

INTEGRATION OF ELECTRIC ENERGY STORAGE INTO POWER SYSTEMS
WITH RENEWABLE ENERGY RESOURCES

A Dissertation

by

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ABSTRACT

This dissertation investigates the distribution and transmission systems reliability and economic impact of energy storage and renewable energy integration. The reliability and economy evaluation framework is presented. Novel operation strategies of energy storage and renewable energy are proposed. The method for optimizing the energy storage sizing and operation strategy in order to achieve optimal reliability and economy level is developed.

The objectives of the movement towards the smart grid include making the power systems more reliable and economically efficient. The rapid development of the large scale energy storage technology makes it an excellent candidate in achieving these goals. A novel Model Predictive Control (MPC)-based operation strategy is proposed to optimally manage the charging and discharging operation of energy storage in order to minimize the energy purchasing cost for a distribution system load aggregator in power markets. Different operation strategies of energy storage have different reliability and economic impact on power systems. Simulation results illustrate the importance of the energy storage operation strategies. A hybrid operation strategy which combines the MPC-based operation strategy and the standby backup operation strategy is proposed to flexibly adjust the reliability and economic improvement

brought by energy storage. A particle swarm optimization approach is developed to determine the optimal energy storage sizing and operation strategy while maximizing reliability and economic improvement. A reliability and economy assessment framework based on sequential Monte Carlo method integrated with the operation strategies is proposed. The impact on the transmission systems reliability brought by energy storage and renewable energy with the proposed operation strategies is investigated. Case studies are conducted to demonstrate the effectiveness of the proposed operation strategies, optimization approach, and the reliability and economy evaluation framework. Insights into how energy storage and renewable energy affect power system reliability and economy are obtained.

DEDICATION

I dedicate my dissertation work to my family and many friends. Particularly to my loving mother, Huilin Wang, who emphasized the importance of education, hardworking spirit, persistence, and who encourages me to set high goals to achieve them, and my father, Guosheng Xu, who taught me how to think creatively and critically.

I also dedicate this dissertation to my many friends who have supported me throughout the process.

-In Chinese-

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NOMENCLATURE

$C(k)$	Power charged to energy storage in period k
C_{Max}	Energy storage maximum charging power limit
$D(k)$	Power discharged from energy storage in period k
D_{Max}	Energy storage maximum discharging power limit
$L(k)$	Load in current period k
$L_f(k)$	Forecasted load in future period k
$P(k)$	Energy price for period k
$P_f(k)$	Forecasted energy price for future period k
$R(k)$	Utilized renewable energy in period k
$R_f(k)$	Forecasted renewable energy utilization in period k
$R_{Max}(k)$	Available renewable energy in period k
$R_{f,Max}(k)$	Forecasted available renewable energy in period k
$U(k)$	Energy purchased in power market for period k
$U_f(k)$	Energy planned to be purchased in future period k
$SOC(k)$	State of charge level at the end of period k
SOC_{Min}	Energy storage minimum state of charge level
SOC_{Max}	Energy storage maximum state of charge level

η_c Energy storage charging efficiency

η_d Energy storage discharging efficiency

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1. INTRODUCTION

1.1 Energy Storage Technologies

The U.S. electric power grid and national grids in other countries such as China are being transformed into a more reliable, secure, and efficient smart grid. Within this smart grid, many technologies are included. Large scale energy storage is one of them.

Many large scale energy storage technologies are being investigated. Currently, compressed air energy storage (CAES) is one of the energy storage technologies receiving significant attention. A 115 MW CAES demonstration power plant placed in service in the early 1990s has proven to be effective [1]. CAES systems could be practical in a power range from above 100 MW up to several thousand MW.

The most common form of energy storage in use today is based on lead-acid batteries. This energy storage technology has been utilized in data centers to support the Internet and communications centers for higher reliability. The total consumption of lead-acid batteries in the United States reported in 2008 is \$2.9 billion per year and is growing at an annual rate of 8%.

The utilization of Lithium-ion battery is growing rapidly. The possibility of lithium-ion batteries for high-power transportation applications has contributed to the sales in the United States to \$1 billion in 2007, with expected growth rates of 50–60% per year.

There are many other energy storage technologies in use for electric backup power applications. These technologies are also being investigated and some of them are being deployed for utility-scale applications. For example, the sodium sulfur battery has been widely used in Japanese utilities and is being investigated and deployed in the United States recently.

1.2 Benefits of Deploying Energy Storage Technologies

There are many benefits to deploy energy storage technologies into the grid.

Energy storage can:

1. Improve grid optimization for power production
2. Facilitate power systems balancing variable renewable energy sources such as wind and solar power
3. Help the integration of plug-in hybrid electric vehicle (PHEV)
4. Defer investments in transmission and distribution infrastructure to meet peak loads
5. Provide ancillary services directly to grid/market operators

Energy storage can be utilized as a generation, transmission, distribution, or end-user resource depending upon its principal application and the contributing institution.

1.3 Research Objectives and Approaches

1.3.1 Scheduling and Operation in Distribution Systems with Energy Storage

Electric power systems are operated on the basis of real-time balancing of supply and demand without large-scale electric energy storage (EES) capabilities. With the objective of transformation towards a more reliable, secure, and efficient smart grid, and with the recent rapid development of EES technologies, feasible applications of EES in power systems have started to be investigated [1]-[2]. The major benefits of EES include electric energy time-shift, power supply capacity, and transmission congestion relief, [3]. The type and amount of benefits of EES depend on how it is operated. The problem of scheduling and operation for a distribution system with energy storage focuses on how a load aggregator who participates in the day-ahead market and the real-time balancing market should utilize the energy storage to schedule its energy purchase in day-ahead market and operate in real-time market. The objective is to save energy purchasing cost in the market environment.

Among the research efforts towards energy cost savings by utilizing storage, reference [4] discusses the optimal demand-side response to electricity spot prices for storage-type customers (e.g. municipal water plants); Authors in [5] report on an experiment on the real-time pricing based control of thermal storage to save cost; researchers in [6] investigate the economics of sodium sulfur batteries for the

application of energy arbitrage in New York state's electricity market. Besides operating storage on the demand side, reference [7] discusses the potential of using storage to increase profit of wind power in the day-ahead market and balancing market. Research work reported in [8] proposed a Model Predictive Control (MPC)-based method to solve the dispatch problem with intermittent resources using the short-term wind power and load forecasts. Several forecasting techniques for predicting short term electricity price [9]-[13] and load [14]-[16] are presented. Good short-term (e.g. within 24 hours) price and load forecasts are available. By applying a MPC-based approach, the potential of taking advantage of these forecast technologies to better manage the energy cost of a load aggregator with EES in a market mechanism consists of day-ahead market and real-time balancing market is explored. As the price and load forecasts are crucial for this operation strategy, the impact of the forecast uncertainties is investigated.

1.3.2 Distribution Systems Reliability and Economic Improvement with Energy Storage

Large scale energy storage does not just help reduce energy purchasing cost. It can also be utilized to improve distribution systems reliability. Several papers in the literature have reported on the effect of EES on improving reliability. Reference [17] explores the feasibility of installation of battery storage plant to enhance power system

reliability and security. Reference [18] describes an analytical approach to evaluate reliability improvement by using EES as a backup storage and determine the size of the storage to meet a specified reliability target. Reference [19] presents a reliability cost/worth evaluation method that can incorporate the impacts of wind energy and energy storage utilization in electric power systems.

Previous efforts have been either for the reliability impact of EES integration, or on its economic benefits. Comparatively not much has been done to emphasize the relationship between reliability and economy impact of EES. However, reliability impact and economic benefits are tightly related. Especially with the operational flexibility of energy storage, different operation strategies could bring different reliability impact and economic benefits. For load aggregator of distribution system integrated with EES, it is important to know the reliability and economy impact of the implemented EES operation strategies. Then proper EES operation strategies can be chosen and implemented to achieve desired reliability and economy improvement goals. A Model Predictive Control (MPC)-based operation strategy to improve distribution system economy and reliability is proposed. The reliability and economic impact of the proposed MPC-base operation strategy and standby backup operation strategy for EES is evaluated and compared. Then a hybrid operation strategy to balance reliability improvement and economy improvement is proposed and evaluated.

1.3.3 Adequacy and Economy Analysis of Distribution Systems with Energy Storage and Renewable Energy

Renewable Energy Resources (RER) such as wind and solar energy are the key to reduce pollutants produced by conventional fossil fuel power plants, carbon dioxide emissions and energy purchasing cost associated with rising fuel price. Although the potential benefits of RER are significant, many major challenges need to be conquered first. One of the major challenges is the reliability impact caused by intermittent RER such as wind power. This problem could be ignored earlier because the integrated RER were only a very small percentage (e.g., 3%) of the total generation. The intermittent property of RER does not have a notable reliability impact on systems which are mainly supported by conventional fossil fuel generations. With expected greater penetration of RER (e.g., 20% wind power), their reliability impact can no longer be ignored. A comprehensive reliability analysis considering the impact of high RER penetration is required.

An efficient method of reliability analysis of electric power systems with time-dependent sources, such as photovoltaic and wind generation is presented in [20], in which the reliability impact of fluctuating characteristics of unconventional generation units is studied. Reference [21] investigates the reliability effects on a composite generation and transmission system associated with the addition of

large-scale wind energy conversion systems using the state sampling Monte Carlo simulation technique, where the wind speed correlation is considered. The work in [22] presents a reliability analysis framework which includes both the deterministic and probabilistic approaches for bulk power system adequacy and security assessment when wind power is added. Considerable work has been done on RER integration in transmission systems. Reliability impact of RER integrated in distribution systems is also studied by researchers. In [23], the authors investigate the system reliability benefits of adding wind turbine generation as an alternative supply in a rural distribution system. In [24], both Monte Carlo simulation and analytical methods are used to assess distribution system adequacy including wind-based distribution generation units, with implementation of the islanding mode of operation in the assessment.

With a rapid development of Electric Energy Storage (EES) technologies, and their operational flexibility, interest in integrating both RER and EES into power systems to improve systems reliability and economy has been growing. A reliability cost/worth evaluation method that can incorporate the impact of wind energy and EES utilization in electric power systems is presented in [25]. Research in [26] evaluates system reliability considering wind and hydro power coordination, where hydro facilities with energy storage capability are utilized to alleviate the impact of wind

power fluctuations and also improve the system adequacy. A methodology for the operation of a hybrid plant with wind power and hydrogen storage to maximize economic benefits (i.e., maximizing profits) in a market environment is presented in [7].

With the operational flexibility of EES, different EES operation strategies could bring different sets of reliability impact and economic benefits. To solve this problem, a novel Model Predictive Control (MPC)-based operation strategy for distribution system load aggregator is proposed to improve the economy of system by minimizing energy purchasing cost in power market with the utilization of price, load, and renewable energy forecasts. An islanding operation with power supplies from RER and EES is implemented to enhance distribution system reliability. In order to accurately assess the reliability and economic impact brought by proposed operation strategies, an assessment framework based on sequential Monte Carlo simulation approach is presented.

1.3.4 Multi-objective Design of Energy Storage in Distribution Systems

The objective of energy storage employment is to help build a more reliable and efficient smart grid. The major benefits of energy storage include electric energy time-shift, frequency regulation and transmission congestion relief. Energy storage can help achieve many goals. Among these goals, we focus on two of the most important

objectives which are reliability and economy.

Some researchers have investigated the effect of energy storage on improving reliability. Researchers in [27] explore the feasibility of installation of battery storage plant to enhance power system reliability and security. A reliability cost/worth evaluation method that can incorporate the impacts of wind energy and energy storage utilization in electric power systems is presented in [19].

Among the research efforts towards achieving higher economic benefits by utilizing energy storage, [4] discusses the optimal demand-side response to electricity spot prices for storage-type customers. Authors in [5] reports on an experiment on the real-time pricing based control of thermal storage to save cost.

The energy storage sizing problems are also being investigated. Reference [18] describes an analytical approach to evaluate reliability improvement by using energy storage as a backup storage and determine the size of the storage, which includes the capacity and power rate, to meet a specified reliability target.

Reliability impact and economic benefits are tightly related when considering energy storage integration. Especially with the operational flexibility of energy storage, different operation strategies could bring different reliability impact and economic benefits. For load aggregator of distribution system integrated with energy storage, it is important to know the reliability and economy impact of the implemented energy

storage operation strategies. Then proper energy storage operation strategies can be chosen and implemented to achieve desired reliability and economy improvement goals.

However majority of research done on energy storage design problems mainly considers the impact of energy storage capacity and power rate. The impact of energy storage operation strategy is ignored or not considered as a major factor. Our work demonstrates the significant impact of energy storage operation strategy on reliability level and economic benefits. A modified particle swarm optimization approach is proposed for the designing the problem of energy storage in distribution systems, where not only the energy storage capacity and power rate are determined but also the energy storage operation strategy.

1.4 Impact on Transmission System Reliability

By implementing the proposed operation strategies, the energy storage devices and renewable energy resources integrated in distribution systems are mainly for reducing energy purchasing cost and improving distribution system reliability. However the utilization of energy storage and renewable energy in distribution systems could have an impact on the transmission system reliability. It is necessary to evaluate this impact in order to assess the value of the energy storage and renewable energy integration. With the quantified value of the energy storage and renewable energy integration,

system operator could then determine the proper compensations or incentives for the load aggregator. These compensations and incentives could increase the revenue streams for the high cost energy storage devices and encourage larger scale of energy storage exploration. Evaluating the reliability impact is also beneficial for the system operator to understand the relationship between the energy storage and renewable energy expansion, and reliability improvement. These insights could be helpful in the mid-term or long-term planning in order to maintain and improve system reliability.

1.5 Organization of the Dissertation

This dissertation is organized as follows. A brief background of the large scale energy storage technologies and its benefits to power systems is presented in Section 1. The main research objectives and proposed approaches are also included in Section 1. From Section 2 to Section 5, each section describes in details one research objective and its approaches. Section 2 describes the optimal scheduling and operation strategy for a distribution system integrated with energy storage devices in order to save energy purchasing cost in power markets. Section 3 discusses the important impacts of energy storage operation strategy on power system reliability and economic performance. Reliability and economy of distribution systems integrated not only energy storage but also renewable energy is investigated in Section 4. Section 5 presents a particle swarm based optimization framework for energy storage design problem. The impact on

transmission system reliability brought by the integration of energy storage and renewable energy is investigated in Section 6. The conclusions and outlook are given in Section 7. References are attached at the end.

2. OPTIMAL SCHEDULING AND OPERATION OF LOAD AGGREGATOR WITH ELECTRIC ENERGY STORAGE IN POWER MARKETS*

2.1 Introduction

Electric power systems are operated on the basis of real-time balancing of supply and demand without large-scale electric energy storage (EES) capabilities. With the objective of transformation towards a more reliable, secure, and efficient smart grid, and with the recent rapid development of EES technologies, feasible applications of EES in power systems have started to be investigated [1]-[2]. The major benefits of EES include electric energy time-shift, power supply capacity, and transmission congestion relief, etc.[3]. The types and amount of benefits of EES depend on how it is operated. This section models the EES as operated by a load aggregator that participates in the day-ahead market and the real-time balancing market. The focus of is on the energy cost savings.

Among the research efforts towards energy cost savings by utilizing storage, authors in [4] discuss the optimal demand-side response to electricity spot prices for

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storage-type customers (e.g. municipal water plants); Reference[5] reports on an experiment on the real-time pricing based control of thermal storage to save cost; Research work [6] investigates the economics of sodium sulfur batteries for the application of energy arbitrage in New York state's electricity market. Besides operating storage on the demand side, Researchers in [7] discuss the potential of using storage to increase profit of wind power in the day-ahead market and balancing market. Research work reported in [8] proposed a Model Predictive Control (MPC)-based method to solve the dispatch problem with intermittent resources using the short-term wind power and load forecasts. Several forecasting techniques for predicting short term electricity price [9]-[13] and load [14]-[16] are presented. Good short-term (e.g. within 24 hours) price and load forecasts are available. In this work, by applying a MPC-based method, the potential of taking advantage of these forecast technologies to better manage the energy cost of a load aggregator with EES in a market mechanism consists of day-ahead market and real-time balancing market is explored. In the presented MPC-based approach, the most updated price and load forecast information is integrated in the decision making process.

2.2 Energy Cost Saving with Energy Storage in Distribution Systems

2.2.1 Distribution Systems with Energy Storage

The load aggregator provides power to its customers (i.e. load) in a distribution network. The demand is assumed to be price inelastic. It also operates an EES located within the same distribution network. The topology of the system is simplified as in Figure 1. The distributed loads are modeled into one lumped load. Load in each period, $L(k)$, is price inelastic. The charging $C(k)$ and discharging $D(k)$ operations of the EES are determined by the load aggregator. The summation of the load and the EES power charging and discharging is the imported power $U(k)$ from the power market, delivered from the external grid. The load aggregator's objective is to minimize its energy cost by optimally scheduling the imported power in the day-ahead market and determining the imported power during operation in the real-time balancing market.

2.2.2 Day-ahead and Real-time Power Markets Model

The power market share simplified as the following day-ahead market model and real-time balancing market model. The market models are similar to the models in [7].

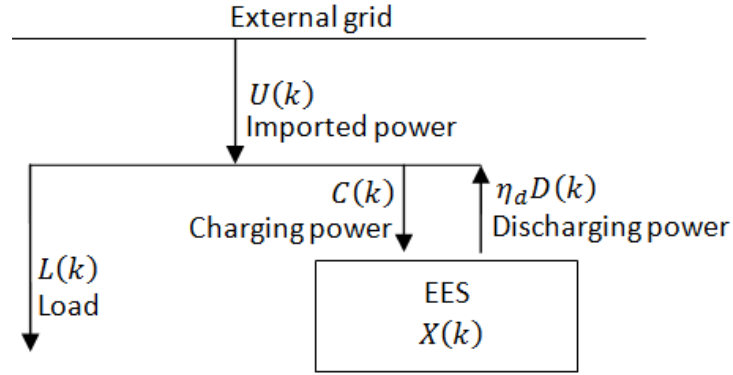


Figure 1 Electric energy storage integrated in the distribution system.

In the day-ahead market, the load aggregator submits its offers to import power to meet its demands for each period in the next day. After the closure of the day-ahead market, system operator will determine which offers are accepted and work out the market clearing price for each period of the next day. All the load aggregator's offers are assumed to be cleared by the market and its bidding is assumed not affecting the market clearing price. In the day-ahead market, the energy cost for each period in the next day is

$$U_{sch}(k) \cdot P(k) \tag{2.1}$$

Where $U_{sch}(k)$ is the amount of power scheduled to be imported in the day-ahead market for the period k in the next day, $P(k)$ is the actual day-ahead market clearing price for the period k in the next day. The total energy cost for a day is the sum of energy cost of each period in the day.

The amount of imported power scheduled by load aggregator is based on their prediction of the load and price, and EES characteristics in each period of the next day. The details of how the load aggregator optimally schedules its imported power are presented in Section 2.3.1.

The prediction is not perfectly accurate. During the real time operation, based on the actual load and price, load aggregator might decide to adjust its actual imported power to minimize energy cost while meet the actual load. The discrepancies between day-ahead scheduled imported power and actual imported power are settled in the real-time balancing market. The balancing cost for each period is

$$[(U_{actual}(k) - U_{sch}(k))] \cdot P_{balancing}(k) \quad (2.2)$$

where $U_{actual}(k)$ is the actual imported power in period k during real-time operation, $P_{balancing}(k)$ is the imbalance cost due to up regulation or down regulation of generators. The balancing cost for a day is the sum of the cost for each period in the day. The real-time balancing market is simplified by introducing two penalty factors p_{up} and p_{down} for up regulation and down regulation. The imbalance cost in period k is expressed as the penalty factor times the day-ahead market price for the same period k

$$P_{balancing}(k) = \begin{cases} p_{up} \cdot P(k), & \text{if } U_{actual}(k) > U_{sch}(k) \\ p_{down} \cdot P(k), & \text{if } U_{actual}(k) < U_{sch}(k) \end{cases} \quad (2.3)$$

where $p_{up} \geq 1$ and $p_{down} \leq 1$.

The imbalance $U_{actual}(k) - U_{sch}(k)$ is based on the scheduled imported power in the

day-ahead market, actual price and load, real-time forecasted price and load in the future periods, and EES characteristics. The details of how the load aggregator optimally determines the actual imported power during real-time operation is presented in Section 2.3.2.

The total energy cost is the sum of the day-ahead cost plus the real-time balancing cost. This is the objective function load aggregator tries to minimize.

2.2.3 Imported Power Model

The load is assumed to be price inelastic which needs to be met all the time. However, the charging and discharging behavior of the EES are fully controllable within its physical limits. Both load and EES are in the same distribution system, thus load and the charging and discharging behavior of the EES are combined together as the imported power for the load aggregator. The imported power is elastic to some extent because of the flexibility of the EES charging and discharging operation. Load aggregator is assumed to be net power importer. Thus

$$U_{actual}(k) \geq 0 \quad (2.4)$$

$$U_{sch}(k) \geq 0 \quad (2.5)$$

2.2.4 Electric Energy Storage Model

EES is modeled by its energy storage capacity, charging power limit, discharging power limit, charging efficiency, discharging efficiency, available periods, initial

storage level and final storage level. The storage level has to be equal or below its capacity. The charging and discharging power have to be within their limits. Power loss during discharging and charging operations are considered in its charging and discharging efficiencies. The storage is only available for operation during the specified available periods. Most of the EES technologies such as sodium sulfur batteries and flywheels are stationary and could be operated all the time after installation. However some EES such as PHEVs are not stationary, and are only available for operation during some specific periods (e.g. from 8AM to 6PM when plugged in charging stations). The operation of EES needs to meet the initial and final storage level constraints. For example, the energy stored in PHEVs' batteries must be higher than certain level before leaving charging station. The storage level at the end of each period is determined by the previous period storage level and the charging and discharging operation during this period, it is expressed as

$$X(k) = X(k-1) + \eta_c \cdot C(k) - D(k) \quad (2.6)$$

where $C(k)$ is the power charged to EES, $D(k)$ is the power discharged from EES, $X(k)$ is the energy storage level at the end of period k . All three variables needs to be within its operation limits, expressed as

$$0 \leq C(k) \leq C_{Max}(k) \quad (2.7)$$

$$0 \leq D(k) \leq D_{Max}(k) \quad (2.8)$$

$$X_{Min}(k) \leq X(k) \leq X_{Max}(k) \quad (2.9)$$

When the EES is not available, $C_{max}(k)$, $D_{max}(k)$, $X_{min}(k)$ and $X_{max}(k)$ are all zeros.

2.3 Scheduling and Operation with Energy Storage

2.3.1 Optimal Scheduling in the Day-ahead Market

In the day-ahead market, the objective of the load aggregator is to schedule the imported power for each period in the next day at the least cost. As the day-ahead market clearing price $P(k)$ is unknown before submitting its offers, and the actual load $L(k)$ during real-time operation is also uncertain, day-ahead predicted price $\hat{P}(k)$ and load $\hat{L}(k)$ are used for day-ahead scheduling. There are several forecasting techniques for predicting electricity price and load. The focus here is on how to use the predicted price and load for optimal scheduling instead of how to predict them.

The objective function of the day-ahead market optimal scheduling problem can be formulated as a linear programming problem which minimizes the energy cost in the day-ahead market based on price and load forecast

$$Min. \sum_{k=1}^K U_{sch}(k) \cdot \hat{P}(k) \quad (2.10)$$

Subject to the constraints (5)-(9) and

$$U_{sch}(k) = \hat{L}(k) + C(k) - \eta_c D(k) \quad (2.11)$$

where K is the total number of periods in the next day. After submitting its schedule to the system operator, the market clearing price is worked out. The actual energy cost in

day-ahead market can be calculated as

$$\sum_{k=1}^K U_{sch}(k) \cdot P(k) \quad (2.12)$$

The forecasted day-ahead market price and load play an important role in the minimizing the total energy cost. If it can be perfectly forecasted, the load aggregator could optimally operate its EES to take advantage of the low prices periods by importing more power and storing it while reducing the imported power during the high price periods by supporting the load with the stored energy.

2.3.2 Optimal Operation in the Real-time Balancing Market

Day-ahead forecasted price and load are not perfectly accurate, the discrepancies of scheduled imported power in the day-ahead market and actual imported power during operation are settled in the real-time balancing market. A MPC-based method is proposed to determine the optimal real-time operation.

The basic approach of MPC is that a finite-horizon optimization problem determining the series of optimal control operations is solved before each control step, but only the first control operation is implemented. A predictive model is used to estimate the state space trajectory over the prediction horizon, with the initial state being the actual state of the system. After implementing the first control operation, the system updates the actual state of the system and the future states using the predictive model. Then the optimal control routine is repeated to determine the next step's

optimal operation. This method of receding-horizon strategy has been successfully applied in the real world, such as in chemical process industry. Applying the above MPC-based approach, balancing cost minimization problem with uncertain price and load at period i can be implemented as follows

- 1) Obtain the actual load and price in the current period i .
- 2) Select a receding optimization horizon N periods (e.g. 24 hours). Use a load and price forecast model to obtain the most updated load and price forecast for the future periods from $i+1$ to $i+N$.
- 3) Solve the balancing cost minimization problem, which is a linear programming problem, formulated as

$$\begin{aligned} \text{Min. } & [U_{actual}(i) - U_{sch}(i)] \cdot P_{balancing}(i) + \\ & \sum_{k=i+1}^{i+N} [U_{actual}(k) - U_{sch}(k)] \cdot \hat{P}_{balancing}(k) \end{aligned} \quad (2.13)$$

s.t. (4), (6) - (9),

For (4), (6) - (9), $k = i, i+1, \dots, i+N$,

$$U_{actual}(i) = L(i) + C(i) - \eta_c D(i),$$

$$U_{actual}(k) = \hat{L}(k) + C(k) - \eta_c D(k), k = i+1, \dots, i+N$$

The first part $[U_{actual}(i) - U_{sch}(i)] \cdot P_{balancing}(i)$ is the balancing cost of the current period i , its actual load $L(i)$ and actual imbalance cost $P_{balancing}(k)$ is known. The second part $\sum_{k=i+1}^{i+N} [U_{actual}(k) - U_{sch}(k)] \cdot \hat{P}_{balancing}(k)$ is the balancing cost of the following periods $i+1$ to $i+N$. Its load $\hat{L}(k)$ and price $\hat{P}_{balancing}(k)$ are real-time forecasted values. The solution of this

optimization problem gives an optimal operation schedule for the periods from i to $i+N$.

