ENERGY STORAGE DEVICES FOR SEAMLESS INTEGRATION OF RENEWABLE ENERGY

by

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Abstract

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Renewable energy, as a promising resource for supporting continuously growing electricity demand, bears the disadvantages of un-controllable variability and partial unpredictability, which present challenges for large-scale integration into power systems. To maintain stable system frequency, the mechanical energy driving the generators should be balanced with the electrical energy consumed by loads and losses at all times. However, high penetration level of renewable energy presents challenges for this basic requirement. Energy storage system (ESS) is one of the most promising solutions to shape the variable renewable generation to follow certain production plans which benefits both system operation and market participation. In addition, ESS can contribute to grid reliability needs, defer transmission and distribution upgrade investments as well as integrate renewable generation resources. Currently, it requires significant financial commitment for the implementation of large-scale ESS. Therefore, designing efficient ESS and developing effective operation algorithms for seamless integration of renewable energy are of great importance.

The Electrical Reliability Council of Texas (ERCOT) launched a nodal market in December, 2010, aiming at improving grid reliability, increasing market efficiency, and enabling transparency of wholesale energy prices. Under the new market design, the grid

congestion and the Locational Marginal Price (LMP) will be captured more rapid and granular across the network. LMP is defined as the “marginal cost of supplying, at least cost, the next increment of electric demand at a specific location on the electric power network, taking into account both supply bids and demand offers and the physical aspects of the transmission system including transmission and other operation constraints”. The variations of LMP across the network and the variations of LMP at any specific node along a day provide market participants more opportunities to pursue financial benefits. Moreover, participating energy efficiency programs like demand response (DR) program may bring market participants extra revenue. Texas Legislature passed Senate Bill (SB) 1125 in 2011, and one purpose of SB1125 is to qualify residential and commercial customer classes for participation in DR programs.

Considering the market opportunities for renewable energy, ESS is the key to reshape the random output dominated by weather condition to follow certain desired pattern. ESS can also work as the bridge between convenience and revenue when participating in demand response programs.

This dissertation presents the efforts involved in developing ESS operating strategies for different market participants, including renewable energy generation and end-user customers DR participation on both residential level and aggregated level. For renewable generation side, this dissertation addresses the idea of developing wind and solar PV hybrid system using ESS to compensate the intermittent output and match system load profile considering the facts that wind power has higher output at late night and early morning while solar PV only generates during day time. A hybrid ESS is also designed to dispatch wind farm output for maximizing financial revenue based on wind and LMP forecasting using Artificial Neural Networks (ANN). For end-user customer side, different scenarios are designed and studied for demand response program participation.

Residential appliances are classified and controlled accordingly to take advantage of the LMP information. Thus, ESS is utilized to integrate renewable energy at distribution level so that under different operation schemes, significant financial revenue can be collected and system reliability can be maintained.

Table of Contents

List of Illustrations

List of Tables

Chapter 1

Introduction

1.1 Current Development of Renewable Energy in Power Grids

The continuous growth of electricity demand poses challenges to the utility industry due to limited resources and potential environmental impacts. Figure 1-1 shows the net electricity generation of the United States from 1949 to 2011 based on the data published by the U.S. Energy Information Administration [1, 2]. According to the prediction, the net generation is projected to exceed 5000 billion kWh by 2035 [1, 2] . It usually takes 5-10 years to complete a nuclear plant [3]; 6 years to build a coal fire plant, and the construction lead time for a natural gas combined cycle power plant is about 3 years [4]. Moreover, this time-consuming process is constrained by many external factors such as government policies, economic conditions, and environmental concerns.

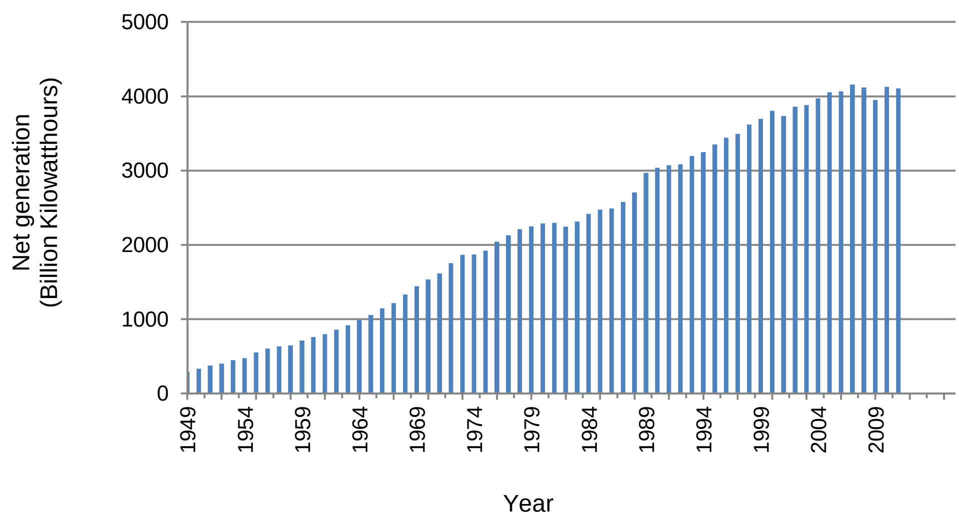


Figure 1-1 Net Electricity Generation of the United States from 1949 to 2011

As an alternative to fossil fuel plants, renewable energy draws more and more attention owing to its sustainable nature. Renewable energy is defined as “energy that is produced by natural resources such as sunlight, wind, rain, waves, tides, and geothermal heat that are naturally replenished within a time span of a few years” [5]. Some household and industrial waste is also considered as renewable energy source. The installation capacities of the renewable electricity generation have been growing in recent years and will continue to do so as shown in Figure 1-2. This growth will be dominated by wind and solar energy, while other renewable sources are more likely to be restricted by geographical conditions [6]. The development of renewable energy sources is supported by the renewable portfolio standards, the federal renewable fuels standards, federal tax credits, and etc. The Texas legislature passed Senate Bill 7 which restructured the electric market in Texas in 1999; and in 2005, Senate Bill 20 in Texas launched a goal to reach an additional 5880 MW of renewable energy capacity by 2015, while 500 MW are mandated to be non-wind resources. A further target for additional renewable energy capacity is 10000 MW by 2025 [7].

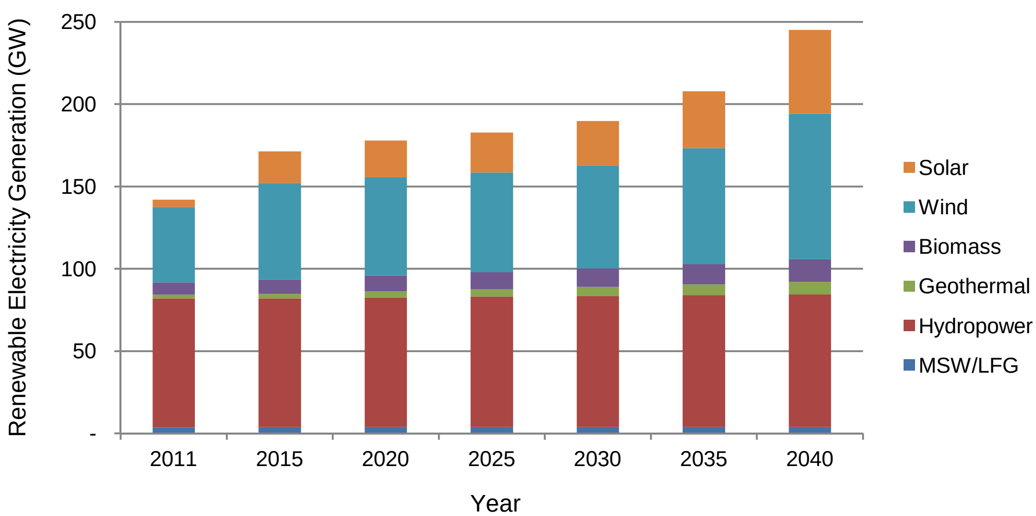


Figure 1-2 Renewable Electricity Generation Capacity by Energy Source

Using wind and solar to produce electrical energy are attractive because they have the following advantages: 1) no fuel cost and less pollution; 2) shorter construction time compared with conventional power plants; and 3) highly modular structure that more easily enables future expansion [8]. However, the non-dispatchable output of wind and solar energy presents significant challenges for system operators; especially the penetration level is high. To maintain a stable system frequency, the required mechanical energy to drive the generators should be equal to the electrical energy consumed by the loads and losses. The intermittent nature of wind and solar is no doubt an unstable factor for system operation. The day-night cycle causes extremely unevenly distributed solar power over the course of 24 hours, while wind power is typically higher at night and during early morning. Moreover, the output pattern of neither wind power nor solar power is synchronized with system load profile at most times. Figure 1-3 plots the system load and wind generation on 5/30/2013 of the Electricity Reliability Council of Texas (ERCOT), where the mismatch is shown. The peak load of the system is around 5 pm, while the wind generation is at the valley by that time.

