purposes. Although the concepts introduced in the present work are expected to be consistent for different electricity markets, several other electricity markets around the world can be used to evaluate the performance of the proposed methods in this thesis.

- In this thesis, the proposed adaptive RTOD is only used for energy shifting, but the ESS can be employed to provide additional financial and operational benefits by contribution to ancillary services, such as peak-shaving, frequency regulation, and deferred transmission and distribution investments. These benefits can be considered in development of the adaptive RTOD in the future studies. Additionally, the appropriate policies to determine the amount of financial compensation which the ESS owners should receive for their contribution in ancillary services can be investigated.

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Curriculum Vitae

Name:	Hadi Khani
Post-secondary Education and Degrees:	Shiraz University Shiraz, Iran 2006 B.Sc.
	Isfahan University of Technology Isfahan, Iran 2009 M.Sc.
	Western University London, ON, Canada 2014 M.E.Sc.
Honors and Awards:	Second award for the poster entitled "Real-Time Optimal Dispatch of Large-Scale Energy Storage Systems" Sustainability and the Environment Research Showcase Western University, 2014.
	The best M.Sc. thesis of the year, Isfahan University of Technology Isfahan, Iran, 2009.
	Third rank in B.Sc. Degree Shiraz University, Shiraz, Iran, 2006.
Related Work Experience	Research and Teaching Assistant Western University 2012-2014.
	Consultant Engineer Pajoohandeh-Niroo Consultation & Industrial Research Company Isfahan, Iran 2009-2012.

Publications:

Peer-Reviewed IEEE Journals:

- **H. Khani**, M. R. Dadash Zadeh, "Adaptive Real-Time Optimal Dispatch of Privately Owned Energy Storage Systems," *IEEE Trans. On Power System*, Submitted in 2014.

- **H. Khani,** M. Moallem, S. Sadri, M. Dolatshahi, "A New Method for Online Determination of the Location of Switched Capacitor Banks in Distribution Systems, "*IEEE Trans. on Power Delivery*, vol. 26, no.1, pp. 341-351, Jan. 2011.

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