- 4) Implement the first period operation of the above solution, which is the period i to determine how the EES should be operated and the actual imported power $U_{actual}(i)$.
- 5) Update the EES storage level state, move to the next period, then repeat the algorithm from step 1.

The actual imbalance cost is simplified as the day-ahead price multiplied by a penalty factor. Thus both actual imbalance cost $P_{balancing}(k)$ and forecasted imbalance cost $\hat{P}_{balancing}(k)$ are expressed as

$$\begin{aligned}
 P_{balancing}(k) &= \hat{P}_{balancing}(k) \\
 &= \begin{cases} p_{up} \cdot P(k), & \text{if } U_{actual}(k) > U_{sch}(k) \\ p_{down} \cdot P(k), & \text{if } U_{actual}(k) < U_{sch}(k) \end{cases} \\
 &k = i, i+1, \dots, i+N,
 \end{aligned} \tag{2.14}$$

The short-term (e.g. next 2-3 hours) forecast is more accurate than the relatively longer term (e.g. 23-24 hours) forecast. Thus, by using this MPC-based method, the most updated price and load forecast could be effectively integrated into the operation decision making process to minimize the balancing cost.

2.4 Case Studies

2.4.1 Case I: Stationary Energy Storage

In this case, the proposed method is applied to a load aggregator with a stationary EES. Both the day-ahead scheduling periods and real-time receding optimization horizon are 24 hours. Each hour is considered as a period.

The forecasted and actual day-ahead market clearing price is shown in Figure 2. The penalty factors $p_{up} = 1.2$ and $p_{down} = 0.8$. The day-ahead forecasted load and actual load during real-time operation are shown in Figure 3. The actual load curve has the peak load at 10MW.

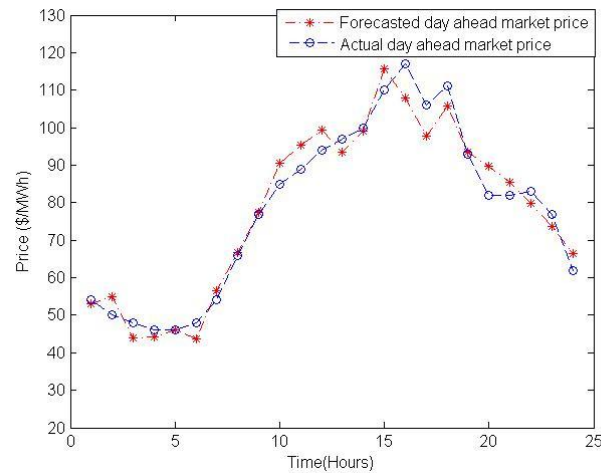


Figure 2 The forecasted and actual day-ahead market clearing price.

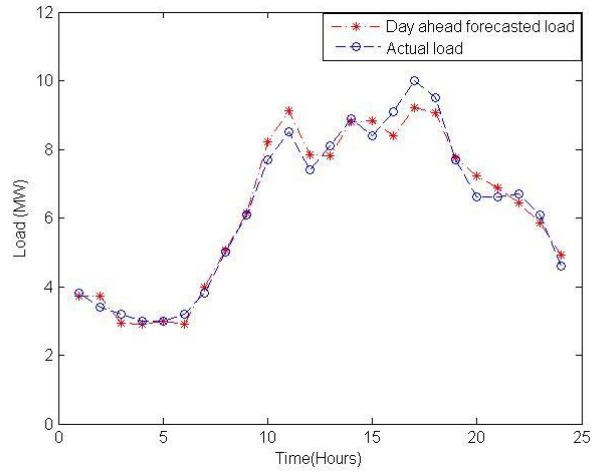


Figure 3 Day-ahead forecasted load and actual load.

The parameters of the EES are shown in Table 1. “Initial storage level” means the storage level at the beginning of 0AM. “Final storage level” means the storage level at the end of 11PM.

Table 1 Energy Storage Parameters

Capacity(MWh)	10
Charging Power Limit(MW)	1
Discharging Power Limit(MW)	1
Charging Efficiency	0.95
Discharging Efficiency	0.95
Available Periods	24/7
Initial storage level(MWh)	3
Final storage level(MWh)	3

The energy costs of the following scenarios are simulated and compared:

- 1) Load aggregator does not have EES. It schedules its import power in the day-ahead market based on perfect load and price forecast.
- 2) Load aggregator operates EES. It uses the proposed method to schedule its imported power in the day-ahead market based on perfect load and price forecast.
- 3) Load aggregator does not have EES. It schedules its imported power in the day-ahead market based on not perfect day-ahead load and price forecast. The discrepancies during real-time operation are settled in balancing market.
- 4) Load aggregator operates EES. It uses the proposed method to schedule its imported power in the day-ahead market and operate in the real-time balancing market based on not perfect day-ahead and real-time load and price forecast.

The day-ahead and real-time forecast uncertainties in scenario 3 and 4 are set to be equal. The simulation results are shown in Table 2.

Table 2 Case I Cost Comparison

	Scenario 1 No EES/ Perfect forecast	Scenario 2 EES/ Perfect forecast	Scenario 3 No EES/ Not perfect forecast	Scenario 4 EES/ Not perfect forecast
Day-ahead market cost(\$)	12958	12605	13280	12943
Real-time balancing market cost(\$)	0	0	-187	-275
Total cost(\$)	12958	12605	13093	12668

The results in Table 2 show the cost savings the optimal scheduling and operation methods can bring, and the importance of the forecast accuracy. The negative cost in the real-time balancing market means the load aggregator over estimated the load in the day-ahead market, surplus power is sold during real-time operation. By comparing the cost difference caused by imperfect forecast, it also suggests that the proposed method is more robust to forecast uncertainty.

Figure 4 shows the difference of the day-ahead scheduled imported power between scenario 1 and 2. Generally, more energy is imported during the low price periods and less energy is imported in the high price periods. As the load correlates with price to some extent, the imported power curve is leveled to some extent.

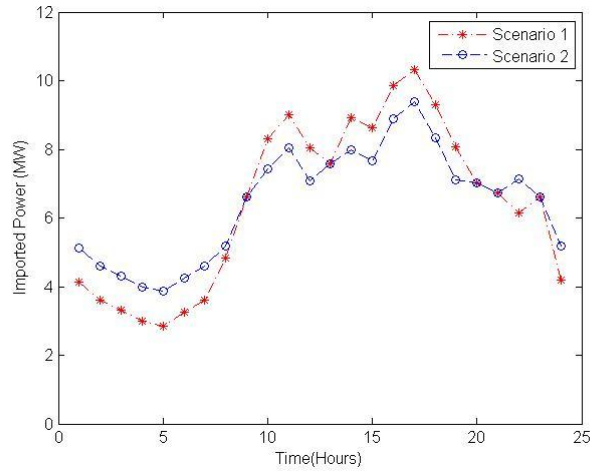


Figure 4 Day-ahead scheduled imported power comparison.

Figure 5 shows the day-ahead scheduled storage level variation based on the perfect forecasted day-ahead market price of scenario 2. EES is generally charged during the low price periods and discharged during high price periods.

Figure 6 shows the difference of the scheduled and actual imported power of scenario 4. The optimal real-time operations do not necessarily follow the day-ahead schedule.

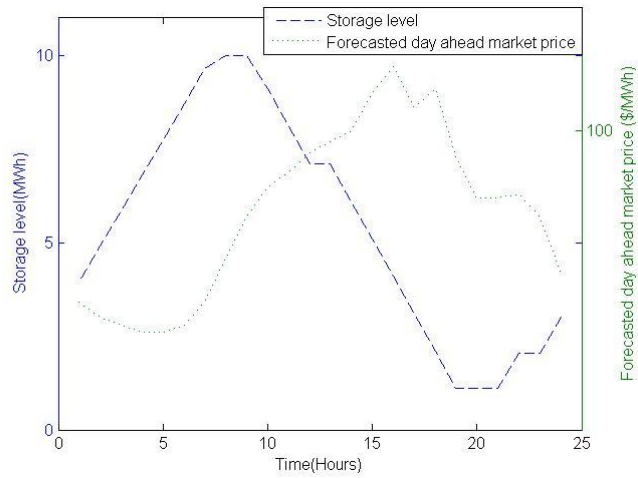


Figure 5 Day-ahead scheduled storage level variation based on the forecasted day-ahead market price of scenario 2.

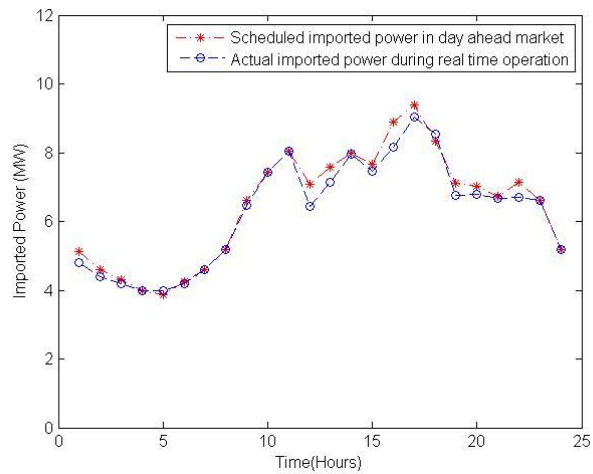


Figure 6 The comparison of scheduled imported power in day-ahead market and actual imported power during real-time operation in scenario 4.

2.4.2 Case II: Mobile Energy Storage

In case II, V2G (vehicle to grid) capable PHEVs' batteries are utilized as the EES which can be charged and discharged according to control signals from the load aggregator. The PHEVs are assumed to be plugged in the charging stations located in the load aggregator's distribution network where other commercial activities also reside in. Load aggregator is assumed to have certain contracts with the PHEVs parked in the charging stations which allow it to operate the PHEVs' batteries when they are plugged in. The topology of the distribution network could be simplified as in Figure 1. All the individual PHEVs are combined and modeled as one EES. The load aggregator can operate the batteries as they wish, but need to ensure that before the PHEVs leave the charging station, the stored energy has to be above certain required level. The proposed methods are applied to help load aggregator optimally operate these PHEVs' batteries to minimize its energy cost. The PHEV battery parameters used in the simulation are shown in Table 3. While we recognize that studying the inherent uncertainty of PHEVs' availability at any given time is an important future research direction, here in this work we assume that 50 PHEVs are available for operation from 8AM to 6PM in the simulation day.

Table 3 PHEV Battery Parameters

Capacity(kWh)	5.2
Charging Power Limit(kW)	2
Discharging Power Limit(kW)	2
Charging Efficiency	0.95
Discharging Efficiency	0.95
Available Periods	8AM to 6PM
Initial storage level(kWh)	1
Final storage level(kWh)	5

A load curve of an aggregation of commercial activities is used. A price curve with large variation is used to show the volatile behavior of the electricity price in downtown load centers. The load without PHEVs and price curves are shown in Figure

7.

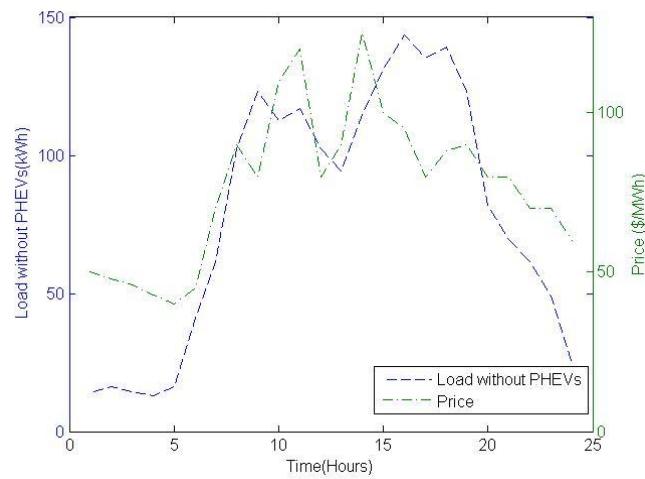


Figure 7 Load without PHEVs and price curves.

The costs of the following two scenarios are compared:

- 1) Perfect day-ahead price and load forecast is assumed. The PHEVs are immediately charged when plugged in until reaching the required storage level. Load aggregator does not utilize the PHEVs' batteries to reduce its energy cost.
- 2) Perfect day-ahead price and load forecast is assumed. The load aggregator uses the proposed method to optimally schedule the imported power in the day-ahead market and operate the PHEVs' batteries to reduce its energy cost while ensuring the required energy storage level before PHEVs' leaving charging stations.

Figure 8 compares the imported power of scenario 1, scenario 2 and the load curve without PHEVs. In scenario 1, the imported power jumped up from 8am to 1pm, because the PHEVs are being charged during those periods. In scenario 2, PHEVs' charging and discharging operations are determined by load aggregator to manage its energy cost. Figure 9 shows the storage level variation in scenario 1 and scenario 2. In scenario 1, the storage level climbs up to the required level and stays there for the rest of the available periods. In scenario 2, the batteries are generally charged when the price is low and discharged to support the load when the price is high.

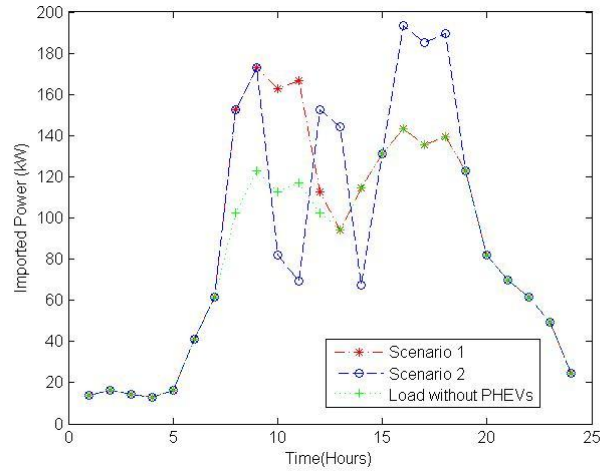


Figure 8 Imported power comparison between scenario 1 and scenario 2 with load curve without PHEVs.

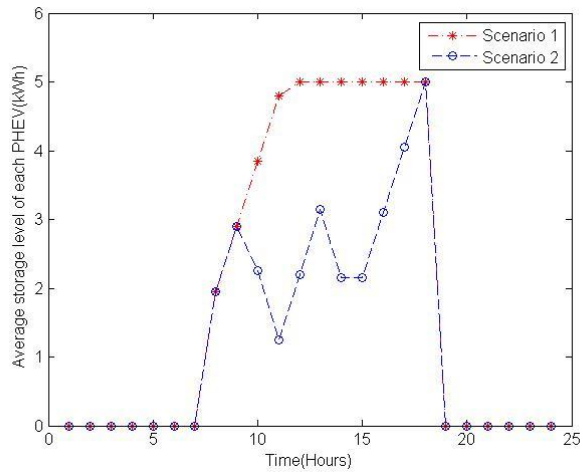


Figure 9 Average storage level of each PHEV in Scenario 1 and Scenario 2.

The cost comparison is shown in Table 4. The results in Table 4 show the cost savings by optimal scheduling the imported power and operating the PHEVs' batteries.

Table 4 Case II Cost Comparison

	Scenario 1 Charging immediately/ Perfect forecast	Scenario 2 Optimal charging and discharging/ Perfect forecast
Day-ahead market cost(\$)	189.12	183.43

In the day-ahead market, a load aggregator can use the proposed method to schedule the imported power in each period of the next day with day-ahead forecasted price and load. During real-time operation, the discrepancies caused by the forecast errors are compensated in the real-time balancing market. The load aggregator can use the proposed MPC-based method to optimally determine its actual imported power in balancing market and EES operations during real-time operation. The proposed MPC-based method integrates the most updated price and load forecast data over a receding horizon to achieve the optimal operation.

Simulations of a load aggregator with stationary storage and PHEVs' batteries demonstrate the energy cost savings. The energy cost savings is optimal if the forecast is perfect.

For the proposed MPC-based operation strategy, forecasts are a crucial part. The following section discusses the impact brought by the accuracy of the forecasts.

2.5 Scheduling and Operation Facing Price and Demand Uncertainties

Competitive electricity markets have been established and operated in many regions in America. Load serving entities (load aggregators) participate in the wholesale electricity market to purchase electric energy to serve their customers. In order to meet the demand while minimizing energy purchasing cost, load aggregator needs to predict the price and load to determine transactions in power markets. Accurate price and load forecasts are crucial for achieving the goal of minimizing cost while meeting demand. However, with increasing penetration of renewable energy resources such as wind power, the electricity price becomes more unpredictable. Renewable distributed generation (DG) technologies suitable for residential use, such as solar panel roof, are being gradually adopted by residential customers and with these DGs, the load is partially offset. Although the penetration of such distributed generation is relatively small, load forecast accuracy could be affected by the unpredictable generation from renewable DGs. As a result, load aggregator is facing a higher level of price and load uncertainties.

Load aggregators may suffer high electricity cost facing high levels of price and load uncertainties. The MPC-based strategy and two other strategies are evaluated using the proposed simulation method. Their performances under different levels of price and load uncertainties are compared to demonstrate the advantages of the

proposed strategy.

2.5.1 Comparison of Different Operation Strategies

In order to compare the forecast accuracy impact under different operation strategies, three operation strategies are presented first.

Strategy 1 is for distribution System without EES. As discussed before, for a distribution system without EES, when the load is determined by customers and is inelastic, the scheduling and operation strategy has very limited flexibility. The strategy for this situation is as follows.

In the day-ahead market, the load aggregator schedules the imported power according the load forecast for the next day, as in following equation

$$U_{sch}(k) = \hat{L}_{da}(k) \quad (2.15)$$

where $\hat{L}_{da}(k)$ is the day-ahead forecasted load in period k in the next day.

The electricity cost in day-ahead market is

$$\sum_{k=1}^{24} U_{sch}(k) \cdot P_{da}(k) \quad (2.16)$$

where $P_{da}(k)$ is the day-ahead market clearing price for period k , each period is considered as an hour here.

As load forecast is not perfect, in order to satisfy the load during operation, load aggregator needs to turn to real-time market to purchase more power when the load is higher than forecasted and sell excess power when day-ahead scheduled power is more

than actual needed. Thus we get

$$U_{actual}(k) = L_{actual}(k) \quad (2.17)$$

where $L_{actual}(k)$ is the actual load in period k .

The electricity cost in real-time market is calculated as

$$\sum_{k=1}^{24} [(U_{actual}(k) - U_{sch}(k)) \cdot P_{rt}(k)] \quad (2.18)$$

where $P_{rt}(k)$ is the actual real-time market energy price.

Strategy 2 is for distribution system with EES. With EES the scheduling and operation strategy is more flexible. Because of this flexibility, strategies could be different from each other. Strategy 2 and MPC-based strategy presented later both utilize EES, but their approaches to its utilization are different. The details of strategy 2 are as follows.

In the day-ahead market, the load aggregator utilizes EES to minimize electricity cost according the day-ahead forecasted load and energy price.

The objective function of day-ahead optimal scheduling problem can be formulated as

$$Min. \sum_{k=1}^{24} U_{sch}(k) \cdot \hat{P}_{da}(k) \quad (2.19)$$

Subject to operation constraints and

$$U_{sch}(k) = \hat{L}_{da}(k) + C(k) - \eta_c D(k) \quad (2.20)$$

where $\hat{P}_{da}(k)$ is the predicted day-ahead energy price before the final market clearing price is computed. After submitting its schedule to system operator, market

clearing price is worked out. The actual electricity cost in day-ahead market can be calculated as

$$\sum_{k=1}^{24} U_{sch}(k) \cdot P_{da}(k) \quad (2.21)$$

By using this day-ahead scheduling method, load aggregator can optimally operate EES to take advantage of the low price periods by importing more energy and storing it while reducing the imported power during high price periods by supporting the load with the stored energy.

During real-time operation, the load aggregator needs to settle any discrepancy in real-time market. The principle of strategy 2 during operation is that in each operation period EES is utilized to minimize the mismatch between day-ahead scheduled imported power and actual imported power, $[(U_{actual}(k) - U_{sch}(k))]$. Only when EES reaches its operation limits including power charging/discharging limit or energy storage capacity limit, load aggregator turns to real-time market to settle the remaining mismatch. In this way, the scheduled imported power and actual imported power can match with each other for most of the periods.

In day-ahead scheduling, strategy 3 or the MPC-based strategy is the same as strategy 2. In the real-time operation stage, MPC-based strategy utilizes the real-time updated price and load forecasts to determine optimal operations.

2.5.2 Day-ahead Price and Real-time Price Model

In day-ahead market, load aggregator schedules imported power according to the predicted day-ahead price. As day-ahead price is relatively stable and predictable, the actual day-ahead price is assumed to be the same as the predicted energy price.

However, energy price in day-ahead market and real-time market could be very different, especially under high price uncertainty. Three real-time market energy price curves are constructed to represent three different levels of price uncertainty. The method for constructing these curves is as following. One real-time market energy price curve is first constructed. The maximum price deviation from day-ahead market is set to be 5%, where maximum price deviation is defined as the largest mismatch between day-ahead market energy price and real-time market energy price in the same period divided by real-time market energy price. This curve represents low price uncertainty. The second price curve is constructed by increasing the price deviation from the first price curve, such that the maximum price deviation is 15%. This curve represents medium price uncertainty. The same procedure is applied to construct the third curve in which the maximum price deviation is 30%. This one represents high price uncertainty. The day-ahead market energy price and real-time market energy price with three different levels of price uncertainty are shown in Figure 10. In simulation, the same day-ahead price and corresponding real-time price are utilized for

each price uncertainty level.

2.5.3 Day-ahead Forecasted Load and Actual Load Model

In day-ahead market, day-ahead forecasted load is used for load aggregator to determine the imported power for each period in the next day.

Compared with energy price, load can be more accurately predicted according to the past experience. Three load curves are constructed to represent three different levels of load uncertainty. The method for constructing these curves is the same as for the real-time price curves. The maximum load deviation for low load uncertainty is 2%, for medium load uncertainty is 5%, and for high load uncertainty is 10%. Maximum load deviation is defined as the largest mismatch between day-ahead forecasted load and actual load in the same period divided by the actual load. These three load curves are shown in Figure 11 with the day-ahead forecasted load. Similar to the price model, the same day-ahead load forecast and corresponding actual load curve are utilized for each load uncertainty level in simulation.

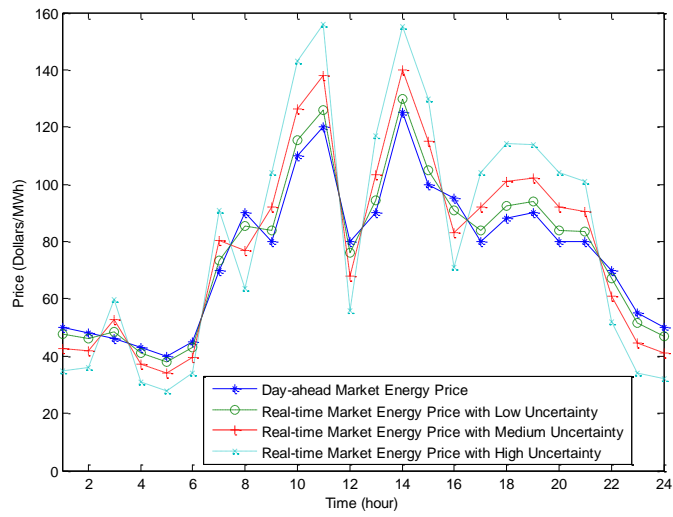


Figure 10 Day-ahead market energy price and real-time market energy price with three different levels of price uncertainty.

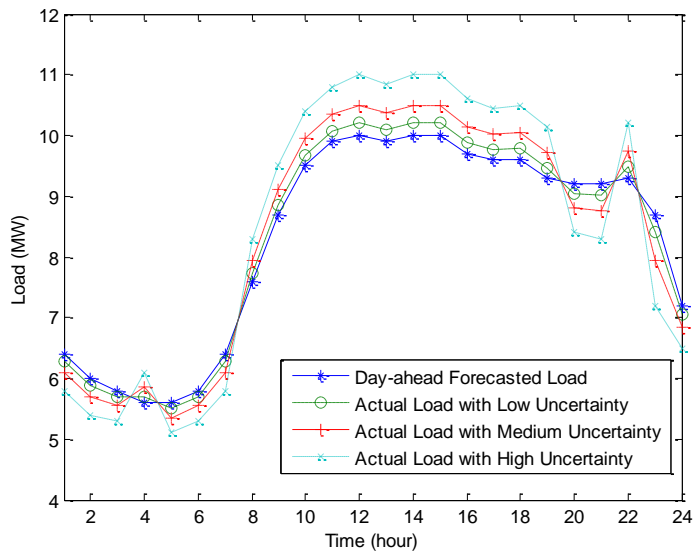


Figure 11 Day-ahead forecasted load and actual load with three different levels of load uncertainty.