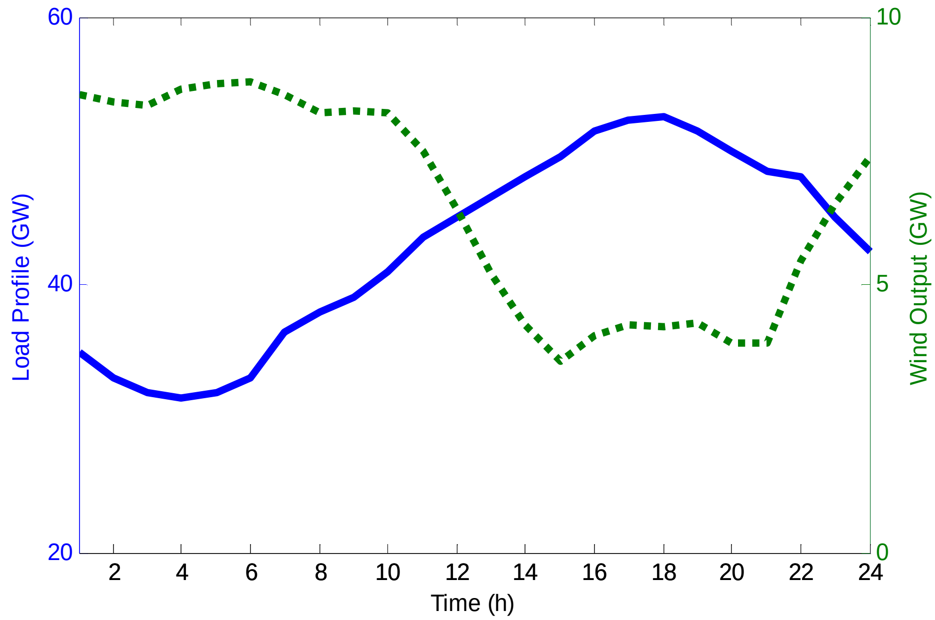


Figure 1-3 ERCOT System Load and Wind Power Production of 5/30/2013

1.2 Study Objectives

Energy storage systems (ESS) offer possible solutions to improve the effective utilization of renewable energy by shaping renewable generation to follow certain desired production plans, which benefit both system operation and market participation. Furthermore, ESS can contribute to grid reliability needs, defer transmission and distribution upgrade investments as well as promote seamless integration of renewable generation resources.

This dissertation presents the efforts involved in developing ESS operating strategies for the seamless integration of renewable energy. For renewable generation side, this dissertation addresses the idea of developing wind and solar PV hybrid system using ESS to compensate the intermittent output and match system load profile considering the facts that wind power has higher output at late night and early morning while solar PV only generates during day time. A hybrid ESS is also designed to dispatch wind farm output for maximizing financial revenue based on wind and LMP forecasting using Artificial Neural Networks. Demand response participation with ESS is discussed for end-user customer side; different scenarios are designed and studied for demand response program. Residential appliances are classified and controlled accordingly to take advantage of the LMP information. Thus, ESS is utilized to integrate renewable energy at distribution level so that under different operation schemes, significant financial revenue can be collected and system reliability can be improved.

1.3 Synopsis of Chapters

The organizational structure of this dissertation is as follows:

Chapter 1 introduces the current situation of renewable energy utilization in power grid and illustrates the importance, motivation and study objectives of this dissertation.

Chapter 2 compares the characteristics of the different energy storage technologies, and reviews several ongoing wind/solar power and energy storage hybrid projects in the United States. The increasing trend of utilizing energy storage devices is also discussed.

Chapter 3 proposes a wind and solar PV hybrid system design using ESS. The wind/PV capacity ratio is optimized and the hybrid system is later dispatched with batteries to better match system load profile.

Chapter 4 designs different scenarios for demand response program participation under ERCOT nodal market with ESS. The participation of end-use customers at both residential level and aggregated level are studied respectively. The participation of Voluntary Load Response program is studied for residential customers, and the application of renewable energy resources at distribution level with ESS are studied. For aggregated customers, the appliances are classified into different groups according to their criticality to human lives, and different control algorithms are designed to participate in demand response programs for financial benefits.

Chapter 5 discusses the dispatch scheduling of a wind farm with hybrid ESS. The day-ahead wind power and LMP are forecasted by Artificial Neural Networks, and the forecasted data are used to optimize the operation of the primary ESS. A secondary ESS is utilized to address the forecasting errors and improve the optimization results.

Chapter 6 presents the conclusions and future work directions of this dissertation.

Chapter 2

Literature Review

2.1 Characteristics of Different Storage Technologies

As a promising solution for solving the large-scale integration of renewable energy problem, energy storage has drawn more and more attention in recent years. As defined by the California Public Utilities Code Section 2835 (a) (1), energy storage system is “commercially available technology that is capable of absorbing energy, storing it for a period of time, and thereafter dispatching the energy” [9]. Many types of storage devices are available nowadays. Several criteria such as application type, reliability, feasibility, power rating, storage capacity, electrical efficiency, lifetime, response time and costs should be considered when selecting storage devices for different applications..

Function and form are two typically categories when classifying different ESSs [10]. As for function, the high power rating category can be applied for power quality control, and this category includes capacitors, supercapacitors, flywheels, superconducting magnetic energy storage (SMES), and batteries. On the other side, the high energy rating category is commonly employed for energy management and the ESS technologies include: pumped hydroelectric storage (PHS), compressed air energy storage (CAES), large-scale batteries, fuel cells, solar cells, etc.

Electricity can be stored in different forms, and converted back easily when needed. A summary of different forms of storage technology is shown in Table 2-1.

Table 2-1 Energy Storage Form Summary [10]

Electrical Energy Storage	Mechanical Energy Storage	Chemical Energy Storage	Thermal Energy Storage
• Electrostatic Storage - Capacitors - Supercapacitors • Magnetic/current energy storage - SMES	• Kinetic energy storage - Flywheels • Potential energy storage - Pump Hydro Storage - Compressed Air Energy Storage	• Electrochemical energy storage - Conventional batteries • Chemical Energy storage • Thermochemical energy storage	• Low temperature energy storage - Aquiferous cold energy storage • High temperature energy storage - Sensible heat systems

A detailed summary of the commonly used energy storage devices is presented in Table 2-2, where the power ratings, discharge characteristics, storage durations and capital costs between different technologies are compared respectively.