2.5.4 Real-time Price and Load Forecasts Model

Many publications have dealt with the price forecast and load forecast methodologies. These techniques could be used in the strategies presented in this work. However, as the focus is on the scheduling and operation strategies, a simplified real-time price and load forecasts model is presented and used for simulation instead. Real-time price forecasts are generated as follows.

$$\hat{P}_{rt}(k) = P_{rt}(k) \cdot (1 + E_{P,\max}(k) \cdot R_p) \quad (2.22)$$

where $\hat{P}_{rt}(k)$ is the forecasted price for a future period k , $E_{P,\max}(k)$ is the maximum price forecast error percentage for future period k , R_p is a random number with a uniform distribution from -1 to +1. This price forecast model simulates the forecast errors and controls the forecast errors within a certain range, $\pm E_{P,\max}(k)$. Real-time load forecast is generated using the same method as in the following equation

$$\hat{L}_{actual}(k) = L_{actual}(k) \cdot (1 + E_{L,\max}(k) \cdot R_L) \quad (2.23)$$

Given the fact that price and load forecasts tend to be more accurate for near-term such as within the following 3 hours, and less accurate for relatively longer term, such as 20 hours from the current period, this characteristic is modeled by linearly increasing the maximum forecast error ($E_{P,\max}(k)$ for price forecast and $E_{L,\max}(k)$ for load forecast) as the forecast range increases. An example of maximum real-time price and load forecasts errors in the next 24 hours is shown in Figure 12.

The hour on x axis is the time from current period, not the absolute hour. For example, in Figure 12, the maximum load forecast error in the last period, the 24th period, are $\pm 5\%$. It means the load forecast error for the period which is 24 hours in the future from the current period will be within the range of $\pm 5\%$.

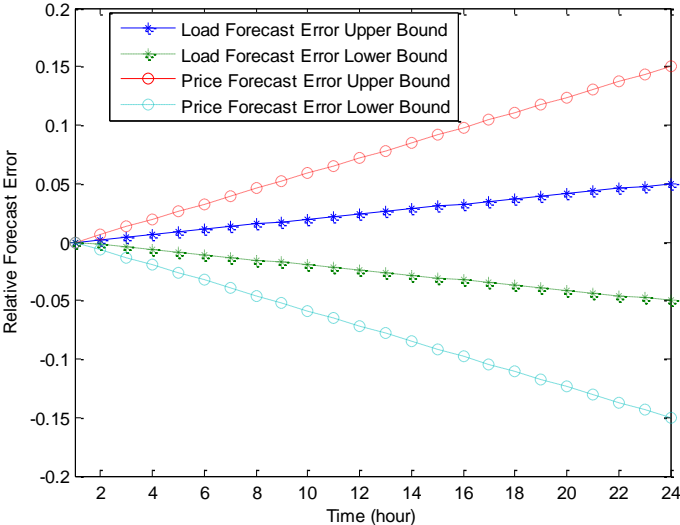


Figure 12 Price and load forecasts error boundaries for the next 24 hours.

As the real-time market energy price and actual load for current period is known, the forecasts errors in current period are zeros. If the maximum forecast error for the ending period ($E_{P,max}(24)$ and $E_{L,max}(24)$ in Figure 12) is also known, the maximum forecast errors for each period could be calculated.

2.5.5 Case Studies Considering Forecasts Uncertainties

The above three scheduling and operation strategies are implemented in case studies. Each strategy is applied to a distribution system facing different levels of price and load uncertainties. Three levels of load uncertainty and three levels of price uncertainty constructed previously are applied. A price uncertainty level matches with a load uncertainty level to form a price and load uncertainty scenario. Thus there are a total of 9 scenarios of different price and load uncertainties.

In MPC-based operation strategy, the real-time price and load maximum forecast errors for the 24th hour from current hour are set to be the load uncertainty and price uncertainty of the corresponding price and load uncertainties scenario respectively to emulate that real-time forecast accuracy is related to the price and load uncertainties. The higher the uncertainties the harder it is to forecast accurately. The EES parameters used in case studies are shown in Table 5, which are similar to the parameters of a sodium-sulfur batteries system [1].

Table 5 EES Parameters

Minimum energy storage level (MWh)	2
Maximum energy storage level (MWh)	12
Maximum charging/discharging power limit (MW)	2.5
Charging/discharging efficiency	95%

Simulation results are shown in the following. With strategy 1, the actual imported power during real-time operation is shown in Figure 13 with day-ahead scheduled imported power.

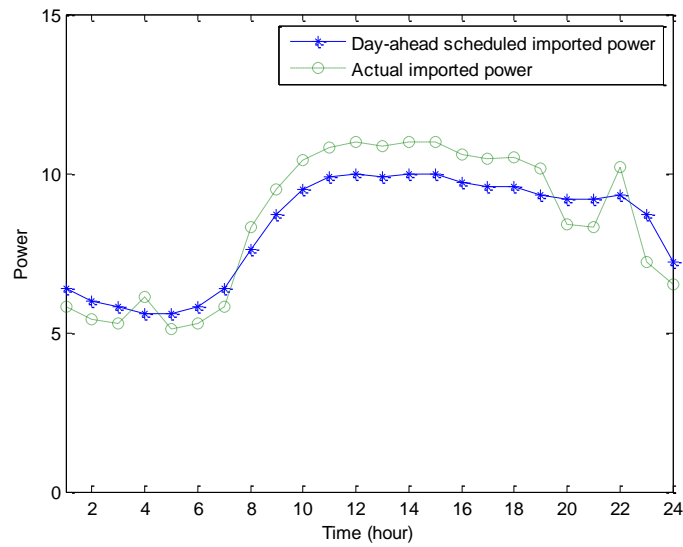


Figure 13 Day-ahead scheduled imported power and actual imported power with strategy 1.

As there is no EES for a flexible operation, the actual imported power is identical to the actual load. The mismatches between scheduled and actual imported power are settled in real-time market. The real-time market energy price and real-time energy cost for load aggregator are shown in Figure 14.

For strategy 2, facing high price and load uncertainties, the scheduled and actual

imported power are shown in Figure 15. Real-time energy cost and real-time EES operations are shown in Figure 16.

With this strategy, EES is utilized to minimize the mismatches between scheduled and actual imported power. Thus for many periods, scheduled and actual imported power are the same. However, when EES reaches its operation limits, such as reaching capacity limit in hour 7, or reaching discharging power limit in hour 13, scheduled and actual imported power mismatch cannot be totally compensated by EES. In this situation, the remaining mismatch is settled in real-time market. Positive energy cost means load aggregator needs to purchase more energy, while negative energy cost means load aggregator sells excess power back the real-time market.

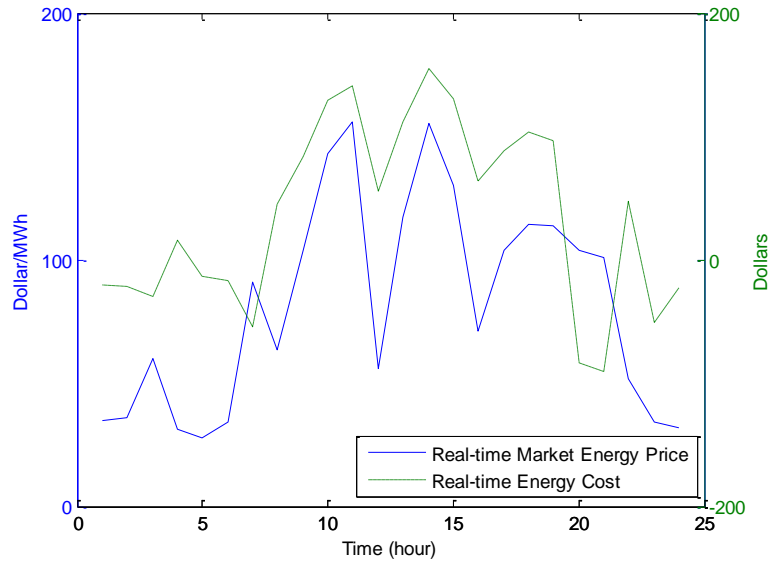


Figure 14 Real-time market energy price and real-time energy cost for strategy 1.

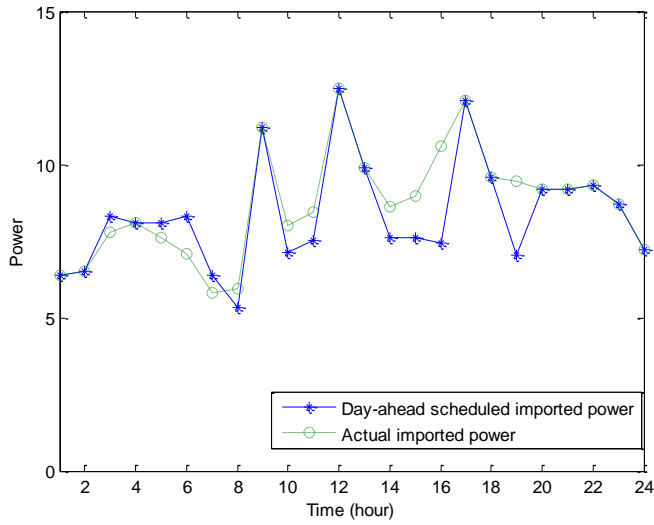


Figure 15 Day-ahead scheduled imported power and actual imported power with strategy 2.

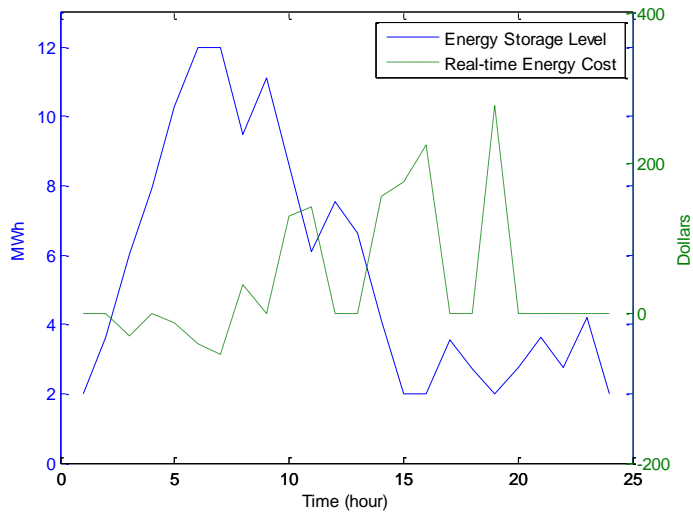


Figure 16 Real-time energy cost and real-time EES operations with strategy 2.

The operations of the proposed MPC-based strategy under high price and load uncertainties scenario are illustrated below to show its characteristics. With MPC-based strategy, day-ahead scheduled imported power and actual imported power are shown in Figure 17. Figure 18 shows the real-time market electricity cost and real-time EES operations. Compared with strategy 2, MPC-based strategy actively participates in real-market to manage electricity cost by utilizing the flexible control of EES.

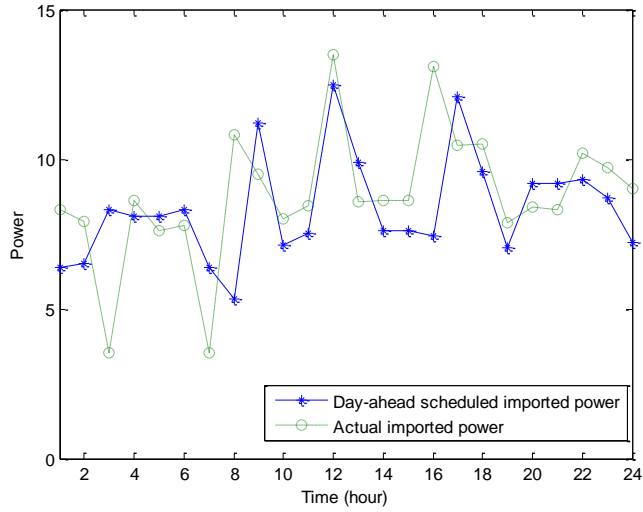


Figure 17 Day-ahead scheduled imported power and actual imported power with MPC-based strategy.

Table 6 shows the day-ahead electricity cost for three strategies. Strategy 2 and strategy 3 choose the same day-ahead scheduling method, thus their day-ahead electricity costs are the same. Because of the flexible operation of EES, the day-ahead electricity cost with strategy 2 and strategy 3 is less than strategy 1. As the same day-ahead price and load forecasts are used for all scenarios, the day-ahead electricity cost for each strategy under all 9 levels of price and load uncertainties are the same. Table 6 shows the real-time electricity cost of three strategies facing 9 different levels of price and load uncertainty scenarios respectively.

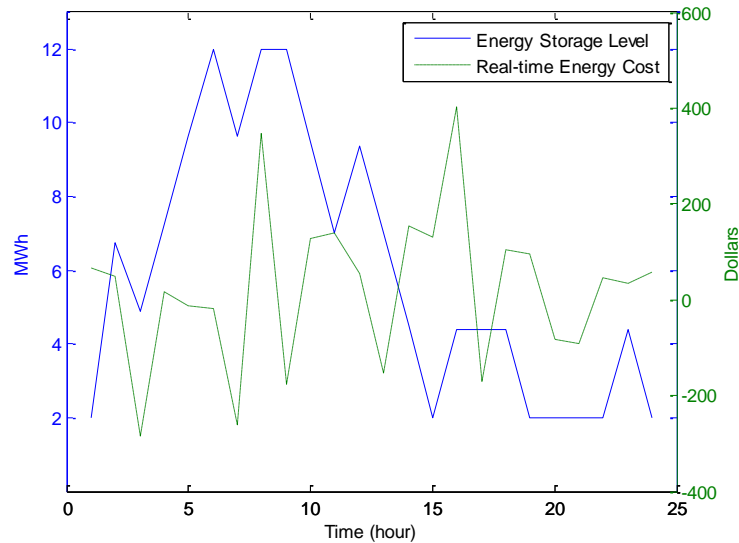


Figure 18 Real-time electricity cost and real-time EES operations with MPC-based strategy.

It can be observed in Table 7 that the real-time electricity cost with strategy 1 increases sharply with the increase of price and load uncertainties. That is because without EES, load aggregator has to purchase energy at any real-time market price to meet load when day-ahead scheduled imported power falls short.

With strategy 2, the real-time electricity cost is less than with strategy 1 when load uncertainty is low. However when load uncertainty becomes higher, real-time electricity cost with strategy 2 is even higher than with strategy 1. That is because during real-time operation, strategy 2 only minimizes the mismatch between day-ahead scheduled imported power and actual imported power in current period

while not considering the mismatches in future periods which could be large enough to cause much more real-time electricity cost. Despite of this, the total cost combining day-ahead and real-time electricity cost with strategy 2 is still less than that with strategy 1 as the cost savings in day-ahead market is much greater than with strategy 1.

Table 6 Price and Load Uncertainties Scenarios

	Strategy 1	Strategy 2	MPC-based Strategy
Day-ahead Electricity cost (Thousand Dollars)	15.935	15.295	15.295

Table 7 Real-Time Electricity Cost (\$) For Strategy 1, Strategy 2 and MPC-Based Strategy

	Low Load Uncertainty (2%)	Medium Load Uncertainty (5%)	High Load Uncertainty (10%)
Low Price Uncertainty (5%)	Strategy 1: 145 Strategy 2: 136 MPC-based: 117	Strategy 1: 362 Strategy 2: 391 MPC-based: 335	Strategy 1: 725 Strategy 2: 788 MPC-based: 698
Medium Price Uncertainty (15%)	Strategy 1: 156 Strategy 2: 146 MPC-based: 2.8	Strategy 1: 389 Strategy 2: 413 MPC-based: 236	Strategy 1: 778 Strategy 2: 837 MPC-based: 625
High Price Uncertainty (30%)	Strategy 1: 171 Strategy 2: 162 MPC-based: -255	Strategy 1: 429 Strategy 2: 446 MPC-based: 3	Strategy 1: 857 Strategy 2: 911 MPC-based: 432

Real-time electricity cost with MPC-based strategy is much lower than that with

the other two strategies. MPC-based strategy reduces the cost by determining the operation in current period while considering the operations in the following periods with the most updated price and load forecasts. In Table 7, facing high price uncertainty and low load uncertainty, the real-time electricity cost turns out to be negative. This is caused by load aggregator selling more energy surplus during high price periods and make up the needed energy during low price periods. It is the same reason for that the real-time cost decreases with the increase of price uncertainty while fixing load uncertainty. High price uncertainty is favored by load aggregator with MPC-based strategy as there are more opportunities for energy arbitrage utilizing EES.

2.6 Summary

In competitive power markets, with increasing penetration of variable renewable energy resources such as wind power, electricity price becomes more uncertain. In distribution systems, adoption of renewable distributed generation technologies adds another dimension of uncertainty in load forecast. Facing these higher price and load uncertainties, it becomes more challenging for load aggregators to manage their electricity cost. Within this context, a Model Predictive Control (MPC)-based scheduling and operation strategy is proposed for the load aggregator with electric energy storage (EES) to manage electricity cost in day-ahead and real-time power markets with different levels of price and load uncertainties. Price and load forecasts

are actively integrated into the scheduling and operation decision making process to determine the optimal operation. Two other strategies are also discussed and studied for comparison. Case studies demonstrate better performance of the proposed MPC-based strategy compared to the other two strategies facing different levels of price and load uncertainties. The MPC-based strategy is also shown to be robust with the increase of price and load uncertainties. The benefit of energy arbitrage with MPC-based strategy is also illustrated.

With this MPC-based strategy, load aggregators schedule purchase of power in the day-ahead market with day-ahead price and load forecasts. Then during real-time operation, real-time price and load forecasts are updated constantly in each period. By utilizing these forecasts, load aggregator optimally adjusts its operations to reduce real-time electricity cost.

Case studies show that with the increase of price and load uncertainties, MPC-based strategy can manage the electricity cost much better than the other two strategies. With the other two strategies, electricity cost increases sharply with the increase of price and load uncertainties. MPC-based strategy is more robust with the increase of price and load uncertainties.

Another advantage of MPC-based strategy is that with the increase of price uncertainty while fixing load uncertainty, real-time electricity cost could be even

reduced. This is due to the fact that there are more opportunities for energy arbitrage.

3. DISTRIBUTION SYSTEMS RELIABILITY AND ECONOMIC IMPROVEMENT WITH DIFFERENT ELECTRIC ENERGY STORAGE OPERATION STRATEGIES*

3.1 Introduction

Electric power systems have been operated, in the past, on the basis of real-time balancing of supply and demand without large-scale electric energy storage (EES) capabilities. The objective of smart grid deployment is to make current grid more reliable, secure, and efficient. With the recent rapid development of EES technologies, many feasible applications of EES in power systems have been investigated [1]-[2]. The major benefits of EES include electric energy time-shift, frequency regulation and transmission congestion relief. The focus in this section is on the reliability and economy improvement by utilizing EES.

Several papers in the literature have reported on the effect of EES on improving reliability. Reference [17] explores the feasibility of installation of battery storage plant to enhance power system reliability and security. Reference [18] describes an analytical approach to evaluate reliability improvement by using EES as a backup storage and determine the size of the storage to meet a specified reliability target.

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Reference [19] presents a reliability cost/worth evaluation method that can incorporate the impacts of wind energy and energy storage utilization in electric power systems.

Among the research efforts towards energy cost savings by utilizing EES, [4] discusses the optimal demand-side response to electricity spot prices for storage-type customers (e.g. municipal water plants).

Previous efforts have been either for the reliability impact of EES integration, or on its economic benefits. Comparatively not much has been done to emphasize the relationship between reliability and economy impact by EES. However, reliability impact and economic benefits are tightly related. Especially with the operational flexibility of energy storage, different operation strategies could bring different reliability impact and economic benefits. For load aggregator of distribution system integrated with EES, it is important to know the reliability and economy impact of the implemented EES operation strategies. Then proper EES operation strategies can be chosen and implemented to achieve desired reliability and economy improvement goals. A Model Predictive Control (MPC)-based operation strategy to improve distribution system economy and reliability is proposed. The reliability and economic impact of the proposed MPC-base operation strategy and standby backup operation strategy for EES is evaluated and compared. Then a hybrid operation strategy to balance reliability improvement and economy improvement is proposed and evaluated.

Because of the unique features of EES such as inter-temporal and energy limited characteristics, conventional reliability evaluation method cannot accurately capture the reliability and economy impact brought by EES, especially when advanced operation strategies are implemented. A sequential Monte Carlo method integrated with EES operation strategies for reliability and economic evaluation is presented.

3.2 System Description

3.2.1 Segmented Distribution System Integrated with Electric Energy Storage

The load aggregator provides electric energy to its customers in a distribution system. The objective of the load aggregator is to serve its customers reliably and economically.

Electric energy storage (EES) devices integrated in the distribution system could be utilized to improve system reliability and economy. As most distribution systems are radial, the focus is on considering such distribution systems. Figure 19 shows an example of a radial distribution system integrated with EES, where “X” represents protective devices such as circuit breaks and reclosers. The transformers and all the generation and transmission systems are represented as the external grid, through which the electric energy is delivered to the distribution system.

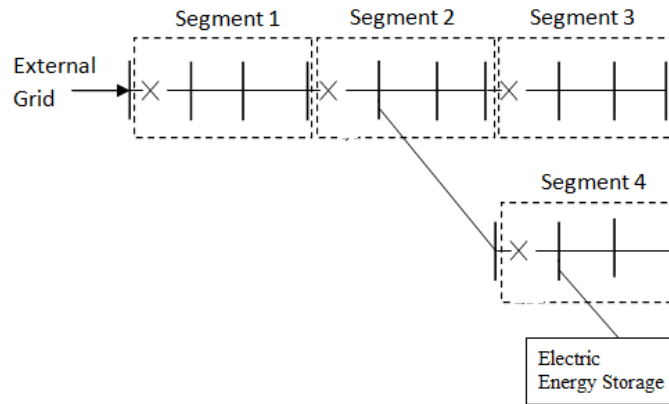


Figure 19 Schematic diagram of a radial distribution system integrated with energy storage.

A distribution system consists of components such as wires, circuit breakers, reclosers, etc. A group of components can be modeled into one segment if the entry component is a protective device such as a switch or a recloser. The entry protective device is the only protective device of this segment of grouped components. In this way, the distribution system is modeled by segments instead of components. The rationale behind this segment modeling [28] is that if there is a component failure downstream of a protective device and within its protection zone, the protection zone will be isolated and all the customers in that protection zone will lose power supply. Even if there are distributed generations or energy storage devices integrated into this segment, once a component failure occurs within this segment, the power supply from these energy resources is cut off. For example, in Figure 19, the components of the

distribution are grouped into 4 segments according to the location of protective devices. If a component failure occurs in segment 4, the protective devices isolate this segment, external grid power cannot be supplied to this segment, the power supply from EES is also cut off, so the load demand in this segment cannot be met and a loss of load event occurs.

The external grid is considered in either success state or failure state. The external grid is in success state when power could be supplied from external grid to distribution system. It is assumed that whenever power could be supplied to distribution system from external grid, there is enough power to meet the load inside distribution system. The external grid is in failure state when no power could be supplied to distribution system.

3.2.2 Modes of Operation

In a radial distribution system without distributed generation (DG) or EES, if a component failure occurs within a segment, the segment is isolated. Grid power cannot be supplied to the load within this segment and the segments downstream. The load demand in all these segments cannot be met. However, when DG or EES are integrated, if a component failure occurs within a segment, the segment is still isolated but the downstream segments can utilize power supply from integrated DG or EES to support its load. In this case, the loss of load event might be avoided if there is enough

power from these energy resources. In Figure 19, when segment 2 fails and is isolated, as there is no DG or EES integrated in segment 3, there is no power supply for its load. Instead, power from EES can be used to supply the load within segment 4.

To summarize the above discussion, when there is a failure within a segment, all the power supply for this segment is cut off. When there is no failure within a segment, there are two modes of operation, grid connected mode and islanding mode. In the grid connected mode, the external grid is in success state grid power can be supplied to this radial distribution system and there is no failure within any upstream segment. Thus the grid power can go through all the upstream segments and reach the studied segment. In the islanding mode, at least one failure occurs in upstream segments or the external grid is in failure state. Thus grid power cannot be supplied to the segment under study. If there are no DGs and EES integrated in the studied segment, load in this segment cannot be met. If there are DGs and EES integrated in the studied segment, power from DGs and EES is utilized to support its load. Loss of load might be avoided or loss of energy is minimized.

3.3 Reliability and Economic Impact of Different EES Operation Strategies

The operation of electric energy storage (EES) is very flexible and behaves very different from either generation or load. When energy stored in EES is discharged to provide power for load, EES behaves similar to generation. When EES is charged with

power from distribution system, it consumes power and behaves like a load. EES can be flexibly controlled to act as generation, load or simply standby according to the needs of load aggregator. Thus different EES operation strategies could be implemented to improve distribution system reliability and economy. In this section, a standby backup operation strategy, a Model Predictive Control (MPC)-base operation strategy and a hybrid operation strategy are presented. The reliability and economy improvement of these operation strategies are evaluated and compared.

3.3.1 Standby Backup Operation Strategy

One of the purposes of utilizing EES is to improve system reliability. One commonly used operation strategy is utilizing EES as a standby backup energy resource. The standby backup operation strategy is implemented as follows.

In islanding mode, power from external grid cannot reach the studied segment. EES integrated in this segment is discharged to sustain the service in this segment. The objective is to avoid a loss of load event or minimize the loss of energy. When the load is less than the maximum discharging rate of EES, EES discharges at the load level to meet the load demand and avoid a loss of load event until the energy storage level reaches its lower limit when no power can be discharged. When the load is higher than the EES maximum discharging rate, EES discharges at its highest discharging rate to minimize loss of energy until reaching the energy storage lower limit.

When the system is restored and the segment is back to the grid connected mode, EES is immediately charged until it reaches its energy storage upper limit and then is put as standby to prepare for the next system failure.

When a failure occurs inside the segment, EES cannot be operated, load cannot be met.

3.3.2 MPC-based Operation Strategy

Another purpose of utilizing EES is to improve the economy of the system. The economy of the system is considered as the energy cost for load aggregator to provide electric energy to its customers. A MPC-based operation strategy which maximizes the economic benefit by minimizing energy cost is proposed. This operation strategy is implemented during grid connected mode. In the MPC-based operation strategy, short term forecasts of energy price and load are utilized to determine the optimal operation. Power market modeling and energy storage modeling are introduced first before further description of the MPC-based operation strategy.

The power market is simplified as a real time power market model. During each market period (e.g. an hour), load aggregator determine how much energy it needs to purchase from power market, then submits its offer to get that amount of energy. The market clearing mechanism determines the energy price for each period. Load aggregator is assumed to be a price taker who cannot affect the clearing price

determined by the market. The energy cost for period k is

$$U(k) \cdot P(k) \quad (3.1)$$

where $U(k)$ is the amount of energy purchased in power market in period k , $P(k)$ is the market clearing price in period k . As load aggregator can only purchase energy, we have

$$U(k) \geq 0 \quad (3.2)$$

The total energy cost for the period i and the following N periods is

$$\sum_{k=i}^{i+N} U(k) \cdot P(k) \quad (3.3)$$

No specific energy storage technology is addressed. Rather the energy storage unit is modeled as a set of parameters and operation limits. Energy storage is modeled by its energy storage capacity, charging power limit, discharging power limit, charging efficiency, discharging efficiency. The storage level has to be equal or below its capacity. The charging and discharging power have to be within their limits. Power loss during discharging and charging operations are considered in its charging and discharging efficiencies. The storage level at the end of each period is determined by the previous period storage level and the charging/discharging operation during this period, it is expressed as

$$X(k) = X(k-1) + \eta_c \cdot C(k) - D(k) \quad (3.4)$$

where $C(k)$ is the power charged to energy storage, $D(k)$ is the power discharged from

energy storage, $X(k)$ is the energy storage level at the end of period k , η_c is the charging efficiency. All three variables need to be within their operation limits, expressed as

$$0 \leq C(k) \leq C_{Max} \quad (3.5)$$

$$0 \leq D(k) \leq D_{Max} \quad (3.6)$$

$$X_{Min}(k) \leq X(k) \leq X_{Max}(k) \quad (3.7)$$

The basic approach of MPC is that a finite-horizon optimization problem determining the series of optimal control operations is solved before each control step, but only the first control operation is implemented. A predictive model is used to estimate the state space trajectory over the prediction horizon, with the initial state being the actual state of the system. After implementing the first control operation, the system updates the actual state of the system and the future states using the predictive model. Then the optimal control routine is repeated to determine optimal operation for the next step. This method of receding-horizon strategy has been successfully applied in the real world, such as in chemical process industry. Applying the above MPC-based approach, energy cost minimization problem at period i can be implemented as follows

- 1) Obtain the actual load and price in the current period i .

- 2) Select a receding optimization horizon N periods (e.g. 24 hours). Use load and price forecast tools to obtain the most updated load and price forecasts for the future periods from $i+1$ to $i+N$.
- 3) Solve the energy cost minimization problem, which is a linear programming problem, formulated as:

$$\text{Min. } U(i) \cdot P(i) + \sum_{k=i+1}^{i+N} U(k) \cdot \hat{P}(k) \quad (3.8)$$

Subject to operation constraints and

$$U(i) = L(i) + C(i) - \eta_d D(i), \quad (3.9)$$

$$U(k) = \hat{L}(k) + C(k) - \eta_d D(k), k = i+1, \dots, i+N \quad (3.10)$$

The first part $U(i) \cdot P(i)$ is the energy cost in the current period i . Its actual load $L(i)$ and energy price $P(k)$ are known. The second part $\sum_{k=i+1}^{i+N} U(k) \cdot \hat{P}(k)$ is the total energy cost of the following periods from $i+1$ to $i+N$. Its load $\hat{L}(k)$ and energy price $\hat{P}(k)$ are forecasted values. The solution of this optimization problem gives an optimal operation schedule for EES from periods i to $i+N$.

- 4) Implement the first period's operation of the above solution, which is the period i to determine how the energy storage should be operated and the amount of energy $U(i)$ needs to be purchased.

- 5) Update the energy storage level state, move to the next period, and then repeat the algorithm from step 1.

Several forecasting techniques for predicting short term electricity price and load have been presented by researchers. Good short-term (e.g. within 24 hours) price and load forecasts are available. The very short-term (e.g. next 2-3 hours) forecast is more accurate than the relatively longer term (e.g. 23-24 hours) forecast. Thus, by using this MPC-based method, after each control step, the price and load forecast are updated according the newest prediction. Then the most updated and accurate price and load forecast could be effectively integrated into the operation to minimize the energy cost.

The proposed MPC-based control method is implemented in grid connected operation mode. Then in the islanding mode, the EES operation is the same as in the standby backup operation strategy. EES is discharged to sustain the service in this segment to avoid a loss of load event or minimize the loss of energy, within operation limits. In failure mode, the load in the segment cannot be met.

3.3.3 Reliability and Economic Analysis Methods

In reliability analysis, a power system is considered to be operating in either success state or failure state. A system is considered operating in success state when it has enough generation to serve the load. When there is not sufficient generation to meet the load demand, and loss of load occurs, the system is in failure state. Loss of

load expectation (LOLE) and loss of energy expectation (LOEE) are the reliability indices.

For a system with EES, when EES is discharged to provide power, the discharged power is included in generation. When EES is charged to restore energy storage level, the charging power is included in load. When EES is neither charged nor discharged, it does not affect the system. Energy storage could behave like generation, load, or standby according to its actual operation. Monte Carlo simulation is used to model the complexity introduced by the storage and its sequential nature.

There are two types of Monte Carlo simulation methods, non-sequential and sequential methods. In the non-sequential methods, in each period random sampling on state space is performed to determine system state. The sampling in each period is independent from the sampling in other periods. The chronological characteristic of the system is thus not captured. The inter-temporal characteristic of EES is, however, a key factor for system reliability level which cannot be ignored. When EES is discharged to provide power, it is similar to generation. But one major difference is the energy stored in EES is limited. The energy EES can provide in this period is determined not only by its discharging rate but also the previous discharging operation and the scheduled discharging operation in the future periods. Non-sequential cannot chronologically model the inter-temporal characteristic of EES, thus it cannot be used

for reliability analysis in our approach.

Sequential Monte Carlo simulation can capture the chronological characteristic of the system. Thus it can capture the inter-temporal characteristic of EES. Also it can capture the actual operation of EES as generation, load or standby. Specified EES operation strategies can be integrated into the simulation. Sequential Monte Carlo Simulation has to be utilized for reliability analysis.

In the sequential Monte Carlo Simulation, time horizon is divided into periods (hourly). Once the component simulation is done, the operation mode of each segment during each period is determined. The success or failure state of each segment is evaluated according to their operation mode.

When the segment is in grid connected mode, the load is compared with the total available generation capacity which consists of the available generation capacity from external grid and EES when EES is integrated into the studied segment. Here the generation capacity of EES is the energy EES could supply in this period. It is determined by the minimum of the discharging rate and available energy which can be discharged. If the total generation capacity is not sufficient for the load, the system is identified as in failure state, if the total generation capacity can serve the load, it is in success state. After evaluating the segment state in the studied period, corresponding EES operation strategies are implemented. EES energy storage level is updated

accordingly.

When the segment is in islanding mode, the load is compared with the generation capacity from EES, if there is EES connected to the studied segment. The system is in failure state if the generation capacity from EES cannot serve the load. If the generation capacity can cover the load, it is in success state. With reliability evaluation finished, specified EES operation strategies are implemented and the EES energy storage level is updated.

After reliability evaluation and operation for each segment, the process moves to the next period and start another round of evaluation and operation. Energy cost in the period is calculated by multiplying the imported energy and energy price in the studied period. Energy cost is recorded for economic analysis. Simulation stops when maximum number of simulation years is reached or the probability of system in failure state converges.

3.3.4 Reliability and Economic Analysis of Standby Backup Operation Strategy and MPC-based Operation Strategy

The purpose of the standby backup operation strategy and MPC-based operation strategy is to improve distribution system reliability and economy. In order to meaningfully compare the reliability and economic improvement of these two operation strategies, three cases are studied.

The first case is the base case for purposes of comparison. Figure 20 shows the distribution system under study which is a modified practical radial distribution system. The radial distribution system could be grouped into two segments. In the first case, EES is not integrated into the distribution system.

In the second case, EES is integrated into the same distribution system at node 28 in segment 2. Standby backup operation strategy for EES is implemented.

In the third case, as in case two, the same EES is integrated into the same distribution at node 28 in segment. The difference is in this case, proposed MPC-based operation strategy is implemented.

Reliability and economy of the three cases are analyzed using sequential Monte Carlo simulation integrated with specified EES operation strategies. The parameters and operation limits of the integrated EES are shown in Table 8.

The up state and down state of all the components in the distribution system and external grid are simulated using exponential distribution with their own failure rates and repair rates. Once the history of the state of each component is generated, the state of each segment is determined.

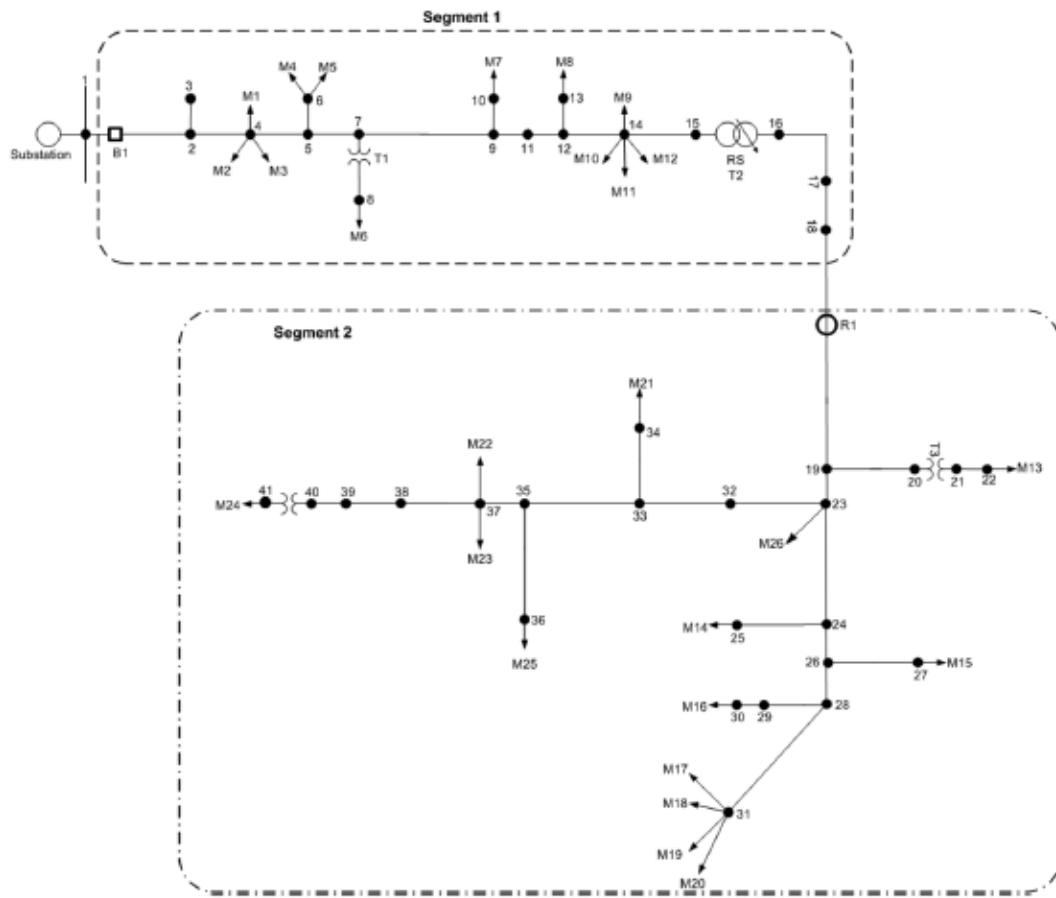


Figure 20 Modified practical radial distribution system with electric energy storage integrated in segment 2.

IEEE-RTS load data is used to generate sequential load data. The peak load of the distribution system is 8MW. Segment 1 shares 50% of the load, and segment 2 shares the other 50%

Table 8 Electric Energy Storage Parameters

Capacity (MWh)	14
Charging Power Limit (MW)	4
Discharging Power Limit (MW)	4
Charging Efficiency	0.95
Discharging Efficiency	0.95
Lower Capacity Limit (MWh)	1
Upper Capacity Limit (MWh)	13

Figure 21 shows the energy price in each period in a day. Energy price is set to be the same on each day. In MPC-based operation, forecast tools are needed to obtain the forecasted energy price and load. The actual forecasts are not perfect. However, as the focus is the reliability and economic analysis instead of forecasting techniques, the forecasts are assumed to be accurate for simplification.

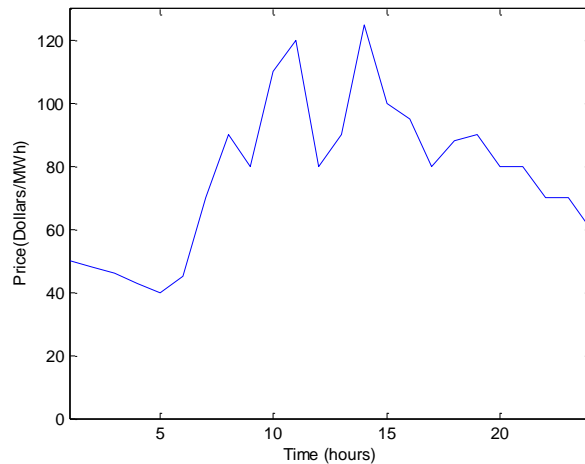


Figure 21 Energy price in each hour in a day.

Table 9 shows the reliability and economy indices of the three cases. . Standby backup operation strategy improves the system reliability the most. LOLE and LOEE are reduced compared to the base case and MPC-base operation strategy. The energy cost for case 2 is higher than the energy cost in case 1 because in case 2 more energy is purchased to charge EES to serve the load during the islanding mode. MPC-base operation strategy improves the economy the most by actively utilizing EES to participate in power market to save energy cost. Comparing to the base case and standby backup operation strategy, even though there are more energy purchased annually, the total energy cost is still less because of the energy cost saving during the grid connected mode.

Table 9 Reliability and Economy Indices of Three Cases

Case #	LOLE (hr/year)	LOEE (MWh/year)	Cost (Million Dollars/year)
Case 1 w/o EES	48.04	226.14	3.435
Case 2 Standby backup	40.43	73.43	3.462
Case 3 MPC-based	47.85	226.08	3.150

It can be seen from the simulation results that even with the same EES in the same distribution system, different EES operation strategies could have very different

reliability and economy impact on the distribution system. The operator of the EES could choose which operation strategy to implement according to its objectives. Standby backup operation strategy could most improve distribution system reliability but not have much effect on economic improvement, while MPC-base operation strategy can greatly improve economy but fall short on reliability improvement. A hybrid control method which combines the two operation strategies to balance the reliability and economy improvement is proposed.

3.3.5 Hybrid Operation Strategy

The basic idea of this hybrid operation strategy is conceptually dividing the EES device storage capacity into two portions. One portion of EES is implemented with standby backup operation strategy, while the other portion is implemented with MPC-based operation strategy. In this way, the standby backup portion maintains a certain specified energy storage level to prepare for the failure event. In this way, when segment transits from grid connected mode to islanding mode, there is always a guaranteed amount of energy stored in EES to provide power to the load, as long as the energy storage level is restored after previous discharging operation. Meanwhile, the MPC-based portion is taking the advantage of the EES control flexibility to minimize energy cost. With a certain EES storage capacity, if the standby backup portion increases, the MPC-base portion decreases. Accordingly the reliability of the system is

further improved but the economic benefit is reduced. There is a tradeoff between reliability and economic improvement. This hybrid operation strategy provides a flexible control option for load aggregator to choose the percentage of each portion according to their reliability and economic objectives. The reliability and economic improvement for a set of percentage settings for each portion using the proposed hybrid operation strategy is evaluated. The same EES and distribution system as in previous case studies are used for meaningful comparison.

Table 10 shows the reliability and economic improvement results for each percentage setting. Figure 22 shows the tradeoff curve between reliability improvement and economy improvement. Here LOEE is used as the reliability indicator. With this curve, load aggregator and EES could choose the corresponding percentage for each portion to achieve their reliability and economy goals.

Table 10 Reliability and Economic Indices Using Hybrid Operation Strategy for

Different Percentage Settings

Standby backup operation strategy portion (%)	MPC-based operation strategy portion (%)	LOLE (hr/year)	LOEE (MWh/year)	Cost (Million Dollars/year)
100	0	40.43	73.432	3.462
90	10	40.43	73.461	3.416
80	20	40.43	73.478	3.369
70	30	40.43	73.495	3.322
60	40	40.43	73.709	3.293
50	50	40.53	74.280	3.270
40	60	40.54	74.900	3.248
30	70	42.80	83.899	3.216
20	80	47.28	107.581	3.207
10	90	47.85	178.680	3.173
0	100	47.85	226.079	3.150

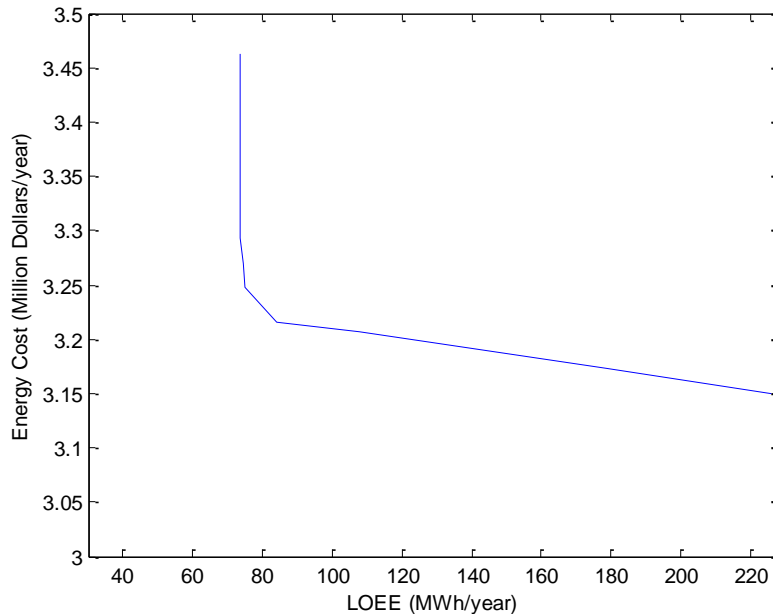


Figure 22 Trade-off Curve between LOEE and Energy Cost.

In Figure 22, there is a turning point when increasing standby backup operation strategy portion to 60%. After that percentage, LOEE is almost not reduced any further. This is because the standby backup energy storage can only be used to reduce LOEE during islanding mode. When segment 2 is in failure mode, energy storage cannot be discharged to support load. LOEE during these failure events is not reduced. When standby backup operation strategy portion increases to a certain point, 60% in this study, LOEE introduced during segment 2 operating in the islanding mode is reduced to near zero. However LOEE introduced during segment 2 in failure modes cannot be reduced. The reliability improvement is saturated. If further reliability

improvement is needed, one option is to integrate another EES in segment 1.

Different types of customers desire different reliability and economic benefits. Normally for residential customers, the service interruption damage cost is low and acceptable. Thus their requirement for reliability level is relatively low but the energy savings might be attractive and more. For other types of customers, such as industry and commercial customers, the interruption of power supply could lead to huge financial loss. Higher reliability level for them are more desirable rather than energy cost saving. Load aggregator could use the proposed hybrid operation strategy to improve system reliability and economy according their customer needs.

3.4 A Modified MPC-based Operation Strategy

The flowchart of the MPC-based operation strategy is illustrated in Figure 23.

MPC-based operation strategy can take into account what will happen in the future to optimize its current operation. In the islanding mode, the energy storage operation is the same as in the standby backup operation strategy. Energy storage is discharged to support the load. An operation simulation with the proposed MPC-based operation strategy in grid connected mode is presented in Figure 24. In the simulation, a single segment distribution system is studied. The forecasts are assumed to be perfect. The peak load is 4MW, the energy storage capacity is 8MWh, charging/discharging power limit is 4MW, charging/discharging efficiency is 90%.

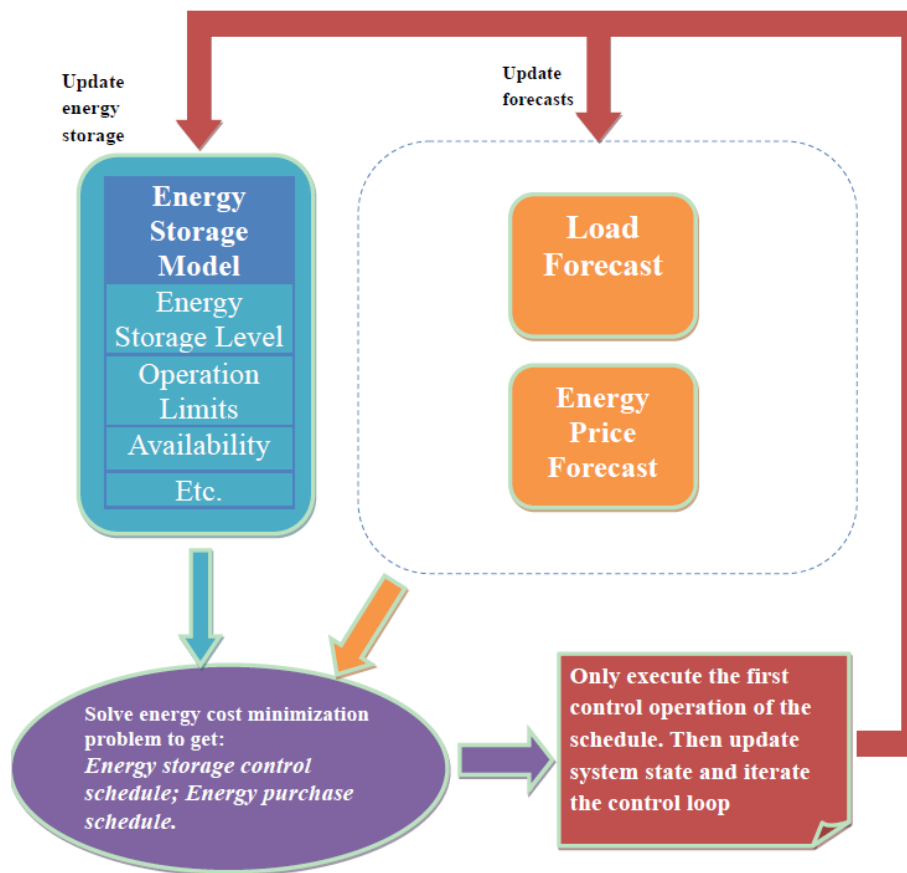


Figure 23 MPC-based operation strategy flowchart.

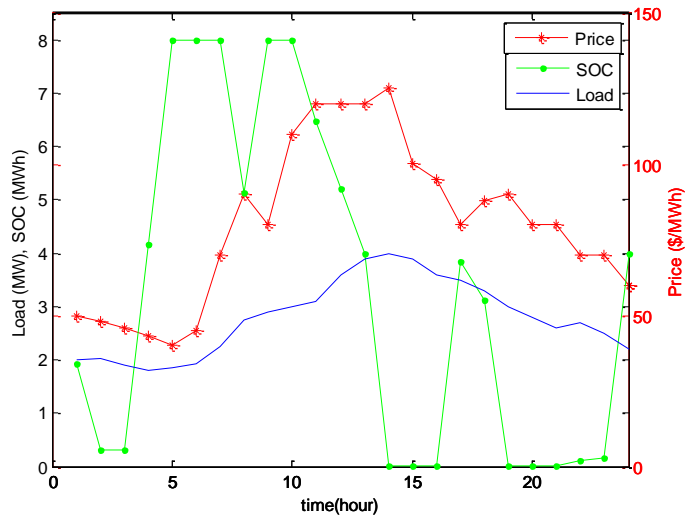


Figure 24 MPC-based operation strategy simulation.

It can be observed in Figure 24 that the energy storage is generally charged when the price is low and discharged when the energy price is high. Also the energy storage SOC is increasing before the high energy price periods, and decreasing when the energy price is high. There is a strong correlation between load demand and energy price. Normally the energy price is high when the load is high. Meanwhile the system's reserve margin decreases when the load increases. When the load is high the system becomes more vulnerable to any generation outage. System is less reliable when the load is high. Thus there is a stronger need for more backup power source available during the peak load periods to ensure reliability. However, by utilizing the MPC-based operation strategy, the SOC is low during the peak energy price periods

which coupled with peak load and less reliable system. Low energy storage SOC limits its capability of providing backup power supply to improve distribution system reliability. In order to solve this problem, a Modified MPC-based operation strategy is proposed to improve both reliability level and economic benefits.