Table 2-2 Characteristic Comparison of Different Storage Technology [10]

Systems	Power Rating and Discharge Time		Energy and Power Density		Life Time and Cycle Life		Capital Cost		
	Power Rating	Discharge Time	Wh/kg	W/kg	Life time (years)	Cycle life (cycles)	$/kW	$/kWh	c/kWh-Per cycle
PHS	100-5000MW	1-24h+	0.5-1.5	-	40-60	-	600-2000	5-100	0.1-1.4
CAES	5-300MW	1-24h+	30-60	-	20-40	-	400-800	2-50	2-4
Lead-acid	0-20MW	seconds-hours	30-50	75-300	5-15	500-1000	300-600	200-400	20-100
NaS	50kW-8MW	seconds-hours	150-240	150-230	10-15	2500	1000-3000	300-500	8-20
Li-ion	0-100kW	minutes-hours	75-200	150-315	5-15	1000-10000+	1200-4000	600-2500	15-100
Fuel cells	0-50MW	seconds-24h+	800-10000	500+	5-15	1000+	10000+	-	6000-20000
Metal-Air	0-10kW	seconds-24h+	150-3000	-	-	100-300	100-250	10-60	-
SMES	100kW-10MW	milliseconds-8s	0.5-5	500-2000	20+	100000+	200-300	1000-10000	-
Flywheel	0-250kW	milliseconds-15min	10-30	400-1500	~15	20000+	250-350	1000-5000	3-25
Capacitor	0-50kW	milliseconds-60min	0.05-5	~100000	~5	50000+	200-400	500-1000	-
Super-capacitor	0-300kW	milliseconds-60min	2.5-15	500-5000	20+	100000+	100-300	300-2000	2-20

2.2 Ongoing Wind/Solar Energy Storage Hybrid Projects

Winds are caused by uneven heating of the atmosphere by the sun, together with the irregularities of the Earth's surface and the rotation of the Earth; all these factors influence the wind source of a specific location. The wind flow, if captured by the wind turbines, is an abundant and valuable source of generating electricity. As shown in Figure 2-1, the United States (U.S.) has tremendous wind sources especially in the central part of the continent.

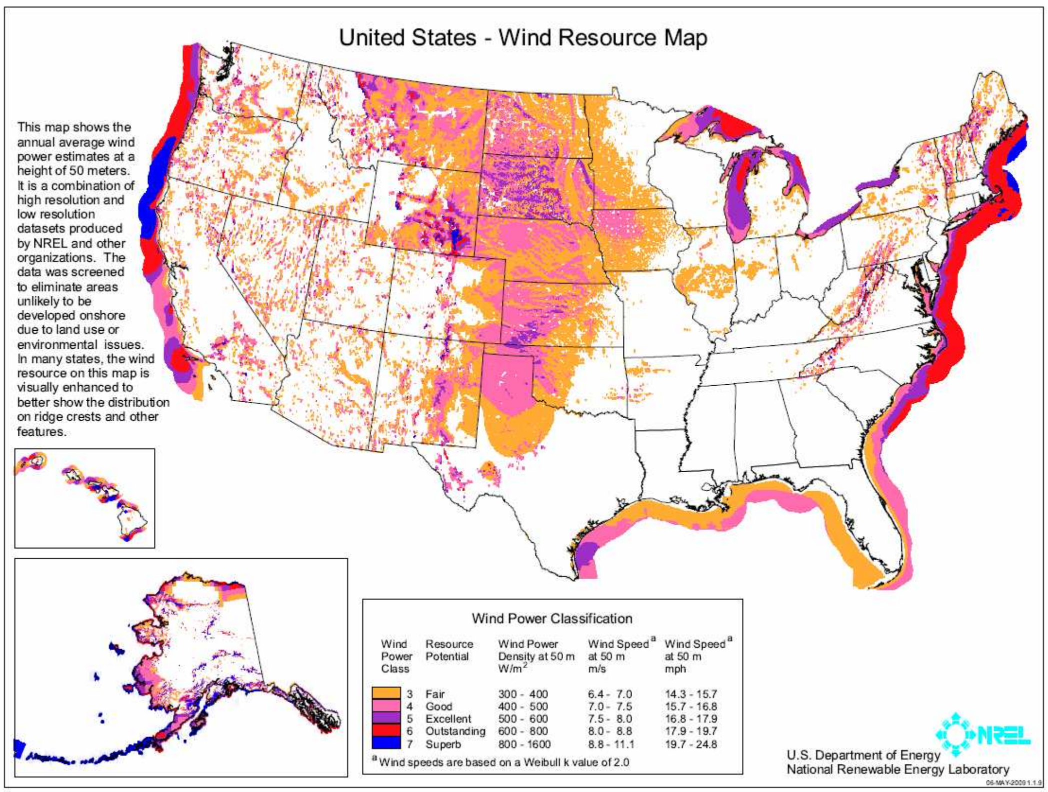


Figure 2-1 U.S. 50m Wind Resource Map [11]

Besides wind resource, the U.S. is also abundant of solar power, as shown in Figure 2-2, especially in southwestern states. Different technologies are developed to deploy solar power, including solar photovoltaic technology, concentrating solar power, solar process heat, passive solar technology, solar water heating, etc. As one of the most widely used technology, photovoltaic is drawing more and more attention because it is highly modular structure. Electricity can be generated from the photovoltaic effect of the semiconductors resulted from solar radiation, which makes solar power sustainable. Similar as wind power, PV generation is largely influence by the weather conditions. In addition, there is only PV generation in the daytime.

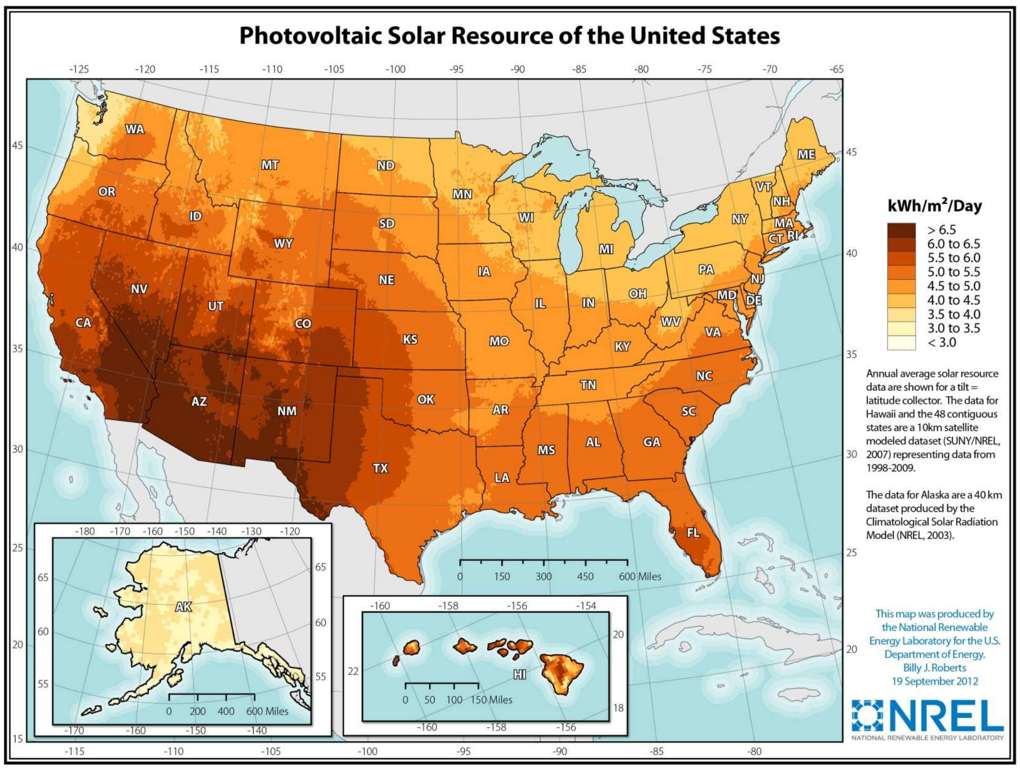


Figure 2-2 U.S. Photovoltaic Solar Resource Map [12]

Acting an active role in alleviating renewable resources impacts to the power system, ESS can also serve grid reliability needs and defer transmission and distribution upgrade investments. There has been a continuous growing trend of employing renewable resources, and a number of renewable resources/ESS hybrid projects have been built across the country. Here is a brief review of several typical wind/solar hybrid projects where ESS plays different roles [13]:

2.2.1 Notrees Battery Storage Project [14]

As the largest battery storage project at a wind farm, the 36 MW (24MWh) Notrees Battery Storage Project owned by Duke Energy is designed to increase the practical application of wind generation and alleviate the intermittency issues at utility scale. Completed in January, 2013, the project is located in west Texas, and the total generation capacity of the wind farm is 152.6 MW. A picture of the project is shown in Figure 2-3. The ESS is developed by Xtreme Power [15], and it is located at the substation and tied on the distribution side [16]. This demonstration project has several targets: 1) integrate the ESS with variable renewable production; 2) save the energy during non-peak periods; 3) provide ancillary services for grid management; 4) dispatch energy according to market price signals or pre-determined schedules; and 5) stabilize system frequency.