The basic idea of this Modified MPC-based operation strategy is that at each point a portion of the energy storage capacity is utilized as a standby backup power source, the other portion is utilized to manage energy cost using the MPC-based approach. Through this approach, the standby backup portion always reserves some amount of energy to prepare for the failure event. When segment transits from grid connected mode to islanding mode, the reserved energy stored in energy storage can be discharged to prevent a loss of load event or reduce energy not served. Meanwhile, the other portion is able to take advantage of the energy storage control flexibility to reduce energy cost. With a certain energy storage capacity, if the standby backup portion increases, the portion for energy cost management decreases. Accordingly the reliability of the system is improved, but the energy cost saving is reduced. There is a tradeoff between reliability and energy cost saving. In order to better utilize limited energy storage capacity, the portion for standby backup power source is adjusted as needed in each period. During peak load periods, system is less reliable. Thus a larger portion of energy storage is assigned for the purpose of standby backup power source.

On the other hand, during non-peak load periods, system is more reliable. The loss of load probability during non peak load periods is very small. Accordingly, a smaller portion of energy storage is required as standby backup power source; a larger portion of energy storage can be used to reduce the energy cost. The previously presented MPC-based operation strategy can be modified as follows.

- 1) In step one, not only the current load and energy price needs to be obtained, but also the required energy storage SOC level for standby backup operation strategy in the current period needs to be determined.
- 2) In step two, besides load and price forecasts, the required energy storage SOC level for standby backup power source in the future periods also needs to be forecasted.
- 3) In step three, the objective function stays the same. But the following constraints are added for required energy storage SOC level.

$$SOC(k) \geq SOC_{req}(k)$$

- 4) Step four and five remain unchanged.

There could be different ways of determining what should be the SOC level of energy storage dedicated to standby backup power source in order to ensure system reliability. The load profile could be used as the indicator for determining the percentage. The SOC level of energy storage using standby backup operation strategy is proportional to the load. Thus the required energy storage SOC levels in future

periods can be forecasted according to the load forecast.

The Modified MPC-based operation strategy is illustrated through simulation. The parameters for the simulation are the same as in the previous MPC-based operation strategy simulation. The required energy storage SOC level is set to support 50% of the load for one hour when power supply from external grid is interrupted. This load could be considered as the critical load. The simulation results are shown in Figure 25. In Figure 25, it can be seen that at any time, if there is a power supply interruption, there is always enough energy stored to support the critical load for an hour. During peak load hours (hour 14 to 16), there is more store energy available for backup power source. Compared to the MPC-based operation strategy, where there is no energy stored during these hours for supporting the load in the event of power supply interruption, the reliability of the system is improved. However, there is a trade-off between reliability and cost saving. With the MPC-based operation strategy, the energy cost is 5.21 thousand dollars for this day; on the other hand with the Modified MPC-based operation strategy, the cost is 5.30 thousand dollars, a 1.7% increase. Load aggregator can flexibly adjust the portion for standby backup operation strategy to achieve the desired balance of reliability improvement and energy cost saving.

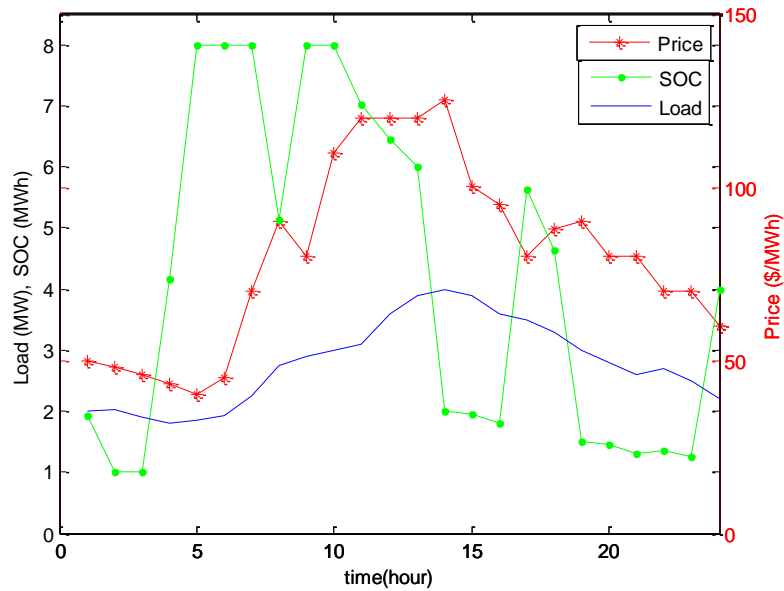


Figure 25 Modified MPC-based operation strategy simulation.

3.5 Summary

In this section, the distribution system reliability and economy improvement brought by EES integration is studied. Because of the operation flexibility of EES, it can be controlled in different ways to affect the distribution systems. Different operation strategies have different reliability and economic impact on the system, even with the same EES. The reliability and economy of radial distribution system integrated with EES are assessed. Three operation strategies, standby backup operation strategy, MPC-base operation strategy, and hybrid operation strategy, are presented. Standby backup operation strategy improves system reliability the most but falls short

on economic improvement. The proposed novel MPC-based operation strategy can maximize distribution system economy but could not improve reliability as much as the standby backup operation strategy. Hybrid operation strategy combines the standby backup operation strategy and MPC-based operation strategy to balance the reliability and economic improvement. The reliability and economic analysis of distribution system integrated with EES using proposed operation strategies illustrates the effectiveness of the proposed methods. These operation strategies provide load aggregator options to achieve its reliability and economy improvement goals.

4. ADEQUACY AND ECONOMY ANALYSIS OF DISTRIBUTION SYSTEMS INTEGRATED WITH ELECTRIC ENERGY STORAGE AND RENEWABLE ENERGY RESOURCES*

4.1 Introduction

Renewable Energy Resources (RER) such as wind and solar energy are the key to reduce pollutants produced by conventional fossil fuel power plants, carbon dioxide emissions and energy purchasing cost associated with rising fuel price. Public awareness of the need to protect the environment and achieve energy independence and sustainability encourages the governments, research agencies and industrial companies to make greater efforts in integrating more RER into the existing transmission and distribution systems. Although the potential benefits of RER are significant, many major challenges need to be conquered first. One of the major challenges is the reliability impact caused by intermittent RER such as wind power. This problem could be ignored earlier because the integrated RER were only a very small percentage (e.g., 3%) of the total generation. The intermittent property of RER does not have a notable reliability impact on systems which are mainly supported by

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conventional fossil fuel generations. With expected greater penetration of RER (e.g., 20% wind power), their reliability impact can no longer be ignored. A comprehensive reliability analysis considering the impact of high RER penetration is required.

An efficient method of reliability analysis of electric power systems with time-dependent sources, such as photovoltaic and wind generation is presented in [20], in which the reliability impact of fluctuating characteristics of unconventional generation units is studied. Reference [21] investigates the reliability effects on a composite generation and transmission system associated with the addition of large-scale wind energy conversion systems using the state sampling Monte Carlo simulation technique, where the wind speed correlation is considered. The work in [22] presents a reliability analysis framework which includes both the deterministic and probabilistic approaches for bulk power system adequacy and security assessment when wind power is added. Considerable work has been done on RER integration in transmission systems. Reliability impact of RER integrated in distribution systems is also studied by researchers. In [23], the authors investigate the system reliability benefits of adding wind turbine generation as an alternative supply in a rural distribution system. In [24], both Monte Carlo simulation and analytical methods are used to assess distribution system adequacy including wind-based distribution generation units, with implementation of the islanding mode of operation in the

assessment.

With a rapid development of Electric Energy Storage (EES) technologies, and their operational flexibility, interest in integrating both RER and EES into power systems to improve systems reliability and economy has been growing. A reliability cost/worth evaluation method that can incorporate the impact of wind energy and EES utilization in electric power systems is presented in [25]. Research in [26] evaluates system reliability considering wind and hydro power coordination, where hydro facilities with energy storage capability are utilized to alleviate the impact of wind power fluctuations and also improve the system adequacy. A methodology for the operation of a hybrid plant with wind power and hydrogen storage to maximize economic benefits (i.e., maximizing profits) in a market environment is presented in [7].

Previous reported work has been on either the reliability impact of RER and EES integration, or on economic benefits of the integration. However, reliability impact and economic benefits are tightly related. Especially with the operational flexibility of EES, different EES operation strategies could bring different sets of reliability impact and economic benefits.

In this section, a novel Model Predictive Control (MPC)-based operation strategy for distribution system load aggregator is proposed to improve the economy of system

by minimizing energy purchasing cost in power market with the utilization of price, load, and renewable energy forecasts. An islanding operation with power supplies from RER and EES is implemented to enhance distribution system reliability. In order to accurately assess the reliability and economic impact brought by proposed operation strategies, an assessment framework based on sequential Monte Carlo simulation approach is presented.

4.2 Distribution System Integrated with Energy Storage and Renewable Energy

A distribution system integrated with distributed RER (e.g., wind-based distributed generation) and EES is shown in Figure 26. Load aggregator of a distribution system participates in the wholesale power markets to purchase electric energy to serve its customers in the distribution system. Meanwhile, load aggregator is also assumed to operate the RER and EES integrated in its served distribution system. Renewable energy generation can be controlled by curtailing available renewable energy output. EES devices are operated by determining the charging/discharging operations. It is assumed that electric energy price is determined by the markets and load is determined by customers, which is inelastic to price. The objective of the load aggregator is to serve its customers with reliable power supply while minimizing the electric energy purchasing cost in power markets. The goals are to propose novel operation strategies to enhance reliability and economy, and present a comprehensive

framework for assessing both reliability and economy.

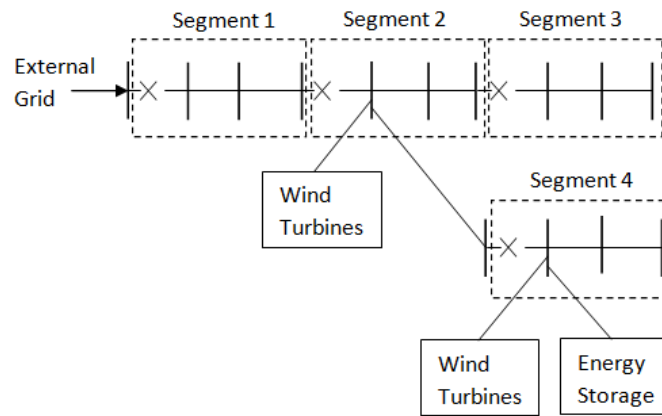


Figure 26 Schematic diagram of a radial distribution system integrated with wind turbines and electric energy storage.

As most distribution systems are operated radial, the focus here is considering radial distribution system with RER and EES integrated. Figure 26 shows an example of a radial distribution system with RER and EES integrated, where “X” sign represents protective devices such as circuit breakers and reclosers. The following assumptions are used in the study of the system. Only the active power is considered. Voltage levels are assumed to be properly regulated. This assumption is normally acceptable in adequacy analysis for planning purposes. If the impact of voltage cannot be ignored, a more detailed distribution system AC power flow could be used instead. Power output from RER is considered constant within a period.

4.3 Operation Strategies

4.3.1 Modes of Operation

A distribution system consists of components such as wires, circuit breakers and reclosers. A group of components can be modeled as one segment if the entry component is a protective device such as a switch or a recloser and the entry protective device is the only protective device of this segment. In this way, the distribution system is modeled by segments instead of components. The rationale behind this segment modeling is that if a component failure occurs downstream of a protective device and within its protection zone, the protection zone will be isolated and all the customers in that protection zone will lose power supply. Even if there are other power sources such as RER or EES integrated into this segment, once a component failure occurs within this segment, the power supply from all energy resources is cut off. For example, in Figure 26, the components of the distribution system are grouped into 4 segments according to the location of protective devices. If a component failure occurs in segment 2, the protective devices isolate this segment, external grid power cannot be supplied to this segment, the power supply from wind turbines is also cut off, the load demand in this segment cannot be met and a loss of load event occurs.

In a radial distribution system without distributed generation (DG) such as RER, if a component failure occurs within a segment, the segment is isolated and grid power

cannot be supplied to the load within this segment and the segments downstream. However, when DG or EES is integrated, if a component failure occurs within a segment, the segment is still isolated but the downstream segments can utilize power from DG or EES integrated to support their load. In this case, the loss of load event might be avoided if there is enough power from these alternate energy resources. Following the previous example, when segment 2 is isolated, as there is no DG or EES integrated in segment 3, there is no power supply for its load. Instead, power from wind turbines and EES can be used to supply the load within segment 4.

To summarize the above discussion, when there is a failure within a segment, all the power supply for this segment is cut off. When there is no failure within a segment, there are two modes of operation, grid connected mode and islanding mode. In grid connected mode, the transformers connecting transmission system and distribution are up, the external grid is capable of delivering sufficient energy. Thus grid power can be supplied to this radial distribution system and no failure occurs within any upstream segment. Thus the power from external grid can go through all the upstream segments and reach the studied segment. In islanding mode, at least one failure occurs in upstream segments, or the transformers are down, or the external grid is unable to deliver sufficient energy to this distribution system caused by outage. Thus power from external grid cannot be supplied to the segment under study. Power from the DG and

EES integrated in this segment is utilized to support the load. The identification of operation modes is not limited for radial system. Operation mode of segment in non-radial system can also be identified through more complicated evaluation considering the distribution system topology.

4.3.2 Operations in Grid Connected Mode and Islanding Mode

EES operation strategies affect the reliability and economic performance of a distribution system. This part presents the proposed operation strategies in different operating modes.

Operation Strategy in Grid Connected Mode: In grid connected mode, the power from external grid, RER and EES can all be utilized to serve the load. The objective of the load aggregator is to minimize its energy purchasing cost in power market while meeting the demand. The allocating of power supplies is crucial in determining the energy purchasing cost.

With more and more accurate methods developed for load forecasting, renewable energy forecasting, and energy price forecasting, EES can utilize these forecasts to reduce the energy purchasing cost. A Model Predictive Control (MPC)-based operation strategy is proposed to minimize the energy purchasing cost by optimally coordinating the energy purchase from the power market, EES charging/discharging operation, and utilization of RER. In the MPC-based operation strategy, short term forecasts of load,

available renewable energy and energy price, are utilized to determine the operation. Power market modeling and EES modeling are introduced first before further describing of the proposed operation strategy.

The power market here is simplified as a real time power market model. During each market period (e.g. an hour), load aggregator determines how much energy it needs to purchase from the market, then submits its offer to get that needed amount of energy. The market clearing mechanism determines the energy price for each period. Load aggregator is assumed to be a price taker whose transactions do not affect the clearing price determined by the market. The energy purchasing cost for N periods starting from period $i + 1$ is

$$\sum_{k=i+1}^{i+N} U(k) \cdot P(k) \quad (4.1)$$

With the proposed operation strategy, no specific EES technology is addressed. Rather the EES unit is modeled by its operation limits which include EES maximum and minimum state of charge level, charging/discharging power limit, charging/discharging efficiency. The energy storage state of charge level at any time has to be within its minimum and maximum range. This range is considered as the effective capacity. The charging and discharging rates have to be within the power limits. Power losses during charging/discharging operations are considered in its charging/discharging efficiencies. The state of charge at the end of each period is

determined by the previous period state of charge level and the charging/discharging operation during this period, it is expressed as

$$SOC(k) = SOC(k-1) + \eta_c \cdot C(k) - D(k) \quad (4.2)$$

All EES operation variables are within their operation limits.

The basic approach of MPC is that a finite-horizon optimization problem determining the series of optimal control operations is solved before each control step, but only the first control operation is implemented. After implementing the first control step, the system updates the actual state of the system and the future states using a predictive model. Then the control routine is repeated to determine the next step's operation. Applying the above MPC approach, energy purchasing cost minimization problem with forecasted, load, available renewable energy and price at period i can be implemented as follows:

- 1) Obtain the actual load, available renewable energy and price in the current period i .
- 2) Select a receding optimization horizon of N periods (e.g. 24 hours). Use load, renewable energy and price forecast models to obtain the most updated load, renewable energy and price forecasts for the next N periods, from period $i+1$ to $i+N$.
- 3) Solve the optimization problem, formulated as follows.

Objective: Minimizing energy purchasing cost from period i to $i+N$

$$\text{Min. } U(i) \cdot P(i) + \sum_{k=i+1}^{i+N} U_f(k) \cdot P_f(k) \quad (4.3)$$

The first part $U(i) \cdot P(i)$ is the energy purchasing cost of the current period i . The second part $\sum_{k=i+1}^{i+N} U_f(k) \cdot P_f(k)$ is the predicted total energy purchasing cost of the following periods from $i+1$ to $i+N$. $U(i)$ and $U_f(k)$ are the decision variables to be solved.

Constraints:

i. EES operation constraints

$$0 \leq C(k) \leq C_{Max} \quad (4.4)$$

$$0 \leq D(k) \leq D_{Max} \quad (4.5)$$

$$SOC_{Min} \leq SOC(k) \leq SOC_{Max} \quad (4.6)$$

Where $k=i, i+1, \dots, i+N$. The charging and discharging operations of EES are to be solved. The maximum charging and discharging rates are constant. As one hour is considered as one period, the charging energy equal to $C(k)$ multiplied by 1 hour. For convenience $C(k)$ is used interchangeably as charging rate and energy charged in one hour. $D(k)$ is treated in the same way.

ii. Available renewable energy constraints

$$0 \leq R(i) \leq R_{Max}(i) \quad (4.7)$$

$$0 \leq R_f(k) \leq R_{f,Max}(k) \quad (4.8)$$

where $k = i+1, \dots, i+N$. The utilized renewable energy is equal to or less than the available renewable energy. Extra energy not utilized is dumped in ways such as adjusting the wind turbines' blade pitch, so wind turbines do not generate the maximum power they can in that period. Utilized renewable energy for current period and future period are to be solved.

iii. Power balance constraints

$$U(i) + R(i) = L(i) + C(i) - \eta_d D(i) \quad (4.9)$$

$$U_f(k) + R_f(k) = L_f(k) + C(k) - \eta_d D(k) \quad (4.10)$$

Where $k = i+1, \dots, i+N$. Load, available renewable energy, and price in current period i are the actual values and known. While load, available renewable energy, and price in future periods are predicted using forecast models, thus are given parameters for the optimization problem. The solution of this optimization problem gives an optimal operation schedule for EES charging/discharging operation, energy purchase and renewable energy utilization from period i to $i+N$.

- 4) Implement the first period's operation of the solved operation schedule, which is the current period i .
- 5) Update the EES state of charge level, move to the next period, and repeat the algorithm from step 1.

The solved operation schedule is optimal with respect to the given forecast. The

accuracy of forecast will affect the optimality of the solution because of the difference between the forecast and the actual values. We have assumed the forecast to be perfect but if information on characteristics of forecast uncertainty were available, it could be incorporated in the determination of the schedule. The short-term (e.g. next 2-3 hours) forecast is more accurate than the relatively longer term (e.g. 23-24 hours) forecast. By using this MPC-based operation strategy, load, renewable energy and price forecasts are updated according to the newest information after each operation step. Then the most updated forecasts could be effectively integrated into the operation decision making process to minimize the energy purchasing cost. By taking into consideration what the future load, renewable energy and price will be, better operation for current period can be determined. 24 hours horizon is chosen as the optimization horizon considering the 24 hours cycling period of load variation, renewable energy variation and energy price variation. Because of the increasing forecast uncertainty into future periods, different choice of optimization horizon such as 12 hours, could lead to different operation schedule. More detailed information about the forecast uncertainty could be used to determine the optimal optimization horizon.

The integration of RER and EES itself could reduce energy purchasing cost. However, the proposed MPC approach optimally determines from which power sources (RER, EES or external grid) to get power supplies to support the load, how

much energy should be supplied by each selected power source, and chronological operations such as whether the renewable energy generated in this period should be used up now or stored for future use to avoid high energy price, and at which period EES should be discharged in order to release more storage capacity for storing lower priced energy in the coming periods. These operation decisions provided by the MPC approach could reduce energy purchasing cost even more than simply integrating RER and EES. The proposed MPC operation strategy reduces the energy purchasing cost by better coordinating the power supply from different power sources and energy usage along the time line.

Operation Strategy in Islanding Mode: In islanding mode, avoiding and minimizing load curtailment is the objective. The available renewable energy is first utilized to serve the load. If it is not enough to cover the load, the energy stored in EES is discharged to avoid or minimize load curtailment. Only when the load demand is met, and there is renewable energy surplus, the extra energy is stored in EES for future usage without violating EES operation limits. The extra energy which cannot be stored in EES is then dumped.

4.4 Reliability and Economy Assessment Framework

The proposed reliability and economy assessment framework is based on Sequential Monte Carlo Simulation. During operation, EES sometimes serves as

generation providing power to the load and sometimes it is charged acting as a load. Current EES state of charge level at a point in time is determined by the previous operations. The utilization of energy from EES in the current period is determined by both its current state of charge level and planned utilization in the future. Because of these unique chronological characteristics of EES, its impact on system reliability and economy is best captured using sequential Monte Carlo method, in which its specific operation strategies are integrated. The assessment flowchart is shown in Figure 27. Details of the assessment framework are presented as follows.

4.4.1 Distribution System Reliability Analysis

In adequacy analysis, a power system is considered to be operating in either success state or failure state. A system is considered operating in success state when it has enough generation capacity to serve the load. When generation capacity is not sufficient to meet the load demand and loss of load occurs, the system is in failure state. The probabilities and durations associated with the system residing in success and failure states and energy not served during failure states are the adequacy indices for reliability analysis.

For a distribution system modeled in terms of segments, a modified reliability analysis is presented to evaluate the reliability of the system in more details. In the modified analysis, besides evaluating the reliability of the distribution system, each

segment of the distribution system is also evaluated. The determination of segment state is explained later. After the states of the segments are determined, the system state is then determined as following: the system is in success state if all the segments are in success state; the system is in failure state if any segment is in failure state. By performing the modified reliability analysis, reliability indices for each segment and the whole system can be obtained. The different reliability levels of segments caused by network topology, RER and EES can be evaluated.

4.4.2 Segment State Determination and Operation

In the assessment framework, time horizon is divided into periods (hourly). Once the component simulation is done, up or down state of each component in the distribution system is determined. Information of distribution system topology is needed with the component state information to determine segment operation mode. Then the success or failure state of each segment could be evaluated considering their operation mode.

Under grid connected mode, the load is compared with the total power supply which consists of the available power from external grid, RER and EES. If the total power supply is not sufficient for the load, the system is identified as in failure state. If the total power supply can serve the load, it is in success state. After evaluating the segment state, MPC-based operation strategy is implemented using the most updated

system state, and load, renewable energy, price forecasts. EES state of charge is then updated accordingly after each operation.

Under islanding mode, the load is compared with the total power supply which only consists of RER and EES. The system is in failure state if the total power supply cannot serve the load. If the power supply can cover the load, it is in success state. With the state determination finished, islanding mode operation is implemented. EES state of charge is then updated accordingly.

If there is a failure within a segment, this segment is in failure state. No operation is performed until the failure is removed.

After state determination and operation for the current period, the process moves to the next period and starts another round of state determination and operation. Simulation stops when the specified maximum number of simulation years is reached or the probability of system in failure state converges. Considering there is generation integrated in the distribution system and the objective of comparing the available generation with the load, adequacy analysis indices, Loss of Load Expectation (LOLE) and Expected Energy Not Served (EENS) are calculated as the reliability indices. Other common distribution system indices, such as SAIFI and SAIDI, could also be calculated if needed.

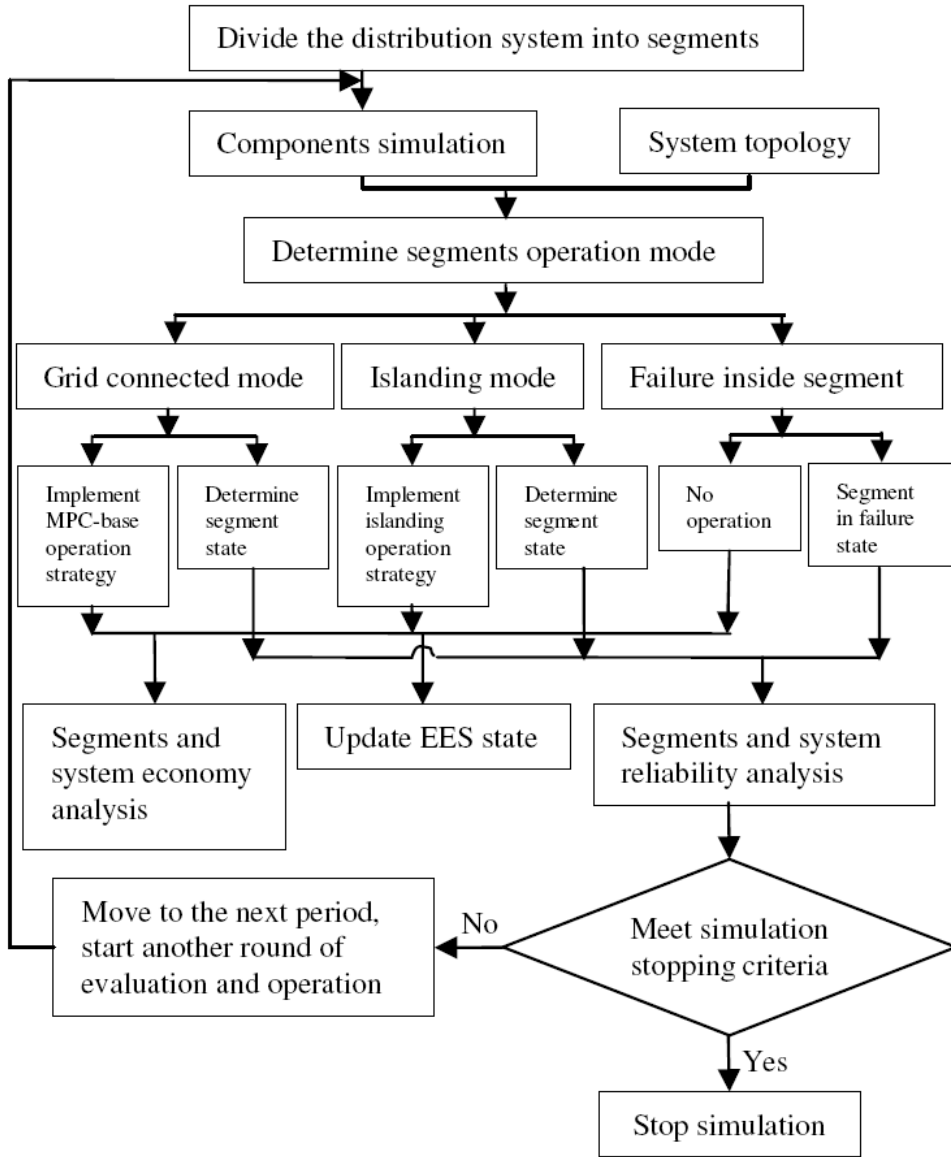


Figure 27 Proposed reliability and economy assessment framework flowchart.