Figure 2-3 Notrees Battery Storage Project in west Texas [14]

2.2.2 Tehachapi Wind Energy Storage Project [17, 18]

This project is sited at Tehachapi Wind Resource Area, one of the largest wind resources in the world, with an expectation of 4500 MW of wind resources online by

2015. One of Southern California Edison's existing substations located approximately 100 miles north of Los Angeles will be equipped with lithium-ion battery and corresponding power electronics devices to improve grid performance and support renewable resource integration. The 8 MW (32 MWh) ESS will store energy from about 5000 wind turbines and any future additions. The primary purpose of the project is to validate the performance of the ESS. At the same time, the project will also bring benefits to the system including voltage support, frequency regulation, ramp management and energy price arbitrage, etc. Figure 2-4 is a picture of the Tehachapi Wind Resource Area.

Figure 2-4 Tehachapi Wind Resource Area in California [18]

2.2.3 Wind Firming EnergyFarm [19, 20]

This project is located in the Modesto Irrigation District, California's Central Valley. The 25 MW (75 MWh) EnergyFarm will replace a planned fossil fuel power plant intended to smooth the intermittent output of wind and solar energy. The ESS is the

Primus Power, which is a highly modularized zinc-flow battery system. The goals of the project include accelerating the adoption of renewable energy resources, enhancing grid stability, improving grid asset utilization and substituting more expensive fossil fuel power plants.

2.2.4 PV Plus Storage for Simultaneous Voltage Smoothing and Peak Shifting [21, 22]

The project is owned by the Public Service Company of New Mexico (PNM), and is located in Albuquerque, New Mexico. A 500 kW solar PV plant and 250 kW (1MWh) Advanced Lead Acid batteries are installed at a utility-owned site to demonstrate a dispatchable distributed generation resource. The hybrid resource provides the functions for both voltage smoothing and peak shifting, while a target of achieving 15% or greater peak-load reduction is expected. Besides, the hybrid project will also improve PV source reliability and mitigate voltage fluctuations caused by PV source.

With the studies and research carried on by the demonstration projects, the advantages of implementing ESS have been explored in recent years and the installation of ESS start to become mandatory in some states of the U.S. For example, to encourage emerging storage technologies and progress towards marking transformation, the California Public Utilities Commission (CPUC) issued its final rule promulgating energy storage requirements in October 2013. These rules are developed according to the Assembly Bill 2514 (AB2514), which was passed by the California Legislature in 2010 [23-25]. The three investor-owned utilities in California – Pacific Gas and Electric Company, Southern California Edison Company, and San Diego Gas & Electric Company are required to have electricity storage capacity of 200 MW by the end of 2014, and 1325 MW by the end of 2020.

Chapter 3

Wind and Solar PV Hybrid System Dispatch Using Energy Storage

Wind power usually has higher power output at night and in the early morning while solar power is only available in the daytime. Researches and studies have been ongoing to alleviate the fluctuations of renewable power output by using energy storage devices. This dissertation proposes an idea of combining wind turbines and PVs at different capacity ratios, to match the hybrid system output to the system load profile. With an optimal capacity ratio, feasibility studies are also made by adding battery storages to the hybrid system to dispatch total output.

3.1 Wind/PV Capacity Ratio Optimization

A wind machine extracts the kinetic energy in the moving air by its rotor blades which are mechanically coupled to a generator [8]. For solar PV, electricity power can be generated by the photovoltaic effect of semiconductors exposed to solar radiation. The capital cost for PV modules has declined significantly in recent years, making large scale application more feasible. As discussed in Section 2.2, U.S. has tremendous wind sources, especially in the Great Plains, while the states located in the southwestern U.S., are extraordinarily rich in solar sources. The geographic and weather conditions of several states like Arizona, California, Nevada, Texas, and New Mexico make them the ideal locations for building wind and PV hybrid farms or adding new wind turbines / PVs to the existing PVs / wind farms. While peak load is a critical factor of generation expansion, currently only less than 10% of wind generation contributes to the peak hours in Texas [26]. By optimizing the capacity ratios of wind and PV hybrid output, a better match can be made to the system load profile.

3.1.1 Data Collection

The hourly load data of ERCOT system in 2008 can be accessed from [27]. Under normal operation, the load changes smoothly, therefore the data have been interpolated to a 15-min basis for future comparison.

The 15-min wind output data is from a wind farm located in West Texas with an installation capacity of 278.5 MW in the year of 2008. The PV generation is from NREL PVWatts Site Specific Data calculator, where the location is chosen at the same place of the wind farm [28]. The calculator uses hourly typical meteorological year weather data, and since the solar radiation only varies slightly from year to year, it is assumed that the PV output can represent the output of the year 2008. The data is also interpolated to a 15-min basis.

Since renewable outputs and load profile are highly dependent on the time of year, the load, wind output and PV output of both winter (January) and summer (July) are studied for two different cases, and decision can be made after considering the simulation results of both cases. To avoid the effects of weather, the monthly average of all three data sets is calculated and used for the study.

3.1.2 Capacity Ratio Optimization

For a valid capacity ratio calculation, the wind and PV output data are both scaled to have a total installation of 100MW. Also, to analyze curve matching without the bias from the magnitude, load curve, scaled wind and PV output data are all transformed to fit in a common range by Min-Max Normalization according to

$$P' = P'_{MIN} + (P - P_{MIN}) \times \frac{P'_{MAX} - P'_{MIN}}{P_{MAX} - P_{MIN}} \tag{3-1}$$

Where P is actual output, P_{MAX} and P_{MIN} are the maximum and minimum of data set P; P' is normalized output, P'_{MAX} and P'_{MIN} are the maximum and minimum of data set P'. The new scale is [0, 1] to simplify calculations, so $P'_{MAX} = 1$ and $P'_{MIN} = 0$.

The normalized monthly average power outputs of wind and PV for January and July are shown in Figure 3-1. The hybrid system is designed in 9 different capacity ratios, where PV output ranges from 10% to 90% in a step of 10%, and the percentage of wind power decreases from 90% to 10%.

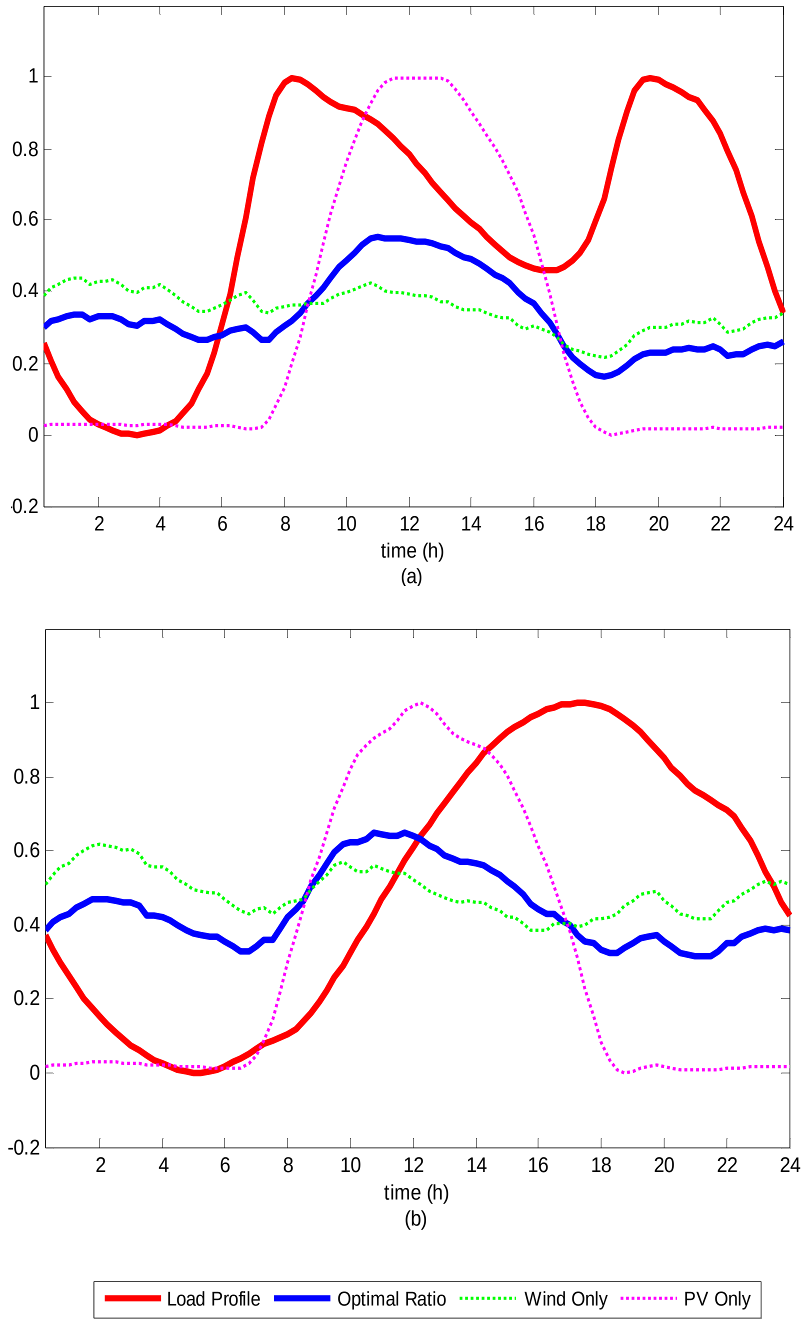


Figure 3-1 Normalized Load Profile and Hybrid Output for

(a) January and (b) July

The mismatch between the hybrid output curve and load curve are calculated by standard average error (SAE), as in

$$SAE = \sqrt{\frac{\sum_{N} (P_{hybrid}(i) - P_{load}(i))^2}{N}} \tag{3-2}$$

SAE calculations for January and July are summarized for different ratios in Table 3-1. With the data in this study, the optimal PV to wind capacity ratio is 3:7 in the winter (January) and 4:6 in the summer (July). The hybrid outputs at optimal ratio are plotted in Figure 3-1 with blue curves. Different capacity ratios are calculated for summer and winter respectively for choosing proper size of storage devices.

Table 3-1 SAE for Different Capacity Ratios

January			July		
PV (%)	Wind (%)	SAE	PV (%)	Wind (%)	SAE
0	100	0.4310	0	100	0.4114
10	90	0.4203	10	90	0.3978
20	80	0.4135	20	80	0.3835
30	70	0.4120	30	70	0.3760
40	60	0.4157	40	60	0.3758
50	50	0.4245	50	50	0.3830
60	40	0.4381	60	40	0.3970
70	30	0.4561	70	30	0.4173
80	20	0.4779	80	20	0.4430
90	10	0.5032	90	10	0.4731
100	0	0.5070	100	0	0.4825

3.2 Dispatch the Hybrid System with Batteries

3.2.1 Dispatch Algorithm

Comparing the curves in Figure 3-1, the hybrid output curve matches the load profile much better than when only wind or PV is used. To maximize the utilization of the hybrid system, especially during peak hours, ESS is added to the hybrid system to dispatch the power output. Because the purpose is to explore the feasibility of matching the renewable energy output with the load profile, the costs of the devices are not taken into consideration.

The batteries are designed to reshape the hybrid system output and maintain a constant output for every hour. ERCOT actual monthly average load data per hour in January and July 2008 are used for calculation. The hybrid system with the optimal PV/wind ratio for January and July are scaled to a total installation capacity of 100 MW. The storage capacities will be calculated after dispatch.

The battery output at the n^{th} hour $P_b(n)$ depends on battery output of the previous hour $P_b(n\text{-}1)$ and the load data of the previous two hours $P_L(n\text{-}1)$ and $P_L(n\text{-}2)$, as shown in

$$P_b(n) = P_b(n-1) + k \times \frac{P_L(n-1) - P_L(n-2)}{P_L(n-2)} \quad n > 2 \tag{3-3}$$

Where k is capacity adjustment factor; by choosing a proper value of k, the total energy charged to the batteries in a single day will be equal to the total energy the batteries import to the grid. When n = 1 in (3-3), which is the first hour of the day, hybrid system output will be its actual generation without considering battery storage, so $P_b(1)$ = 0. When n = 2, the output of the batteries will be calculated with $P_b(1)$, $P_L(1)$ and $P_L(24)$.

With battery storage system added, total system output consists of hybrid system output and battery system output, which can be calculated according to

$$P_{Total} = P_{Hybrid} + P_b \tag{3-4}$$

Where P_{Total} is total output, P_{Hybrid} and P_b are the output of hybrid system and battery system respectively.

The load profile and dispatch results are shown in Figure 3-2 and Figure 3-3. Figure 3-2(a) and (b) show ERCOT monthly average load profile for January and July in the year 2008. In Figure 3-3 (a) and (b), the blue curves are the output of the hybrid system at the optimal ratio, which are 3:7 in winter and 4:6 in summer with a total capacity of 100MW. The red curves are the dispatch results after adding the batteries. When the blue curves are above the red curves, the actual generation is greater than the dispatched generation, and the batteries are storing energy. When the blue curves are below the red curves, the actual generation is lower than the dispatched generation, and the batteries are exporting energy to the system. With batteries added, the hybrid system output depends on the load profile variation, so the magnitude of the load does not affect the results.

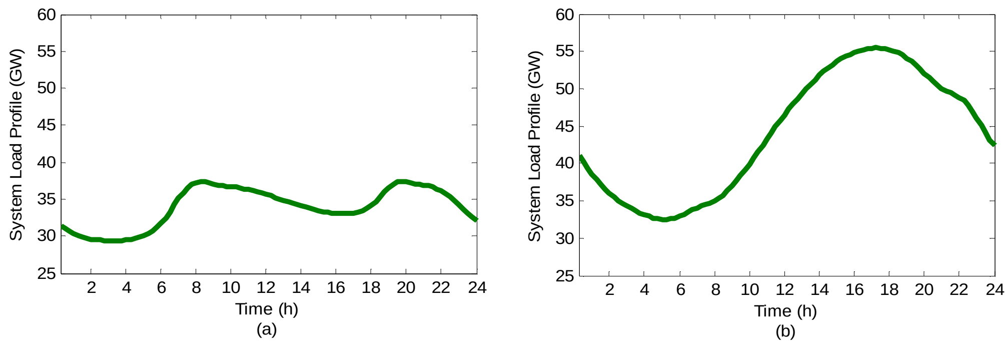


Figure 3-2 ERCOT Monthly Average Load Profile in January (a) and July (b) 2008

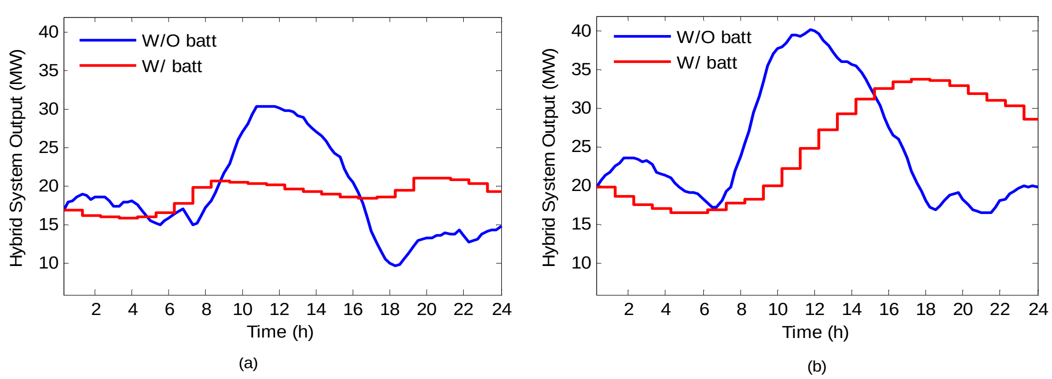


Figure 3-3 Hybrid System Output with and without Batteries for (a) January and (b) July

To compare the result of dispatch, the hybrid system output with batteries are normalized to [0, 1] according to equation (3-1), then SAE is compared with normalized load profile. The results are as follows.