4.4.3 Distribution System Economy Analysis

Annual energy purchasing cost and customer interruption cost are used as the

economic indices. Hourly energy purchasing cost is calculated according to the actual operation. Then annual energy purchasing cost is the sum of hourly energy costs in a year. We focus on the cost during operation. Thus the investment cost of RER and EES are not included in the economic indices, but it can be included if desired. If the optimal capacity of RER and sizing of EES are to be solved, the investment cost should be considered.

Customer interruption cost is the damage cost to customers caused by the power delivery interruption. When a service interruption occurs, the normal activities of customers in the distribution system could be affected and bear certain interruption cost. According to the nature of their activities, customers are grouped into 7 sectors, large user, industrial, commercial, agriculture, residential, government and institution, and office and buildings. Postal surveys have been conducted to estimate the customer interruption cost [29]. The survey data has been analyzed to provide Sector Customer Damage Function (SCDF). Customer damage cost is related to the type of customer and the duration of the interruption. As only limited interruption cost data is available, logarithmic interpolation and linear extrapolation can be used to calculate the cost within and outside the provided cost data. Composite Customer Damage functions (CCDF) are used to evaluate the interruption cost of mix types of customers. SCDF is used to construct CCDF using following equation

$$CCDF = \sum_{i=1}^n k_i SCDF_i \quad (4.11)$$

where k_i is the per unit energy consumption of customer sector i , $SCDF_i$ is the sector customer damage function of customer i , n is the number of customer sectors. SCDF gives the customer damage cost for each sector, while CCDF gives the total customer damage cost for a mix of customer types.

For an unreliable system, its annual energy purchasing cost might be low. But it does not mean this system is more economically efficient. It is because larger amount of energy could not be purchased and delivered to the distribution system due to frequent and long duration service interruptions. By evaluating the customer interruption cost at the same time, a more complete picture of the system economy can be obtained.

4.5 Case Studies

A modified practical radial distribution system integrated with wind turbines and EES, as shown in Figure 28, is studied. A step-down transformer is connecting the external grid and the distribution system. The components of the distribution system are grouped into two segments. Wind turbines and EES are integrated in segment 2 at node 28. The integration node could be determined by the network topology and the capability of handling required power injection. Node 28 is assumed to be able to

accommodate the power injection. Other suitable nodes could also be chosen. If the transformer has a fault or external grid fails to deliver sufficient energy because of outage, power could not be delivered to the distribution system. Thus in this reliability analysis, the transformer and external grid are considered as one component, with Mean Time To Failure (MTTF) of 1440 hours and Mean Time To Repair (MTTR) of 6 hours.

A series of cases are studied to investigate the reliability and economic impacts from integration of EES and wind turbines. Table 11 shows the studied 12 sets of EES effective capacity and power limit. The charging/discharging round efficiency is set to be 90%. EES is assumed to be perfectly reliable.

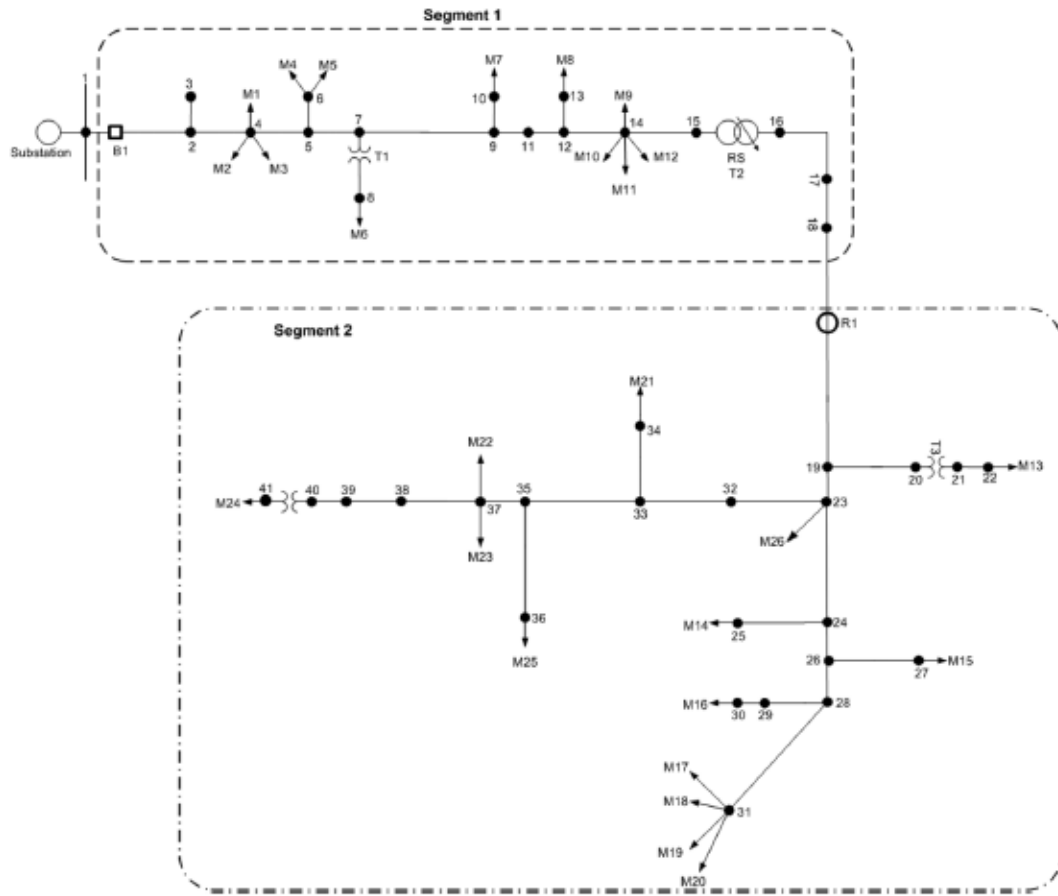


Figure 28 Modified practical radial distribution system with wind turbines and EES integrated in segment 2.

Table 11 Electric Energy Storage Parameters in Case Studies

Capacity (MWh)	Power limit (MW)	Capacity (MWh)	Power limit (MW)	Capacity (MWh)	Power limit (MW)
5	1	10	1	15	1
5	2	10	2	15	2
5	2.5	10	2.5	15	2.5
5	5	10	5	15	5

Six sets of Wind Turbine Generation (WTG) capacities are studied. They are 1MW, 2MW, 4MW, 6MW, 8MW and 12MW. Historical wind power output data is used [30]. 1MW capacity wind turbine's MTTF is 720hrs and the MTTR is 30hrs. Other WTG capacities are obtained by utilizing multiple 1MW wind turbines. The reliability indices for other capacities are also calculated accordingly.

A case is formed by matching an EES unit, which includes its capacity and power limit characteristics, with a WTG capacity. Thus 72 ($12 \times 6 = 72$) cases are formed and studied. A base case with no EES and WTG is also studied for comparison. In each case study, LOLE, EENS, energy purchasing cost, customer interruption cost of each segment and the system are obtained.

When implementing the proposed MPC-based operation strategy, forecast tools are needed to obtain the price, load, and wind power forecasts. The actual forecasts are not perfect. The effect of inaccurate forecasts is investigated in research work [31]. The peak load of the distribution system is 8MW. IEEE-RTS load profile is used as the chronological load profile. Segment 1 and segment 2 each share 50% of the total system load. The MTTF of both segments is 1440 hours and the MTTR is 1 hour. The hourly energy price profile used in the case study is shown in Table 12. Customer interruption cost of three customer mixes representing high commercial activities, high industry activities and high residential activities respectively are studied. The

percentages of each customer sector for the three mixes are shown in Table 13.

Table 12 Electric Energy Price

Hour	1	2	3	4	5	6	7	8	9	10	11	12
Price (\$/MWh)	50	48	46	43	40	45	70	90	80	110	120	80
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Price(\$/MWh)	90	125	100	95	80	88	90	80	80	70	70	60

Table 13 Customer Sector Percentage for Each Customer Mix

	Commercial (%)	Industry (%)	Residential (%)
High Commercial Mix	80	10	10
High Industry Mix	10	80	10
High Residential Mix	10	10	80

Table 14 Base Case Reliability Indices

	LOLE (hours/year)	EENS (MWh/year)
Segment 1	42.79	84.02
Segment 2	48.32	142.01
System	48.32	226.04

Table 15 Base Case Economy Indices (Million \$/Year)

	Segment 1 Customer Damage Cost	Segment 2 Customer Damage Cost	System Customer Damage Cost	Energy Purchasing Cost
High Commercial Mix	0.761	1.262	2.023	3.435
High Industrial Mix	0.584	0.990	1.574	
High Residential Mix	0.268	0.439	0.707	

Base case without EES and WTG, and seventy-two cases with different matching of EES and WTG capacity were studied. For reasons of space limitations, only selected results are presented here. Base case results are shown in Table 14 and Table 15. In Table 14, the LOLE for the system is exactly the same as LOLE for segment 2. It is caused by this particular distribution system configuration, where segment 2 is in series with segment 1 and downstream. For other configurations, LOLE are not necessarily the same for both system and one segment. Selected results of system with EES and WTG are shown in Table 16 and Table 17. The results demonstrate the reliability and economic improvement brought by the EES and WTG integration, and the proposed operation strategies. They also provide insights on how EES capacity, power limit and WTG capacity affect reliability and economy. These results could also be helpful in determining the proper EES capacity, power limit and WTG capacity to

achieve desired reliability level and economy benefit.

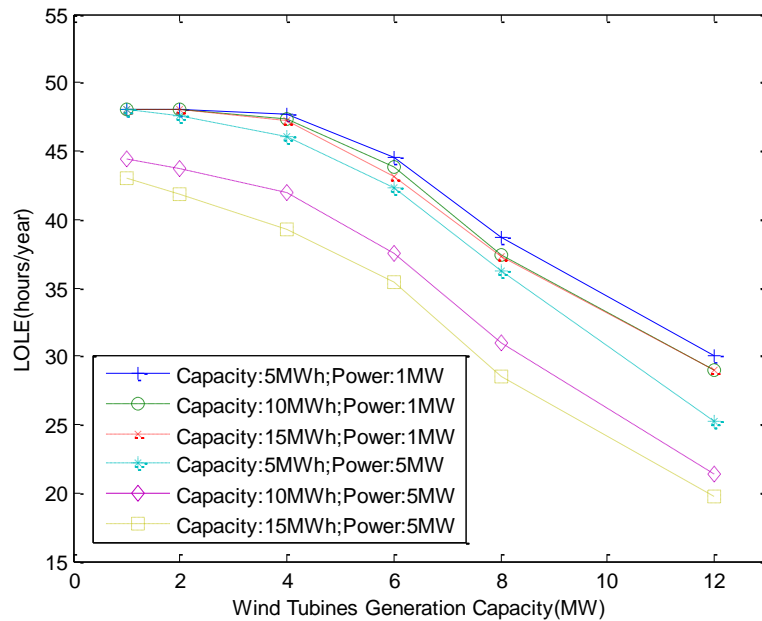


Figure 29 System LOLE when EES power limit is 1MW and 5MW.

Results show that increasing EES capacity, power limit, or WTG capacity can all enhance reliability, save energy cost and reduce customer interruption cost. However, the impact each factor has on reliability and economy depends on the situation. It can be observed from Figure 29 that only when EES power limit increases to a higher level (5MW), the increase in EES capacity can effectively improve system LOLE. That is because when power limit is low (1MW), it becomes the bottle neck preventing sufficient power discharged to support the load even when there is abundant energy

stored. The potential of large EES capacity is not utilized. Meanwhile, with the EES power limit of 5MW, the LOLE improvement tends to saturate when increasing EES capacity from 10MWh to 15 MWh compared with the increase from 5MWh to 10 MWh. This means with EES capacity of 10MWh and power limit of 5MW, a large portion of loss of load events could be avoided. Only a small additional portion of more rare and sever loss of load events would be eliminated with the additional 5MWh EES capacity. When the LOLE improvement will reach saturation with the increase of EES capacity is affected by the specific load level and segments failure rate. The proper matching of EES capacity and power limit is very important in the effectiveness of reliability improvement.

Reliability improvement for both segments is shown in Figure 30. With the increase of WTG capacity, reliability level of segment 2 is improved much faster than segment 1 when increasing WTG capacity to 6MW. After increasing WTG capacity over 6MW, the reliability of segment 2 is still improving faster but not as significant as when the WTG capacity below 6MW. This result implies the possibility of reliability differentiation by integrating proper size of WTG and EES into the segments which need reliability improvement.

Table 16 Reliability Indices of System with EES and WTG

Electric Energy Storage		WTG Capacity (MW)		LOLE (hrs/yr)	EENS (MWh/yr)
Energy Capacity (MWh)	Power (MW)				
5	1	1	Segment 1	42.71	73.95
			Segment 2	48.06	120.56
			System	48.06	194.51
5	1	4	Segment 1	42.30	57.92
			Segment 2	46.14	91.86
			System	47.65	149.78
5	2.5	1	Segment 1	42.67	73.22
			Segment 2	46.59	116.57
			System	48.02	189.79
5	2.5	4	Segment 1	40.78	57.53
			Segment 2	43.05	89.50
			System	46.13	147.02
10	1	1	Segment 1	42.71	70.59
			Segment 2	48.06	114.92
			System	48.06	185.51
10	1	4	Segment 1	41.94	54.68
			Segment 2	45.46	86.45
			System	47.29	141.13
10	5	1	Segment 1	39.10	67.94
			Segment 2	40.63	105.19
			System	44.45	173.13
10	5	4	Segment 1	36.57	52.68
			Segment 2	37.44	80.49
			System	41.92	133.17

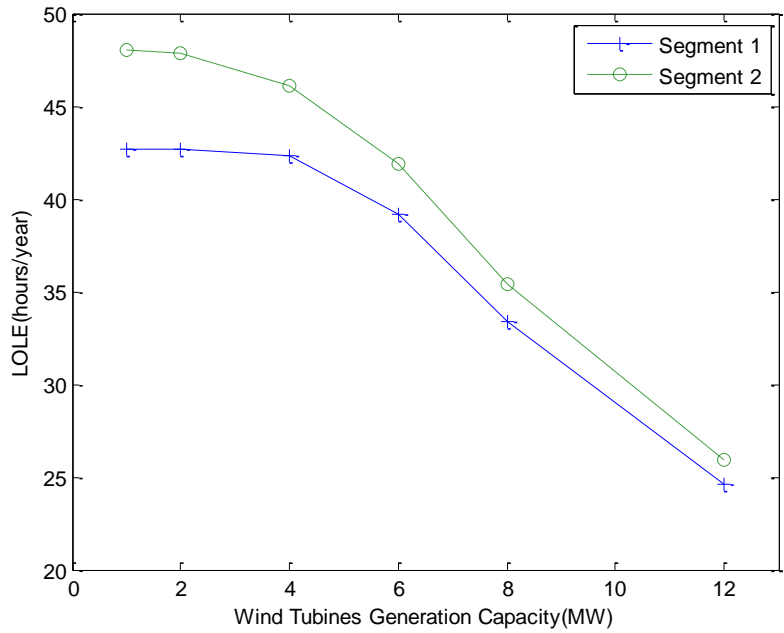


Figure 30 Segment 1 and Segment 2 LOLE when fixing EES capacity at 5MWh and power limit at 1MW.

Figure 31 shows the energy purchasing cost with EES capacity of 5MWh and 15MWh. The energy cost with EES having 15MWh capacity and 1MW power limit is higher than that with EES having 5MWh capacity and 2MW power limit. This phenomenon implies the importance of proper matching of EES capacity and power limit in order to achieve desired economic benefits. Customer interruption cost for high commercial mix system with EES capacity of 15MWh is shown in Figure 32. There is a sharp interruption cost reduction when increasing EES power limit from 1MW to 2MW.

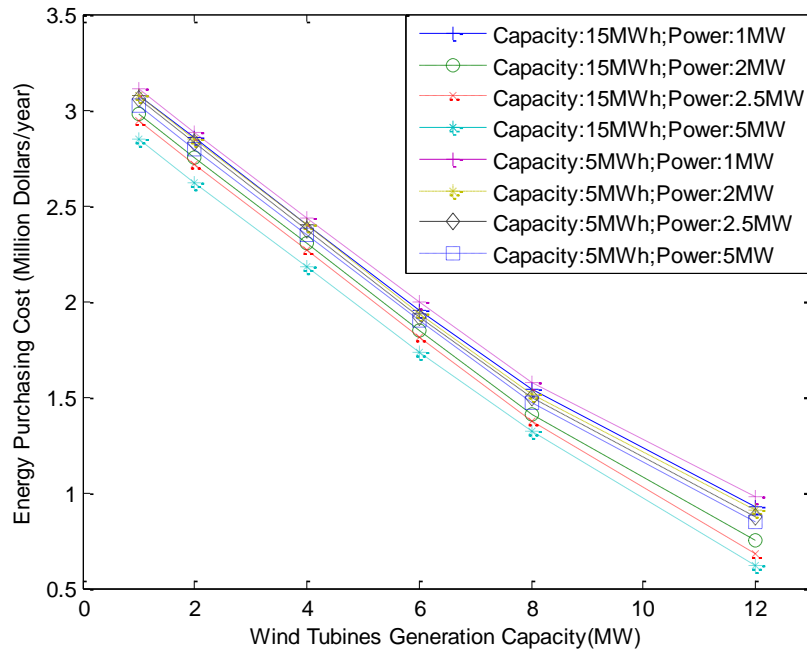


Figure 31 Energy purchasing cost when EES capacity is 15MWh and 5MWh.

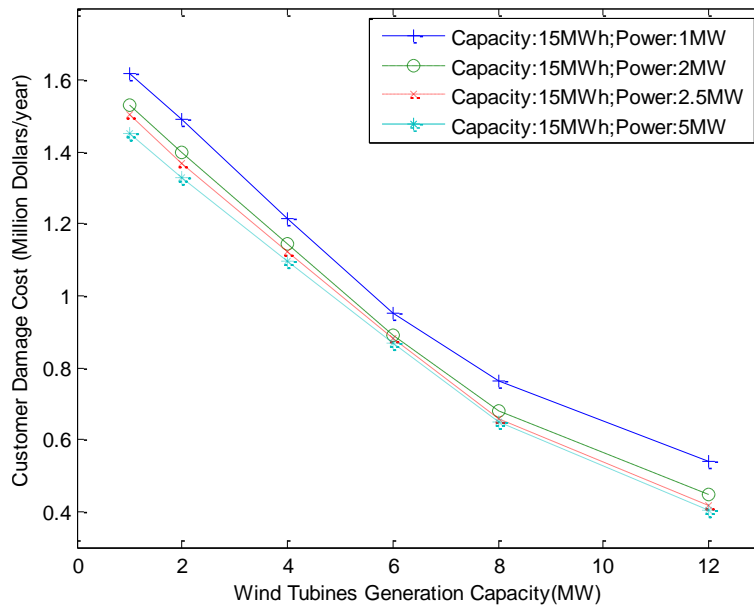


Figure 32 System customer interruption cost for high commercial mix system when fixing EES capacity at 15MWh.

However, the reduction is very limited when increasing power limit beyond 2MW. This result suggests the nonlinear and saturation effect when utilizing EES to improve system economy.

4.6 Summary

The integration of Renewable Energy Resources (RER) into an existing distribution system is an important topic in dealing with energy challenge the world is facing. With rapid development of Electric Energy Storage (EES) technologies, there is a growing interest in integrating both EES and RER into power systems to improve their reliability and economy. The adequacy and economy of distribution systems integrated with both EES and RER are assessed. A novel Model Predictive Control (MPC)-based operation strategy is presented to minimize distribution system energy purchasing cost by coordinating multiple power supplies from EES, RER and external grid. An islanding operation is implemented to improve the distribution system reliability and reduce customer interruption cost. A reliability and economy assessment framework based on sequential Monte Carlo method integrated with the MPC-based operation and islanding operation is proposed. Case studies are conducted to demonstrate the reliability and economy improvement by implementing the proposed operation strategies together with integration of EES and RER, and also investigate how EES capacity, power limit, and wind turbine generation capacity affect system

reliability and economy.

5. MULTI-OBJECTIVE DESIGN OF ENERGY STORAGE IN DISTRIBUTION SYSTEMS BASED ON MODIFIED PARTICLE SWARM OPTIMIZATION*

5.1 Introduction

With the recent rapid development of energy storage technologies, the conventional power systems which have been operated, in the past, on the basis of real-time balancing of supply and demand are evolving towards using such technologies. Many feasible applications of energy storage in power systems have been investigated. The objective of energy storage employment is to help build a more reliable and efficient smart grid. The major benefits of energy storage include electric energy time-shift, frequency regulation and transmission congestion relief. Energy storage can help achieve many goals. Here, we focus on the objectives of reliability and economy.

Among the research efforts towards achieving higher economic benefits by utilizing energy storage, [4] discusses the optimal demand-side response to electricity spot prices for storage-type customers. Authors in [5] reports on an experiment on the real-time pricing based control of thermal storage to save cost.

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The energy storage sizing problems are also being investigated. Reference [18] describes an analytical approach to evaluate reliability improvement by using energy storage as a backup storage and determine the size of the storage, which includes the capacity and power rate, to meet a specified reliability target.

Reliability impact and economic benefits are tightly related when considering energy storage integration. Especially with the operational flexibility of energy storage, different operation strategies could bring different reliability impact and economic benefits. For load aggregator of distribution system integrated with energy storage, it is important to know the reliability and economy impact of the implemented energy storage operation strategies. Then proper energy storage operation strategies can be chosen and implemented to achieve desired reliability and economy improvement goals.

However majority of research done on energy storage design problems mainly consider the impact of energy storage capacity and power rate. The impact of energy storage operation strategy is ignored or not considered as a major factor. This work demonstrates the significant impact of energy storage operation strategy on reliability level and economic benefits. A modified particle swarm optimization approach is proposed for the designing the problem of energy storage in distribution systems, where not only the energy storage capacity and power rate are determined but also the

energy storage operation strategy.

5.2 System Description

5.2.1 Energy Storage Integrated in Distribution System

In a market environment, the load aggregator purchases electric energy from wholesale market and delivers the purchased electric energy to its customers in the distribution system. The objective of the load aggregator is to serve its customers reliably and economically.

With the integration of energy storage devices in the distribution system, they could be utilized to improve distribution system reliability and economy. As most distribution systems are radial, the focus here is on considering such distribution systems. However, the proposed method can be applied to other distribution systems with different configurations. Figure 33 shows an example of a radial distribution system integrated with energy storage, where “X” represents protective devices such as circuit breakers and reclosers. The transformers and all the generation and transmission systems are represented as the external grid, through which the electric energy is delivered to the distribution system.

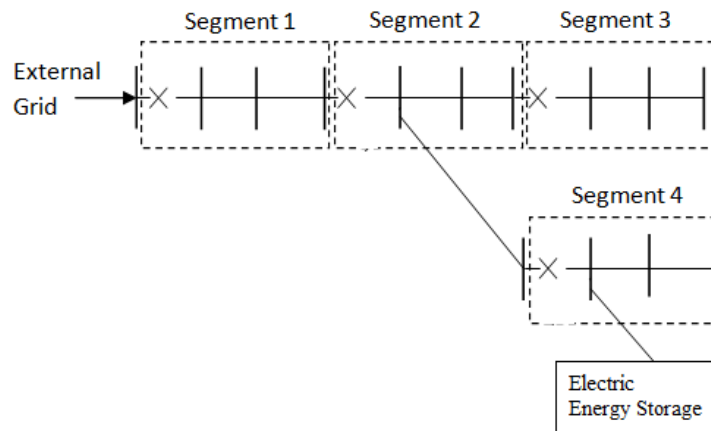


Figure 33 A radial distribution system integrated with energy storage.