SAE (January) = 0.0957

SAE (July) = 0.0823

With batteries added, the SAE for both January and July have been reduced more than 70%.

3.2.2 Battery Capacity Calculation

To keep the batteries working in normal condition, the state of charge for the batteries are kept between 20% and 80% during the dispatch. The round trip efficiency of battery storage is assumed to be 70% [29]. After considering all these aspects, the storage capacities are 53 MWh for January and 72 MWh for July for the 100 MW hybrid systems. To fulfill the requirement of the whole year, the total storage capacity will be the larger value of summer and winter, which is 72 MWh.

3.3 Results Discussion

As an alternative to conventional plants, renewable resources such as wind power and PVs account for an increasing percentage of electricity generation. However, because the renewable resources have different control strategies from conventional generators, they cannot be dispatched by the system operator. The output of wind and PV is highly dependent on meteorological conditions, which is rarely synchronized with the system load profile.

In order to have large scale integration of renewable sources, the intermittent nature of the renewable source output must be addressed. This study is a feasibility study of matching the output of a PV and solar hybrid system to system load by combining PV and wind power in different ratio. The hourly load data of ERCOT in the year 2008 are used as load profile in this study. The output of a wind farm in west Texas in 2008 is used as wind data. The solar data is from the solar calculator provided by NREL. An optimal ratio of 3:7 for summer and 4:6 for winter time has been found. With the optimal ratio, battery storage devices are added into the system to reshape the hybrid output in order to better fit the load profile and reduce the SAEs. With the batteries added, the hybrid output is dispatched and the SAEs have been reduced more than 70% for both summer and winter cases.

The main goal of this study was to determine the feasibility of making the hybrid system dispatchable, so the cost of the batteries is not considered. However, currently the high cost of storage devices is still not feasible for large scale utilization. As technology develops, storage devices will play a more important role in dispatching renewable resources.

Chapter 4

Demand Response Programs with Energy Storage

Deregulated power market has been developed to maximize social benefits for both power generation entities and load customers. Demand response (DR) is an essential part of the competitive wholesale electricity markets. Many ISOs/RTOs have developed load participation or DR programs to provide customers opportunities to choose power. Each ISO/RTO has different system and market design, so DR products and services may be different from each other.

4.1 Current DR programs at Different ISOs/RTOs

North American Electric Reliability Corporation requires all DR programs to be categorized as one of the following products [30]:

“Energy: Demand Resources are compensated based solely on demand reduction performance during a Demand Response Event.

Capacity: Demand Resources are obligated over a defined period of time to be available to provide Demand Response upon deployment by the System Operator.

Reserve: Demand Resources are obligated to be available to provide Demand reduction upon deployment by the System Operator, based on reserve capacity requirements that are established to meet applicable reliability standards.

Regulation: Demand Resource increases and decreases Load in response to real-time signals from the System Operator. Demand Resources providing Regulation Service are subject to dispatch continuously during a commitment period. Demand Resources providing Regulation Service automatically respond to changes in grid frequency (similar to the governor action on a generator), and also are subject to continuous dispatch based on instructions from the System Operator (similar to

Automatic Generation Control). Provision of Regulation Service does not correlate to Demand Response Event timelines, deadlines and durations".

The demand response resource potential at U. S. ISOs and RTOs are shown in Figure 4-1 according to the information from [31].

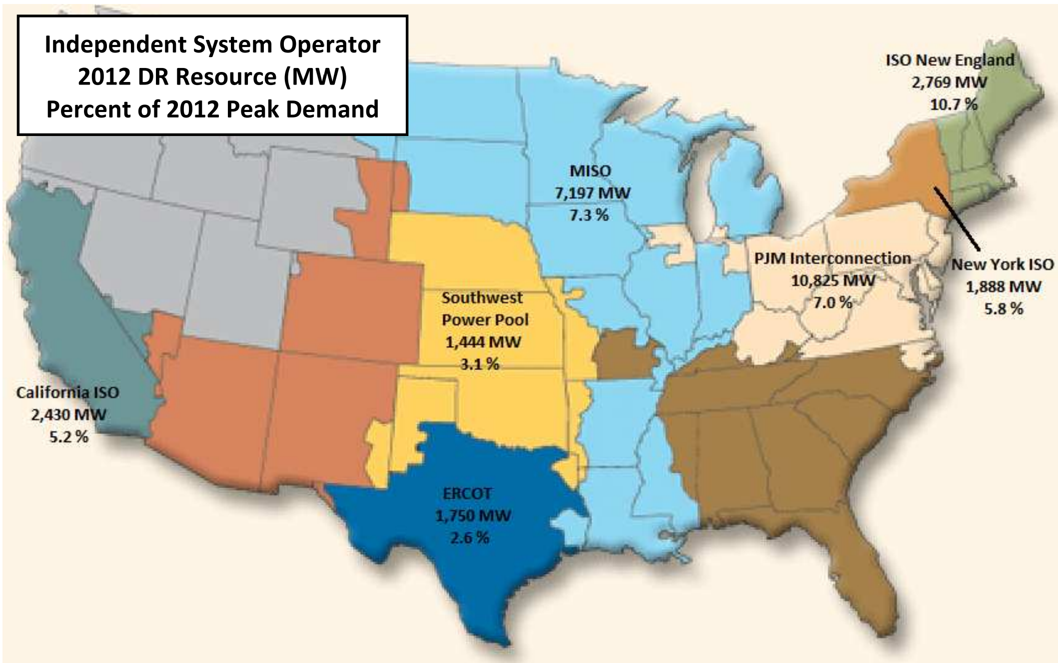


Figure 4-1 2012 Demand Response Resource Potential at U.S. ISOs and RTOs

The following sections are brief summaries of the wholesale electricity DR programs in different ISOs and RTOs, including California ISO, ISO New England, Inc., Midcontinent ISO, New York ISO and PJM Interconnection, LLC.. The DR programs in ERCOT will be used as examples to illustrate the utilization of ESS to participate into the electricity market for financial benefits.

4.1.1 California Independent System Operator (CAISO)

CAISO maintains Participating Load Program (PLP) and the Proxy Demand Resource (PDR) Product to enable aggregators to provide DR resources into the whole sale energy and ancillary services market. The PLP program enables load to participate as price-responsive demand in the non-spinning reserves, replacement reserves and supplemental energy markets in CAISO [32]. “The CAISO shall only accept Bids for Supply of Energy or Ancillary Services or Submissions to Self-Provide Ancillary Services from Loads if such Loads are those of a Participating Load that has entered into a Participating Load Agreement with the CAISO and which meet standards adopted by the CAISO and published on the CAISO Website” [33]. The PDR products allow aggregators to offer demand response resources into the wholesale energy and ancillary services. “The CAISO shall only accept Bids for Energy or Ancillary Services, Submissions to Self-Provide Ancillary Services from Proxy Demand Resources, or Submissions of Energy Self-Schedules from Proxy Demand Resources that have provided Submissions to Self-Provide Ancillary Services, if such Proxy Demand Resources are represented by a Demand Response Provider that has entered into a Proxy Demand Resource Agreement with the CAISO, has accurately provided the information required in the Demand Response System, has satisfied all Proxy Demand Resource registration requirements, and has met standards adopted by the CAISO and published on the CAISO Website”[34].

4.1.2 ISO New England, Inc.

There are two types of load participation programs in ISO New England: Reliability program and price program. The different programs are summarized in Table 4-1.

Table 4-1 Demand Response Programs in ISO New England [35]

Item	Reliability Program	Price Program	
		Real-time Price Response	Day-ahead Price Response
Participant	Any customer	•Any Individual customer •Group of customers greater than 100kW	Any customer enrolled in either the Real-Time Price or Demand Response Program
Description	Participant will be notified by ISO Control Room of a regional reliability problem.	•Customers will be notified by ISO when the wholesale prices are forecasted to exceed $0.10/kWh either the night before or during the event day. •Customer decides when and for how long it will curtail the load voluntarily	If load reduction offer “clears” in the Day-Ahead Market, the customer is notified by their Enrolling Participant around 4:00 p.m. the day before the load reduction is expected. Load reduction must occur during cleared hours.
Response Time	Within 30-Minute or 2-Hour after receiving the request from the ISO.	N/A	N/A
Payment Rate	•Greater of Real Time Price •Guaranteed Minimum $0.50/kWh (30-Minute); $0.35/kWh (2-Hour). •Guaranteed Minimum payment is $0.10/kWh for Profiled Response Program	Greater of Real Time Price or Guaranteed Minimum of $0.10/kWh.	Either greater of the Offer Price or at the Hourly Day-Ahead Market Price for each hour the Offer cleared.
Note	Customer must select option when enrolling.	N/A	N/A

4.1.3 Midcontinent Independent System Operator (MISO)

The market participants that provide DR in MISO include Load Serving Entities, Aggregators of Retail Customers and End-use customers that have Market Participant status [36]. There are four types of DR services: 1) Economic Demand Response; 2) Operating Reserves Demand Response; 3) Emergency Demand Response; 4) Planning Resource Demand Response [36].

4.1.4 New York Independent System Operator (NYISO)

When the NYISO capacity market began operation in December 1999, DR resources have been included in the market. There are four types of DR programs: 1) the Emergency Demand Response Program; 2) the ICAP Special Case Resources program; 3) the Day Ahead Demand Response Program; 4) the Demand Side Ancillary Services Program [37].

4.1.5 PJM Interconnection, LLC

There are two types of load participation in the market of PJM. The first type is for emergency, which provides a method that end users could be compensated by PHM for voluntarily load reduction during emergencies. The second type relies on economic incentive which provides an incentive to customers or curtailment services providers to decrease electricity consumption when the LMP is high.

For the emergency DR type, it represents a mandatory commitment to reduce load or only consume electricity up to a certain level [38]. On the other side, for the economic DR, the program represents a voluntary commitment for customers. There is no firm commitment to reduce a specific amount of electricity consumption, although PJM requires a reasonably accurate estimate to effectively operate the grid [38]. Ancillary service is also included in the economic DR.

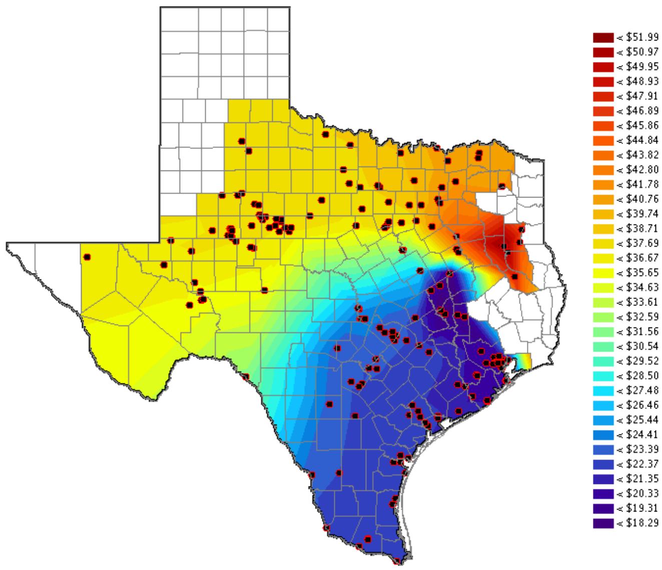
4.2 ERCOT Nodal Market

In Texas, the Electricity Reliability Council of Texas (ERCOT) launched a comprehensive nodal market to improve market and operation efficiency through more rapid and granular pricing and scheduling of energy services [39]. To provide demand resources with the opportunities to provide services, different inclusive DR programs are designed to sustain the reliability and improve the operation efficiency of the grid [40, 41]. The U.S. Department of Energy defines DR as “Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized.” [42]. In ERCOT market, DR programs can be generally classified into three categories: Voluntary Load Reduction, Load Resources and Emergency Interruptible Load Service. All these DR types can be procured in either Day-Ahead Operations or Operating Period. While the locational marginal price (LMP) focuses on the supply side in the wholesale market that contains the cost of generation, transmission congestion and losses, the ability to redispatch the load resources may provide efficient alternatives during peak hours, where 20% of power generation capacity is only used to maintain peak demand, which happens only 5% of the time [43, 44].

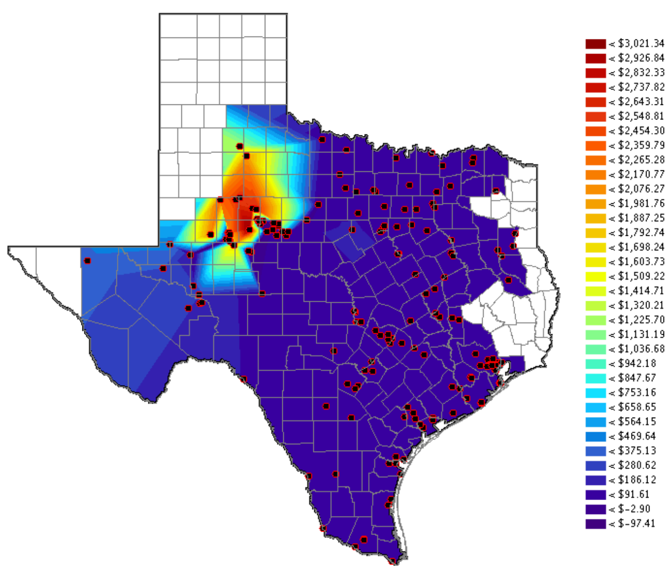
In 2011, Texas Legislature approved Senate Bill (SB) 1125, an act focusing on energy efficiency goals and programs, public information regarding energy efficiency programs, and the participation of loads in certain energy markets [45]. One of the purposes of SB 1125 is to stimulate the participation of residential and commercial customer classes in DR programs while reliability standards are maintained. SB 1125 also encourages utilities in the ERCOT region to facilitate retail electric providers (REPs) in the delivery of efficiency programs and DR programs, including programs for demand-side renewable energy systems which use distributed renewable generation [35, 46]. This chapter of the dissertation discusses the participation of DR programs for residential customers on both individual scale and aggregated scale.

Figure 4-2 ERCOT Region [47]

ERCOT manages 85% of electric power load and 75% of the land area in Texas where 23 million customers are served [47], as shown in blue in Figure 4-2. In September 2003, the Public Utility Commission of Texas (PUCT) required ERCOT to develop a nodal wholesale market to improve market and operation efficiency through more rapid and granular pricing and scheduling of energy services. On 12/1/2010, ERCOT launched a comprehensive nodal market where electric grid congestion and price information will be captured at more than 4000 nodes [39]. Compared with the previous zonal market, a nodal market has the following advantages: 1) price signals are more detailed and generation dispatch is more efficient; and 2) local congestion can be reduced [48]. LMP is the “marginal cost of supplying, at least cost, the next increment of electric demand at a specific location (node) on the electric power network, taking into account both supply bids and demand offers and the physical aspects of the transmission system including transmission and other operational constraints" [49]. LMP includes marginal cost of generation, marginal cost of losses and marginal cost of transmission congestion [43]. In real time nodal market (RTM), ERCOT publishes the LMP for the next 5-min. The ERCOT nodal market consists of several types of day ahead and real time operations. In RTM, the price of the electricity at a single node varies along the day while there could be substantial differences in electricity prices at different nodes. The LMP information RTM in two typical time spot are plotted in Figure 4-3. Figure 4-3(a) and (b) show the RTM price at 19:40 10/7/2012 and 11:15 10/8/2012 respectively [50]. In Figure 4-3 (a), the highest price is around 51.99 $/MWh and the lowest price is less than 18.29 $/MWh, while the price range is from -97.14 $/MWh to 3021.34 $/MWh in Figure 4-3 (b). The extremely high price shown in Figure 4-3 (b) in West Texas is caused by network congestion. The tremendous change in LMP displays the financial opportunities of exploiting price variations if electricity could be kept in energy storage devices when the price is relatively low and consumed or even sold back to the grid when the price reaches a certain level.