A distribution system consists of components such as wires, circuit breakers, reclosers, etc. A group of components can be modeled into one segment if the entry component is a protective device such as a switch or a recloser. The entry protective device is the only protective device of this segment of grouped components. In this way, the distribution system is modeled by segments instead of components. The rationale behind this segment modeling is that if there is a component failure downstream of a protective device and within its protection zone, the protection zone will be isolated and all the customers in that protection zone will lose power supply. Even if there are distributed generators or energy storage devices integrated into this segment, once a component failure occurs within this segment, the power supply from these energy resources is cut off. The external grid is considered in either success state or failure state. The external grid is in success state when sufficient power could

be supplied from external grid to distribution system. Otherwise it is considered as in failure state, which could be caused by outage events with the external grid.

5.2.2 Modes of Operation

In a radial distribution system without distributed generation (DG) or energy storage, if a component failure occurs within a segment, the segment is isolated. Grid power cannot be supplied to the load within this segment and the segments downstream. The load demand in all these segments cannot be met. However, when DG or energy storage are integrated, if a component failure occurs within a segment, the segment is still isolated but the downstream segments can utilize power supply from integrated DG or energy storage to support its load. In this case, the loss of load event might be avoided if there is enough power from these energy resources. In Figure 33, when segment 2 fails and is isolated, as there is no DG or energy storage integrated in segment 3, there is no power supply for its load. Instead, power from energy storage can be used to supply the load within segment 4.

To summarize the above discussion, when there is a failure within a segment, all the power supply for this segment is cut off. When there is no failure within a segment, there are two modes of operation, grid connected mode and islanding mode. In the grid connected mode, if the external grid is in success state grid power can be supplied to this radial distribution system and there is no failure within any upstream segment.

Thus the grid power can go through all the upstream segments and reach the studied segment. In the islanding mode, at least one failure occurs in upstream segments or the external grid is in failure state. Thus grid power cannot be supplied to the segment under study. If there are no DGs and energy storage is integrated in the studied segment, load in this segment cannot be met. If there are DGs and energy storage is integrated in the studied segment, power from DGs and energy storage is utilized to support its load. Loss of load might be avoided or loss of energy is minimized.

5.3 Energy Storage Operation Strategies

The operation of energy storage is very flexible and behaves very different from either generation or load. Energy storage can be flexibly operated to act as generation, load or simply standby according to the needs of load aggregator. How energy storage is operated has a major impact on distribution system reliability level and economic benefits. In this section, a standby backup operation strategy, a Model Predictive Control (MPC)-base operation strategy and a hybrid operation strategy are presented. Approach for the reliability and economy improvement evaluation of these operation strategies is discussed.

5.3.1 Standby Backup Operation Strategy

One commonly used operation strategy is utilizing energy storage as a standby backup energy resource. The standby backup operation strategy is implemented as

follows.

In islanding mode, power from external grid cannot reach the studied segment. Energy storage integrated in this segment is discharged to sustain the service in this segment. The objective is to avoid a loss of load event or minimize the unserved energy within its operation constraints including energy storage capacity limits and power rate limits.

When the system is restored and the segment is back to the grid connected mode, energy storage is immediately being charged until it reaches its energy storage upper limit and then stand by to prepare for the next failure.

5.3.2 MPC-based Operation Strategy

The presented MPC-based operation strategy minimizes the energy purchasing cost. This operation strategy is implemented in grid connected mode. With this strategy, short term forecasts of energy price and load are utilized to determine the optimal operation schedule. Power market modeling and energy storage modeling are briefly introduced first before further description of the MPC-based operation strategy.

The power market is simplified as a real time power market model. However, this strategy can also be implemented in other market structures. During each market period (e.g. an hour), load aggregator determine how much energy it needs to purchase from power market, then submits its offer to get that amount of energy. The market

clearing mechanism determines the energy price for each period. Load aggregator is assumed to be a price taker who cannot affect the clearing price determined by the market. The energy cost for period k is

$$U(k) \cdot P(k) \quad (5.1)$$

Where $U(k)$ is the amount of energy purchased in power market in period k , $P(k)$ is the market clearing price in period k . Assume load aggregator can only purchase energy, we have

$$U(k) \geq 0 \quad (5.2)$$

The total energy cost for the period i and the following N periods is

$$\sum_{k=i}^{i+N} U(k) \cdot P(k) \quad (5.3)$$

The energy storage unit is modeled as a set of parameters and operation limits. Energy storage is modeled by its energy storage capacity, charging power limit, discharging power limit, charging efficiency, discharging efficiency. The energy storage state of charge (SOC) at the end of each period is determined by the previous period SOC and the charging/discharging operation during current period, it is expressed as

$$SOC(k) = SOC(k-1) + \eta_c \cdot C(k) - D(k) \quad (5.4)$$

where $C(k)$ is the power charged to energy storage, $D(k)$ is the power discharged from energy storage, $X(k)SOC(k)$ is the SOC at the end of period k , η_c is the charging

efficiency. All three variables need to be within their operation limits, expressed as

$$0 \leq C(k) \leq C_{Max} \quad (5.5)$$

$$0 \leq D(k) \leq D_{Max} \quad (5.6)$$

$$SOC_{Min}(k) \leq SOC(k) \leq SOC_{Max}(k) \quad (5.7)$$

The basic approach of MPC is that a finite-horizon optimization problem determining the series of optimal control operations is solved before each control step, but only the first control operation is implemented. A predictive model is used to estimate the state space trajectory over the prediction horizon, with the initial state being the actual state of the system. After implementing the first operation, the system updates the actual state of the system and the future states using the predictive model. Then the optimal control routine is repeated to determine optimal operation for the next step. Applying the above MPC-based approach, energy cost minimization problem at period i can be implemented as follows

- 1) Obtain the actual load and price in the current period i .
- 2) Select a receding optimization horizon N periods (e.g. 24 hours). Use load and price forecast tools to obtain the most updated load and price forecasts for the future periods from $i+1$ to $i+N$.
- 3) Solve the energy purchasing cost minimization problem, which is a linear programming problem, formulated as:

$$\text{Min. } U(i) \cdot P(i) + \sum_{k=i+1}^{i+N} U(k) \cdot \hat{P}(k) \quad (5.8)$$

$$\text{s.t. (2), (4), (5) - (7), } k = i, i+1, \dots, i+N,$$

$$U(i) = L(i) + C(i) - \eta_d D(i), \quad (5.9)$$

$$U(k) = \hat{L}(k) + C(k) - \eta_d D(k), k = i+1, \dots, i+N \quad (5.10)$$

The first part $U(i) \cdot P(i)$ is the energy cost in the current period i . Its actual load $L(i)$ and energy price $P(i)$ are known. The second part $\sum_{k=i+1}^{i+N} U(k) \cdot \hat{P}(k)$ is the total energy cost of the following periods from $i+1$ to $i+N$. Its load $\hat{L}(k)$ and energy price $\hat{P}(k)$ are forecasted values. The solution of this optimization problem gives an optimal operation schedule for energy storage from periods i to $i+N$.

- 5) Implement the first period's operation of the above solution, which is the period i to determine how the energy storage should be operated and the amount of energy $U(i)$ needs to be purchased.
- 6) Update the energy storage level state, move to the next period, and then repeat the algorithm from step 1.

Several forecasting techniques for predicting short term electricity price and load have been presented by researchers. Good short-term (e.g. within 24 hours) price and load forecasts are available. The very short-term (e.g. next 2-3 hours) forecast is more accurate than the relatively longer term (e.g. 23-24 hours) forecast. Thus, by using this

MPC-based method, after each control step, the price and load forecast are updated according to the newest forecast. Then the most updated and accurate price and load forecast could be effectively integrated into the operation to minimize the energy purchasing cost.

The proposed MPC-based control method is implemented in grid connected operation mode. Then in the islanding mode, the energy storage is operated to sustain the service in this segment to avoid a loss of load event or minimize the unserved energy within operation limits.

5.3.3 Hybrid Operation Strategy

The standby backup operation strategy can significantly improve reliability level, as the energy storage generally holds maximum amount of energy to support the load when an islanding occurs. The loss of load events and unserved energy can be effectively reduced. The MPC-based operation strategy can significantly improve the economic benefits by reducing energy purchasing cost, as energy storage is actively utilized to store energy when the energy price is low and to discharge energy when the energy price is high. The basic idea of the hybrid operation strategy is conceptually dividing the energy storage device storage capacity into two portions. One portion of the energy storage is implemented with the standby backup operation strategy, while the other portion is implemented with the MPC-based operation strategy. The standby

backup portion maintains a certain specified energy storage level to prepare for the failure event, which helps improve reliability. The MPC-based portion is taking the advantage of the energy storage operation flexibility to minimize energy cost, which contributes to the economic benefits. With a certain energy storage capacity, if the standby backup portion, expressed as $B\%$, increases, the MPC-based portion, $(100\% - B\%)$, decreases. Accordingly, the reliability of the system is further improved but the economic benefit is reduced, and vice versa. Through this operation strategy, a flexible tradeoff between reliability and economic improvements is achieved. The feasible range for $B\%$ is from 0% to 100% . When $B\%$ equals to 0% , it is a pure MPC-based operation strategy; when $B\%$ equals to 100% , it is a pure standby backup operation strategy; when $B\%$ is in between, it is a hybrid operation strategy mixed with the MPC-based and the standby back operation strategy. Thus $B\%$ could be used as a parameter representing which energy storage operation strategy is implemented. This operation strategy parameter is as important as the other energy storage parameters such as energy storage capacity and power rate when it comes to the impact on distribution system reliability and economy.

5.3.4 Reliability and Economy Evaluation

With a given set of energy storage parameters including operation strategy parameter, energy storage capacity and power limit, etc, its impact on distribution

system reliability and economy could be evaluated.

In reliability evaluation, a power system is considered to be operating in either success state or failure state. A system is considered operating in success state when it has enough generation to serve the load. When there is not sufficient generation to meet the load demand, and loss of load occurs, the system is in failure state. Loss of Load Expectation (LOLE) and Expected Energy not Served (EENS) are chosen as the reliability indices. In economy evaluation, the annual energy purchasing cost for load aggregator is used as the economy index.

In order to capture the inter-temporal characteristic of energy storage which has a key impact on distribution system reliability and economy, Sequential Monte Carlo Simulation is used for reliability and economy evaluation.

5.4 Problem Formulation

The objective of the energy storage design is to simultaneously optimize multiple objectives including reliability and economy by choosing the optimal energy storage parameters subject to the constraints for a specific distribution system. In this work, the design variables of energy storage include not only the energy storage capacity and power, but also the operation strategy, which is a major contribution of this research work. Other design variables such as charging/discharging efficiency could also be included.

5.4.1 Energy Storage Design Objectives

Objective 1: Reliability

One of the purposes of utilizing energy storage is to improve distribution system reliability. Reliability indices such as LOLE and EENS could be used to measure the reliability performance. These reliability indices are provided through the previously discussed reliability and economy evaluation using Sequential Monte Carlo Simulation.

Objective 2: Cost

The improvement of reliability normally comes with higher economic cost. Here, two sources of cost are considered. One is the annual energy purchasing cost, and the other is the annual energy storage cost. Annual energy purchasing cost is obtained through the reliability and economy evaluation. Annual energy storage cost is computed as the sum of the annual operation and maintenance cost, annualized total capital cost, and annualized replacement cost [32].

The annual operation and maintenance cost, OMC , is

$$OMC = OM_f \cdot C_{Max} \quad (5.11)$$

where OM_f is the annual operation and maintenance cost per kW.

The total capital cost for energy storage, TCC , consists of three components: the total (power) cost of power electronic rectifiers/inverters, the total (energy) cost for

storage units, and the cost for the balance of plant.

The total cost for the power electronics, PCS, is

$$PCS = PCSU \cdot C_{Max} \quad (5.12)$$

where PCSU is the cost for power electronics per kW.

The total cost of storage units, SUC, is

$$SUC = SUCU \cdot SOC_{max} \quad (5.13)$$

where SUCU is the storage unit cost per kWh.

The total cost for the balance of plant, BOP, is

$$BOP = BOPU \cdot SOC_{max} \quad (5.14)$$

where BOPU is the cost for the balance of plant per kWh.

The TCC is calculated as

$$TCC = PCS + SUC + BOP \quad (5.15)$$

The annualized capital cost, AC, is

$$AC = TCC \cdot CRF \quad (5.16)$$

where CRF is capital recovery factor, expressed as

$$CRF = \frac{i_r (1 + i_r)^y}{(1 + i_r)^y - 1} \quad (5.17)$$

where i_r is the annual interest, y is the lifetime of energy storage (year).

The annualized energy storage replacement cost, ARC, is

$$ARC = SOC_{Max} \cdot F \cdot [(1 + i_r)^{-r} + (1 + i_r)^{-2r} + \dots] \cdot CRF \quad (5.18)$$

where F is the future value of replacement cost per kWh, r is the replacement period (year).

At last, the annual energy storage cost, AEC, is calculated

$$\text{AEC} = \text{OMC} + \text{AC} + \text{ARC} \quad (5.19)$$

5.4.2 Energy Storage Design Constraints

A set of technical and operational constraints need to be satisfied when considering energy storage design.

Energy storage technology constraints: Due the current energy storage technologies development, the choices of available energy storage are limited. Normally, for a specific energy storage technology, such as Sodium Sulfur battery, there are limits on how large the capacity and power rate can be built. The design choices of energy capacity and power rate should be within the feasible range.

Power flow and other operational constraints: During operation, power flow should be balanced. Energy storage operations should be within the operational limits. These constraints are implemented in the reliability and economy evaluation process. Energy storage operation strategy, which is represented by the operation strategy parameter, $B\%$, is within the range from 0% to 100%.

5.5 Modified Particle Swarm Optimization Approach

Particle Swarm Optimization (PSO) is a population-based stochastic

optimization procedure originated from the ideas of swarm intelligence and field of evolutionary computation. It is being used in diverse optimization problems including power systems optimization, such as economic dispatch [33].

In this work, a constrained multi-objective particle swarm optimization approach is proposed to solve the energy storage design problem. Unlike single objective optimization, the optimal solutions of the multi-objective optimization are a set of non-dominated solutions. These solutions form a Pareto front which provides flexible choice of tradeoff among multiple objectives for decision maker.

The decision variables include energy storage capacity, power rate, and operation strategy. The solution candidate can be represented as

$$x_i = [x_{i_1}, x_{i_2}, x_{i_3}] \quad (5.20)$$

where $x_{i_1}, x_{i_2}, x_{i_3}$ represents energy storage capacity, power rate, and operation strategy parameter respectively. i is the number of the particle. i_1, i_2, i_3 represents the 1st, 2nd, and 3rd design variables of the i th particle. Each design variable is constrained within its design limit.

5.5.1 Optimization Procedure

The modified multi-objective particle swarm optimization procedure is implemented as follows:

- 1) Determine the design variables constraints, which include the upper and lower bound of energy storage capacity, power rate, and operation strategy parameter.
- 2) Initialize the first population of particles and their velocity by random generation within design variables constraints.
- 3) Evaluation the predetermined objective values (i.e. reliability and economy) for each particle in the population.
- 4) Select the personal best, $pbest$, through the personal best selection procedure described later.
- 5) Select the global best, $gbest$, through the global best selection procedure described later.
- 6) Update the member velocity vof each individual particle

$$\begin{aligned}
 v_{i_d}(t+1) = & \omega v_{i_d}(t) + c_1 r_1 [pbest_{i_d} - x_{i_d}(t)] \\
 & + c_2 r_2 [gbest_d - x_{i_d}(t)], \quad (5.21) \\
 & i = 1, \dots, N; d = 1, 2, 3
 \end{aligned}$$

The parameters ω, c_1 , and c_2 ($0 < \omega < 1.2$, $0 < c_1 < 2$, $0 < c_2 < 2$) are user-supplied coefficients. r_1 , and r_2 ($0 < r_1 < 1$, $0 < r_2 < 1$) are random values regenerated for each velocity update. $v_{i_d}(t)$ is the velocity of the d th design variable of the i th particle at time t . $pbest_{i_d}$ is the d th design variable of the i th particle's personal best solution. $gbest_d$ is the d th design variable of the global best solution. N is the total number of particles. d is the number of design variables.

- 7) Update the member position (design variable) of each particle

$$\begin{aligned} x_{i_d}(t+1) &= x_{i_d}(t) + v_{i_d}(t+1), \\ i &= 1, \dots, N; d = 1, 2, 3 \end{aligned} \quad (5.22)$$

- 8) Add turbulence factor into the current position.

$$\begin{aligned} x_{i_d}(t+1) &= x_{i_d}(t+1) + R_r \cdot x_{i_d}(t+1), \\ i &= 1, \dots, N; d = 1, 2, 3 \end{aligned} \quad (5.23)$$

where R_T is a random value as the turbulence factor used to enhance the solution diversity.

- 9) Check the feasibility of the design variables for each particle. If the design variables are out of the boundaries, the design variables are corrected to the nearest boundary values.
- 10) Increase the iteration by one. Stop the optimization and output Pareto front if the stopping criterion is reached (e.g. maximum number of iterations). Or go to step 3) to start another round of iteration.

5.5.2 Personal Best and Global Best

In step 4, personal best solution of a particle needs to be selected. This personal best selection procedure is implemented as follows. For each particle, there is a memory space for storing only one personal best solution. Thus N particles correspond to N personal best solutions. In the first iteration, each personal best memory is empty and then is filled in with the corresponding particle from the first population. After the

first iteration, the personal best memory is not empty. Each personal best is then compared with the newly updated particle. If the newly updated particle is not dominated by the personal best in the memory, the newly updated particle replaces the personal best in the memory. And then used as the *pbest* for updating velocity.

In step 5, global best solution of the population needs to be selected. The procedure is as follows. First, an initial size of the global best solutions archive is determined. This global best archive is used to store all the non-dominated solutions from the population. For each iteration, the personal best solution for each particle is added to the global best archive if any of the following criterions is met: 1) The archive is empty; 2) The personal best is not dominated by any solution in the archive. After adding all the personal best solutions meeting the previous criterions, the solutions in the global best archive is checked to eliminate any solution which is dominated by any other solution. This process is to maintain that all the solutions in the global best archive are non-dominated. The initial size of the global best archive is increased if more qualified solutions are to be added. After updating the global best archive, a solution in the archive is randomly selected as the *gbest* for updating velocity. When the iteration process is stopped, the solutions in the global best archive are outputted to provide the Pareto front for decision makers.

5.6 Case Studies

The proposed methodology is applied to the energy storage design problem in a modified practical distribution system, shown in Figure 34, where energy storage is integrated in segment 2. The objectives considered in this case study are ENNS as the reliability index, and the total annual cost as the economy index, which is the sum of the annual energy purchasing cost and energy storage cost. IEEE-RTS load profile is applied. Electric energy price profile is shown in Table 12. The price and load forecasts are assumed to be perfect. The energy storage design constraints and parameters, distribution system parameters, and particle swarm optimization parameters are listed in Table 17.

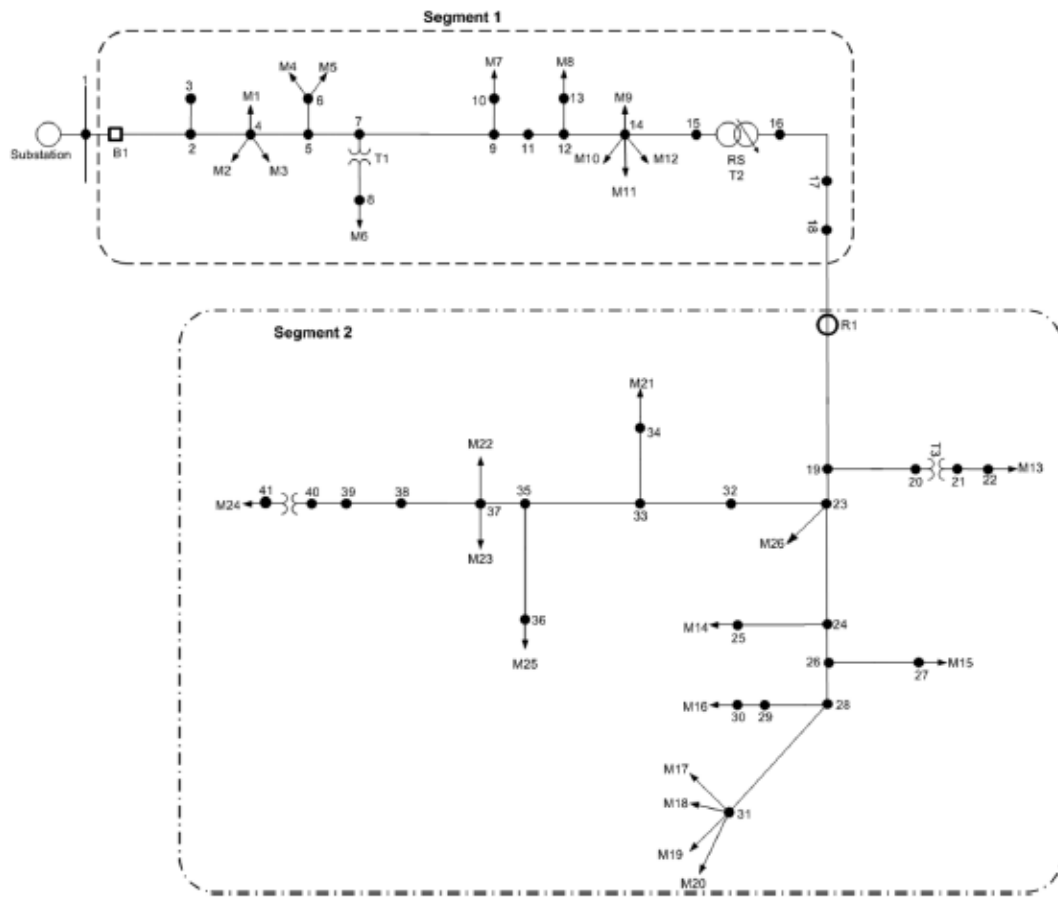


Figure 34 Modified practical radial distribution system with energy storage integrated in segment 2.

Table 17 Case Study Parameters [34][35]

Energy storage capacity	0 to 30MWh
Energy storage power rate	0 to 4MW
Energy storage operation parameter	0% to 100%
Energy storage efficiency	90%
Energy storage technology	Sodium Sulfur
Energy storage unit cost for power electronics (\$/kW)	1000
Energy storage unit cost for storage units (\$/kWh)	500
Energy storage fixed O&M cost (\$/kW)	20
Energy storage unit cost for balance of plant (\$/kWh)	0
Energy storage financing interest rate	5%
Energy storage Lifetime (year)	15
Energy storage replacement times of lifetime	0
Distribution system peak load (MW)	8
External supply: Mean Time To Failure (MTTF) (hours):	1440
External supply: Mean Time To Repair (MTTR) (hours):	8
Segment 1: Mean Time To Failure (MTTF) (hours):	720
Segment 1: Mean Time To Repair (MTTR) (hours):	4
Segment 1: Shared load percentage	50%
Segment 2: Mean Time To Failure (MTTF) (hours):	720
Segment 2: Mean Time To Repair (MTTR) (hours):	4
Segment 2: Shared load percentage	50%
PSO: ω	1
PSO: c_1, c_2	1,1
PSO: R_t	[-0.02,0.02]
PSO: Number of Particles	25
PSO: Maximum number of iterations	100

After implementing the proposed approach on the studied system, the Pareto front is generated and displayed in Figure 35.

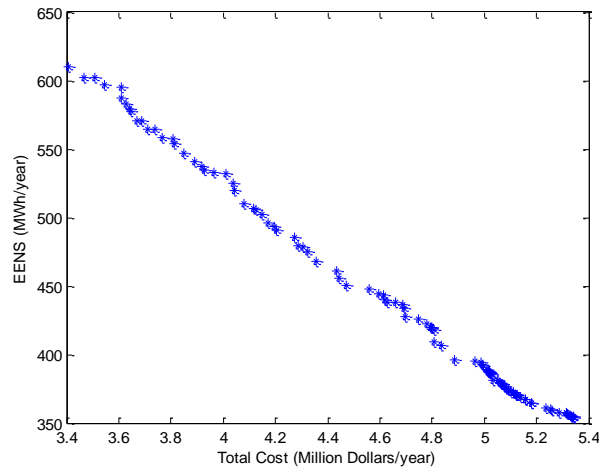


Figure 35 Pareto front with the tradeoff between EENS and total annual cost.

With the Pareto front, the decision makers could have the knowledge of what level of reliability improvement and economic benefits can be achieved through energy storage optimal design. After the desired level of reliability and cost are determined, corresponding energy storage capacity and power sizing, and operation strategy can be determined. Depending on the specific energy storage technology considered, if the energy storage capacities and power rates are only available at discrete level, the nearest discrete level of capacity and power could be chosen as the feasible design. A list of design examples is presented in Table 18. Design #1 to #10 are Pareto optimal designs selected from solutions shown in Figure 35. Design #11 is a dominated design for comparison.

Table 18 Energy Storage Design Solution Examples

#	Objectives		Energy Storage Design		
	EENS (MWh/yr)	Cost (M\$/yr)	Capacity (MWh)	Power (MW)	Operation Parameter
1	610	3.41	0.00	0.00	-
2	547	3.85	5.71	1.92	73%
3	541	3.89	7.99	1.85	45%
4	394	4.99	30.00	4.00	48%
5	377	5.08	30.00	4.00	69%
6	365	5.18	30.00	4.00	86%
7	354	5.34	30.00	4.00	100%
8	570	3.69	4.64	1.06	43%
9	565	3.71	4.52	0.89	87%
10	434	4.69	20.21	2.54	100%
11	437	4.89	30	4.00	10%

As shown in Table 18, one possible design (#1) is simply not having energy storage. In this way, cost is low due to no investment in energy storage, but the reliability is suffering. Design #2 and #3 give similar reliability and cost tradeoff, however the designs are quite different. Design #3 has a much higher energy storage capacity. While design #2 has a much higher operation parameter, which means a larger portion of energy storage is operated with standby backup strategy. This result illustrates the importance of the matching of the energy storage design variables. Design #4, #5, #6, and #7 all choose the same highest energy storage capacity (30MWh) and power (4MW). However, the operation strategies are very different. The same energy storage operated with different strategies leads to very different reliability

level and economic benefits. The energy storage capacity and power of Design #8 are higher than those of Design #9. Accordingly, the annual energy storage cost of Design #8 is higher than that of #9, which is part of the total cost. However, this does not necessarily mean the total cost of Design #8 is higher than Design #9. Design #8 utilizes a lower portion with standby backup operation strategy and a higher portion with MPC-based operation strategy, which reduces the energy purchasing cost. Because of the different operation strategies implemented, the total cost of Design #8 with more expensive energy storage is actually less than the total cost of Design #9. Design #11 is not a Pareto optimal design. Compared to Design #10, which is a Pareto optimal design, design #11 has a better energy storage capacity and power. But because #10 has a better matching of energy storage and operation strategy, both EENS and cost are less than those with design #11. These observations demonstrate the importance of operation strategy consideration when designing energy storage.

5.7 Summary

The objectives of the movement toward the smart grid include making the power systems more reliable and economically efficient. The rapid development of the large scale energy storage technology, such as sodium sulfur batteries, makes it an excellent candidate in achieving the goals of the smart grid. This section presented a modified multi-objective particle swarm optimization approach to solve the energy storage

design problem in distribution systems. A Pareto front is provided by the proposed approach for decision makers to determine the desired tradeoff between multiple objectives. Within the energy storage design variables, not only the conventionally considered energy storage capacity and power rate are included, but also the energy storage operation strategy. Three energy storage operation strategies are presented and their impacts on reliability and economy are illustrated. A case study is performed to demonstrate the effectiveness of the proposed approach. Insights based on the case study results are discussed.

In this section, three energy storage operation strategies, which are standby backup strategy, MPC-based strategy and hybrid strategy, are presented. A parameter is proposed to represent the energy storage operation strategy in energy storage design process. The importance of energy storage operation strategy in reliability improvement and economic benefits is demonstrated. A modified multi-objective particle swarm optimization approach is proposed to solve the energy storage design problem which not only includes energy storage capacity and power rate, but also the operation strategy. The case study results demonstrate the effectiveness of the proposed approach in providing a Pareto front of the multi-objective optimization problem. Insights on the importance of the proper matching of the energy storage design variables and the impact of energy storage operation strategy are illustrated.

6. THE IMPACT ON POWER SYSTEMS WITH THE INTEGRATION OF ENERGY STORAGE AND RENEWABLE ENERGY*

6.1 Introduction

Renewable energy and energy storage integrated in the distribution systems could help reduce energy purchasing cost for the distribution system load aggregators and improve the distribution system reliability. As discussed in the previous sections, the load aggregator who operates energy storage and renewable energy within its distribution system focuses on improving its own economic and reliability level. The proposed operation strategies only consider the optimal objectives for the distribution systems. In a market environment, individual load aggregators should focus on maximizing their own benefits which include economic and reliability benefits. However, as an interconnected power system, each distribution systems is connected to the transmission system. The operation strategies each distribution system load aggregator implements could also affect the performance of the overall power systems. In this section, we investigate the impact on the whole power systems, which includes transmission systems, generation systems and distribution systems, brought by the

*Part of the material in this section is reprinted from “Adequacy and Economy Analysis of Distribution Systems Integrated with Electric Energy Storage and Renewable Energy Resources” by Yixing Xu and Chanan Singh, *IEEE Transactions on Power Systems*. © 2012 IEEE.

integrated energy storage and renewable energy. The quantification of the impact is essential for evaluating the integration project and determining the proper compensations or incentives for the load aggregator. This value for power system could also contribute to the justification of the energy storage and renewable energy investment.

6.2 System Configuration

The investigated power system includes distribution system, transmission system and generation system. The distribution systems are discussed in previous Section 4. Energy storage and renewable energy are integrated within a distribution system. The load aggregator of that distribution system operates the energy storage devices and renewable energy production. It also participates in the power markets to manage its energy purchase. As proposed in Section 4, a novel Model Predictive Control (MPC) – based operation strategy is implemented to reduce energy purchasing cost and improve reliability by optimally coordinating the power supplies from energy storage, renewable energy, and external grid through the timeline. IEEE-RTS 24 Bus System [36] is used for this study, as shown in Figure 36. The failure of generators and transmission lines are considered. The transmission lines capacities are also considered. Optimal Power Flow Calculation is performed using MatPower 4.0 [37].

The energy storage devices and renewable energy resources are integrated at bus

18 in this study, other buses could also be chosen. The load aggregator at bus18 operates with the MPC-base strategy to maximize its own benefits. The electric energy price profile is shown in Table 12. Only during the event of loss of load in the power system, energy storage and renewable energy could be utilized to support the whole power system's demand instead of only the demand in its distribution system. In this way, energy storage and renewable energy could also benefit the power system even it is mainly utilized as a distribution system resource.

6.3 Operation Strategies

The distribution system integrated with the energy storage devices and renewable energy resources at bus 18 is operated with the previously proposed MPC-base strategy in Section 4. The summary of the MPC-based operation strategy is as follows.

Operation Strategy in Grid Connected Mode: In grid connected mode, the power from external grid, renewable energy and energy storage can all be utilized to serve the load. The objective of the load aggregator is to minimize its energy purchasing cost in power market while meeting the demand.

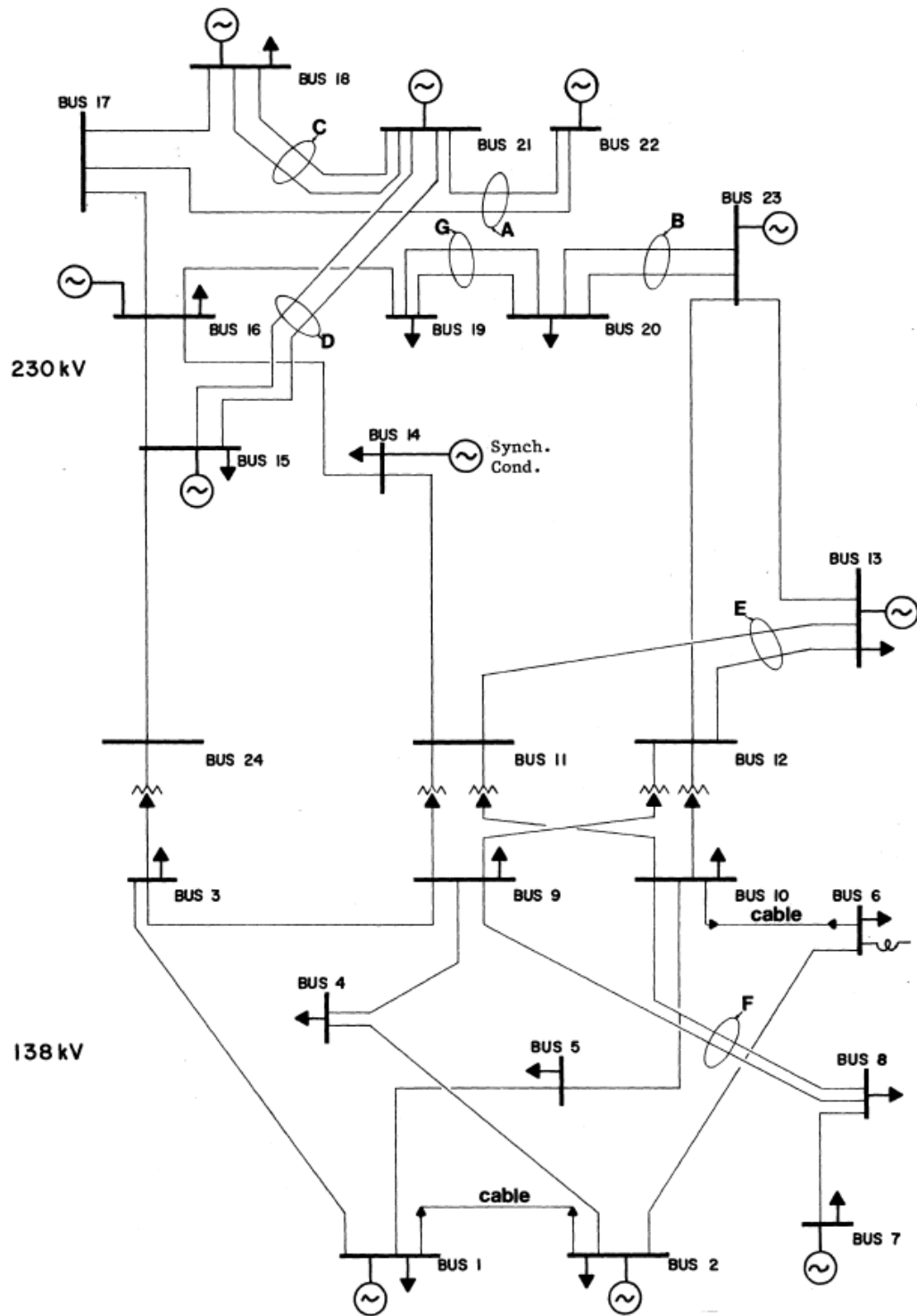


Figure 36 IEEE Reliability Test System.

The energy purchasing cost minimization problem with forecasted, load, available renewable energy and price at period i can be implemented as follows:

- 1) Obtain the actual load, available renewable energy and price in the current period i .
- 2) Select a receding optimization horizon of N periods (e.g. 24 hours). Use load, renewable energy and price forecast models to obtain the most updated load, renewable energy and price forecasts for the next N periods, from period $i+1$ to $i+N$.
- 3) Solve the optimization problem, formulated as follows.

Objective: Minimizing energy purchasing cost from period i to $i+N$

$$\text{Min. } U(i) \cdot P(i) + \sum_{k=i+1}^{i+N} U_f(k) \cdot P_f(k) \quad (6.1)$$

The first part $U(i) \cdot P(i)$ is the energy purchasing cost of the current period i . The second part $\sum_{k=i+1}^{i+N} U_f(k) \cdot P_f(k)$ is the predicted total energy purchasing cost of the following periods from $i+1$ to $i+N$. $U(i)$ and $U_f(k)$ are the decision variables to be solved.

Constraints:

- i. EES operation constraints

$$0 \leq C(k) \leq C_{Max} \quad (6.2)$$

$$0 \leq D(k) \leq D_{Max} \quad (6.3)$$

$$SOC_{Min} \leq SOC(k) \leq SOC_{Max} \quad (6.4)$$

where $k=i, i+1, \dots, i+N$. The charging and discharging operations of EES are to be solved. The maximum charging and discharging rates are constant. As one hour is considered as one period in this paper, the charging energy equal to $C(k)$ multiplied by 1 hour. For convenience $C(k)$ is used interchangeably as charging rate and energy charged in one hour. $D(k)$ is treated in the same way.

ii. Available renewable energy constraints

$$0 \leq R(i) \leq R_{Max}(i) \quad (6.5)$$

$$0 \leq R_f(k) \leq R_{f,Max}(k) \quad (6.6)$$

where $k = i+1, \dots, i+N$. The utilized renewable energy is equal to or less than the available renewable energy. Extra energy not utilized is dumped in ways such as adjusting the wind turbines' blade pitch, so wind turbines do not generate the maximum power they can in that period. Utilized renewable energy for current period and future period are to be solved.

iii. Power balance constraints

$$U(i) + R(i) = L(i) + C(i) - \eta_d D(i) \quad (6.7)$$

$$U_f(k) + R_f(k) = L_f(k) + C(k) - \eta_d D(k) \quad (6.8)$$

where $k = i+1, \dots, i+N$. Load, available renewable energy, and price in current period i are the actual values and known. While load, available renewable

energy, and price in future periods are predicted using forecast models, thus are given parameters for the optimization problem. The solution of this optimization problem gives an optimal operation schedule for EES charging/discharging operation, energy purchase and renewable energy utilization from period i to $i+N$.

- 4) Implement the first period's operation of the solved operation schedule, which is the current period i .
- 5) Update the EES state of charge level, move to the next period, and repeat the algorithm from step 1.

Operation Strategy in Islanding Mode: In islanding mode, avoiding and minimizing load curtailment is the objective. The available renewable energy is first utilized to serve the load. If it is not enough to cover the load, the energy stored in EES is discharged to avoid or minimize load curtailment. Only when the load demand is met, and there is renewable energy surplus, the extra energy is stored in EES for future usage without violating EES operation limits. The extra energy which cannot be stored in EES is then dumped.

Operation Strategy during Loss of Load Events: Beside operation strategies in previous two modes. One more operation strategy is implemented. This operation is only conducted when there is a loss of load event wherever in the power system. In this

situation, avoiding this loss of load event of the system is the priority. The energy storage will discharge to its limit until it can prevent a loss of load event. The renewable energy will be fully utilized to support the load. With the extra power from energy storage and renewable energy resources, the frequency and duration of the loss of load events could be reduced. The unserved energy of the power system could also be reduced. During the loss of load event, the energy storage and renewable energy is temporarily utilized as a whole power system's resource instead of just the distribution system's resource.

6.4 Reliability and Economy Evaluation

Considering the impact of the operation strategy of the energy storage and renewable energy, the reliability and economy evaluation method is based on Sequential Monte Carlo Simulation.

In adequacy analysis, a power system is considered to be operating in either success state or failure state. A system is considered operating in success state when it has enough generation capacity to serve the load considering the transmission lines capacities. When generation capacity is not sufficient to meet the load demand or the power cannot be delivered to meet the load due to transmission lines congestions and the loss of load occurs, the system is in failure state. According to the proposed operation strategies, the power from energy storage and renewable energy resource

could be utilized to support the load of the power system in the situation of insufficient generation. The probabilities and durations associated with the system residing in success and failure states and energy not served during failure states are the adequacy indices for reliability analysis. Loss of Load Expectation (LOLE) and Expected Energy Not Served (EENS) are calculated as the reliability indices. Other common distribution system indices could also be calculated if needed.

6.5 Case Studies

The IEEE RTS Test System, as shown in Figure 36, is studied. Hourly load profile from the test system is used. Considering that the expected growing load demand could lead to a less reliable power system. The load profile is scaled to 120% and 140% of the original load profile to simulate the growing load demand. Energy storage devices and wind turbines are integrated at bus 18. A base case without any energy storage device and wind turbine is studied first. The scenarios with only energy storage are then studied. The results are shown in Table 19.

From the simulation results, it can be observed that energy storage integrated in the distribution system is improving the overall system's reliability even though the energy storage is mainly utilized to benefit the distribution system itself. A more detailed scenarios study is conducted. The capacity and power of the simulated energy storage devices are listed in Table 20. The simulated Wind Turbines Generation (WTG)

capacities are 2MW, 5MW, 10MW, 20MW, 30MW, 40MW and 50MW.

Table 19 Reliability Indices without Wind Turbines

Load	Energy Storage		LOLP	EENS (10 ³ MW)
	Capacity (MWh)	Power (MW)		
1.2 × RTS Load	0	0	2.0719%	31.84
1.2 × RTS Load	40	10	1.9803%	31.10
1.4 × RTS Load	0	0	13.484%	316.31
1.4 × RTS Load	40	10	13.164%	314.22

Table 20 Capacity and Power of the Energy Storage Devices

Energy Storage	
Power (MW)	Capacity (MWh)
20	40
30	40
40	40
10	80
20	80
40	80
60	80
80	80

Each energy storage device will match with a WTG capacity to form a scenario.

The simulated load scale is 120% and 140% of the original load profile. The simulation results are displayed from Table 21 to Table 24.

Table 21 LOLP with 120% Load Scale

Energy Storage		WTG Capacity (MW)						
		2	5	10	20	30	40	50
Power (MW)	Capacity (MWh)							
20	40	1.8773%	1.8773%	1.8773%	1.8544%	1.8201%	1.8086%	1.7972%
30	40	1.8201%	1.8201%	1.8201%	1.7972%	1.7857%	1.7743%	1.7628%
40	40	1.7399%	1.7285%	1.7170%	1.6941%	1.6827%	1.6712%	1.6598%
10	80	1.9460%	1.9345%	1.9002%	1.8773%	1.8429%	1.8086%	1.7857%
20	80	1.8544%	1.8544%	1.8429%	1.8086%	1.7743%	1.7743%	1.7628%
40	80	1.7170%	1.7170%	1.6941%	1.6827%	1.6712%	1.6598%	1.6369%
60	80	1.6026%	1.6026%	1.6026%	1.5797%	1.5453%	1.5453%	1.5224%
80	80	1.5453%	1.5110%	1.4881%	1.4766%	1.4309%	1.4309%	1.4194%

Table 22 EENS (10^3 MWh) with 120% Load Scale

Energy Storage		WTG Capacity (MW)						
		2	5	10	20	30	40	50
Power (MW)	Capacity (MWh)							
20	40	30.84	30.75	30.66	30.44	30.19	30.13	29.99
30	40	30.64	30.55	30.47	30.23	30.05	29.97	29.84
40	40	30.32	30.23	30.10	29.88	29.70	29.60	29.46
10	80	30.57	30.50	30.38	30.19	30.06	29.86	29.76
20	80	30.35	30.29	30.26	29.99	29.77	29.74	29.68
40	80	30.23	30.15	30.00	29.80	29.62	29.52	29.33
60	80	29.66	29.58	29.49	29.26	28.95	28.92	28.69
80	80	29.29	29.04	28.78	28.62	28.17	28.14	27.97

In Table 21 and Table 22, it can be noticed that the system is still relatively reliable with LOLP from 1.4% to 1.9%. When the energy storage has 20MW power and 40MWh capacity, the expansion of WTG from 2MW to 10MW does not improve LOLP. That is because in the loss of load event, the added WTG is too small to cover the generation inadequacy.

Table 23 LOLP with 140% Load Scale

Energy Storage		WTG Capacity (MW)						
		2	5	10	20	30	40	50
Power (MW)	Capacity (MWh)							
20	40	12.935%	12.901%	12.866%	12.740%	12.626%	12.523%	12.374%
30	40	12.763%	12.717%	12.637%	12.523%	12.420%	12.294%	12.157%
40	40	12.500%	12.454%	12.397%	12.283%	12.179%	12.065%	11.928%
10	80	12.981%	12.969%	12.901%	12.706%	12.626%	12.534%	12.454%
20	80	12.866%	12.821%	12.786%	12.649%	12.511%	12.386%	12.225%
40	80	12.374%	12.328%	12.283%	12.145%	12.042%	11.939%	11.813%
60	80	11.985%	11.939%	11.870%	11.756%	11.619%	11.527%	11.390%
80	80	11.573%	11.550%	11.481%	11.344%	11.218%	11.115%	11.035%

However, the added WTG reduces the energy not served from 30.84GWh to 30.66GWh. In Table 23 and Table 24, with a much larger load demand, the system has a LOLP from 11% to 13%. Compared with the results of 120% load scale, the same expansion of energy storage and WTG could reduce more loss of load events. The same phenomenon can also be observed for EENS.

Table 24 EENS (10^3 MWh) with 140% Load Scale

Energy Storage		WTG Capacity (MW)						
		2	5	10	20	30	40	50
Power (MW)	Capacity (MWh)							
20	40	313.86	313.71	313.35	312.55	311.97	311.44	310.85
30	40	313.48	313.27	312.76	311.98	311.35	310.68	310.05
40	40	312.65	312.41	312.02	311.22	310.55	309.90	309.25
10	80	312.98	312.88	312.57	311.73	311.38	310.94	310.66
20	80	312.97	312.83	312.50	311.66	311.12	310.58	309.97
40	80	312.10	311.92	311.51	310.67	310.04	309.39	308.78
60	80	310.30	310.02	309.48	308.57	307.69	306.98	306.24
80	80	307.67	307.52	307.01	305.81	304.87	304.14	303.71

For example, in Table 22, when increase energy storage capacity from 40MWh to 80MWh, power from 20MW to 80MW and WTG from 2MW to 50MW, the reduction of EENS is only 2.87MWh (30.84–27.97). In Table 24, the same expansion leads to an EENS reduction of 10.15MWh (313.86–303.71). The reliability improvement is more effective when the system is less reliable.

6.6 Summary

The proposed operation strategies in Section 4 are to serve the distribution

system integrated with energy storage and renewable energy. However, the operations of the distribution system have an impact on the whole power system's reliability level. This section investigates this impact on the system reliability. The simulation results demonstrate the reliability impact on the power system. Considering that the objective of the MPC-based operation strategy is to serve the distribution system, the reliability improvement for the whole power system is a positive external impact. The evaluation of this reliability impact could be utilized to quantify the benefits of the energy storage and renewable energy which are mainly utilized as the distribution system resources. The quantified benefits for the power system could be utilized to better value the integration of energy storage and renewable energy. Proper compensations or incentives to the energy storage and renewable energy resources owners could later be determined by the system operators.

7. CONCLUSIONS AND OUTLOOK

With the recent rapid development of energy storage technologies, expected large penetration of renewable energy sources, and the movement toward a more reliable and efficient smart grid, many technical challenges need to be solved. This dissertation focuses on the operation strategies, evaluation methods and optimization framework related to the integration of energy storage and renewable energy which could be utilized to make the electric grid more reliable and efficient. Several important topics in this research arena are investigated.

- In the past, electric power systems are basically operated on the basis of real-time balancing of supply and demand. Now, with the relatively more affordable large scale energy storage devices available, the conventional operation strategies should be revisited. In a market environment, a distribution system load aggregator with energy storage devices needs to understand how to optimally operate them. In Section 2, a method for determining the optimal scheduling and operation of a load aggregator with energy storage in power markets is presented. Load aggregators could use this method to minimize its energy purchasing cost in power markets. This method takes in the price and load forecasts as its input to determine what should be the optimal operation in

the current period. With real-time updated forecasts, its operations are also adjusted to be optimal. Simulations are performed to demonstrate the effectiveness of the method and the robustness while facing price and load uncertainties.

- Energy storage has its unique characteristics. It could either be utilized as a generation when the grid needs more energy to support the demand, or behave like a load when being charged. When should the energy storage devices be charged and discharged needs to be carefully investigated during operation. Not only could the energy storage sizing which includes energy storage capacity and power rate affect the power system reliability and economy, but also its operation strategies. Different energy storage operation strategies could have significant impacts on power systems even the size of the energy storage remains the same. In Section 3, three energy storage operation strategies are presented and their impact on power system reliability and economy are investigated. Simulation results shows how different the impacts are with different energy storage operation strategies. A hybrid operation strategy is proposed to flexibly adjust the reliability and economy impact brought by energy storage. The load aggregates could utilize this operation strategy to achieve and adjust their desired reliability and economy level with the same

energy storage devices installed.

- The renewable energy penetration is increasing with the expectation to reach more than 20% of the total generation. Energy storage could be utilized to facilitate the integration of renewable energy. In Section 4, a novel Model Predictive Control (MPC) based operation strategy is proposed to optimally coordinate the power supplies from renewable energy, energy storage and external grid in order to minimize energy purchasing cost. A reliability and economy evaluation framework integrated with the proposed operation strategies is also presented. Case studies results demonstrate the benefits of the proposed operation strategies and also provide insights on how energy storage capacity, power limit and wind turbine generation capacity impact reliability and economy.
- Utility scale energy storage devices are still a high cost investment. During the planning stage of energy storage installation and expansion, an optimization framework needs to be developed to determine the sizing of energy storage and its value to the power systems. In Section 5, a modified multi-objective particle swarm optimization approach is proposed to solve the energy storage design problem which not only includes energy storage capacity and power rate, but also the operation strategy. The case study results demonstrate the effectiveness

of the proposed approach in providing a Pareto front of the multi-objective optimization problem. Insights on the importance of the proper matching of the energy storage design variables and the impact of energy storage operation strategy are illustrated.

- Energy storage devices and renewable energy resources integrated in the distribution systems have an impact on the transmission system reliability. This impact is evaluated in Section 6. With the reliability impact quantified, the system operators could determine the proper compensations and incentives for the load aggregator. This value could contribute to the justification of the energy storage and renewable energy investment.

The proposed MPC-based operation strategy and hybrid operation strategy utilize renewable energy forecast, electric energy price forecast, and load forecast. The accuracy of these forecasts is important to the effectiveness of these strategies. With the development of the more accurate forecast techniques and algorithms, these operation strategies could be more beneficial to the power systems. Meanwhile, large scale stochastic optimization methods could be utilized to deal with the forecast uncertainties. The proposed energy storage sizing and operation strategy optimization framework needs to perform reliability and economy evaluation based on Monte Carlo Simulation. More efficient and accurate reliability and economy evaluation methods

could in turn improve the efficiency of the optimization process. In order to cover the high investment cost, more revenue streams and benefits besides energy purchasing cost savings and reliability improvement needs to be investigated. The possible applications include frequency regulation, spinning reserve and transmission congestion relief, etc. These applications could be included in the proposed multi-objective particle swarm optimization framework to evaluate the investment and determine the energy storage sizing and operation strategy. With the understanding of the reliability impact on the transmission systems brought by the energy storage and renewable energy integrated in the distribution systems, system operators could more efficiently plan for the future demand growth with the utilization of these resources.

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