(a)



(b)

Figure 4-3 ERCOT Locational Marginal Pricing in Real Time Market

Price information at (a) 10/7/2012 19:40 and (b) 10/8/2012 11:15

4.3 Demand Response Program Participation for Residential Households with Renewable Source and Storage Devices

4.3.1 Voluntary Load Response in ERCOT Market

Sustaining the reliability and managing the operation of the grid are the principal missions of ERCOT, while supporting the day-ahead market is another task [40]. ERCOT's objective is to "ensure that sufficient resources in the proper location and required Ancillary Services have been committed for all expected Load on a Day Ahead and Real Time basis" [51]. Resources include both generation resources and load resources. For the load resource, customers will be rewarded by changing consumption patterns to facilitate system reliability under ERCOT's nodal market environment. Different load responses and demand-side programs are summarized in Table 4-2.

Table 4-2 Demand-Side Participation in ERCOT [40]

Resource Type	Resources or Service that can be Provided	Requirements
Voluntary Load Response	Curtailment or reduction in response to load zone price or other factors	• Metering and/or curtailment technology defined in retail electric provider contract
Day Ahead Market bids and response	Load may choose to curtail or reduce consumption in response to prices bid in the Day Ahead energy market	• Day Ahead Market Pricing • Metering and/or curtailment technology defined in Retail Electric Provider contract
Real Time Market and passive response to price	Load may choose to curtail or reduce consumption in response to prices in the Real Time energy market	• Real Time Pricing • Metering and/or curtailment technology
Load Resources	Various ERCOT Ancillary Service: Regulation Up Reserve Service Regulation Down Reserve Service Responsive Reserve Service Non-Spinning Reserve Service	• Interval Data Recorder meter • Telemetry • Qualification

Voluntary load response (VLR), also referred to as "passive load response" or "self-directed load response", is the customers' self-motivated behaviors of adjusting the levels of consumption according to stimulus from market prices. More flexible than other programs, VLR does not obligate customers to respond to the market as a load source; however, if the customers would like to behave as a load resource, further financial compensation could be exploited depending on the contracts with the REPs [40]. The main financial opportunities of VLR can be gained from changing consumption patterns in order to reduce electricity bills, such as reducing electricity usage when prices are high. In RTM, customers can request their REPs to provide ERCOT's real time operation prices; since the price data can be accessed from the public website, customers can accommodate their consumption behaviors to achieve financial benefits [35, 52]. Figure 4-4 shows the consumption pattern of a residential customer after enrolling in a program that provides free electricity between 22:00 and 6:00 the next day. The customer utilized the free energy at night by moving some non-time-sensitive load to 22:00 and later.

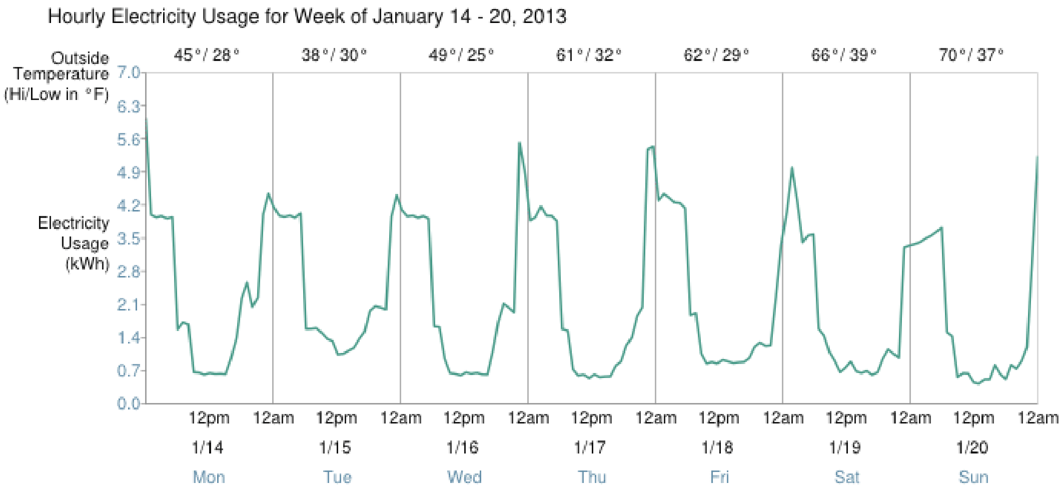


Figure 4-4 Power Consumption of A Residential Customer with Incentive Program

4.3.2 Urban Area Renewable Alternative: Solar Power

4.3.2.1 Solar Resources in Texas

The cost of renewable generation continues to decrease. In urban areas, PVs are the most widely used for exploiting renewable energy because they are CO_2 emission-free and installation locations such as house roofs and building surfaces are easily found [53]. Its free of noise pollution, long life span, and low maintenance requirements make PV a preference among renewable resources in urban areas. There are abundant solar resources in Texas. In general, the daily and seasonal demands of Texas are synchronized with solar power output, which makes it feasible to cover a large portion of energy requirements using solar resources under the condition that the cost of renewable generation can be reduced as technologies develop [54]. The historical trend of average module costs [55] are shown in Figure 4-5. Generation test of a commercially available PV panel has been conducted in the Microgrid lab of Energy Systems Research Center with both Pulse Width Modulated (PWM) and Maximum Power Point Tracking (MPPT) charge controllers, and the generation curve is shown in Figure 4-6. The tested PV panels have a total capacity of 470 W.

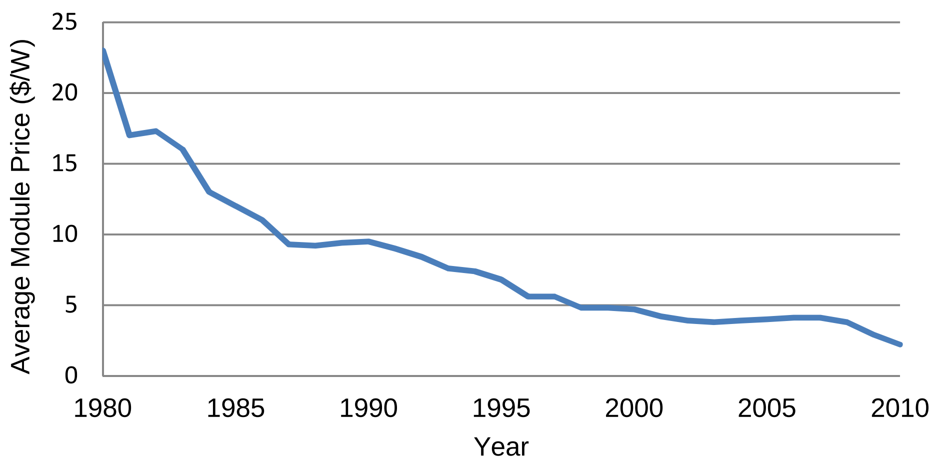
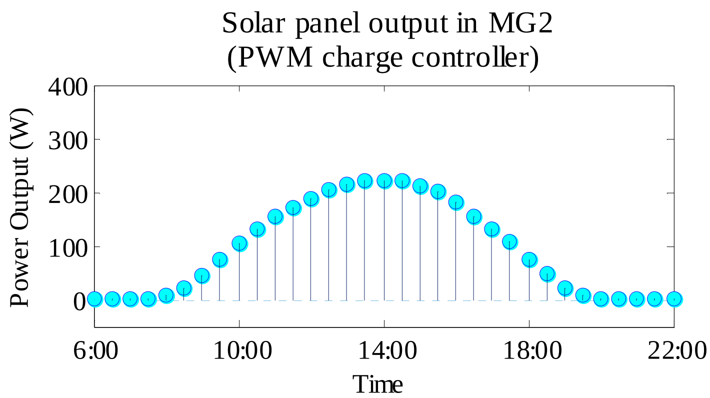


Figure 4-5 Cost of Solar PV Generation [55]



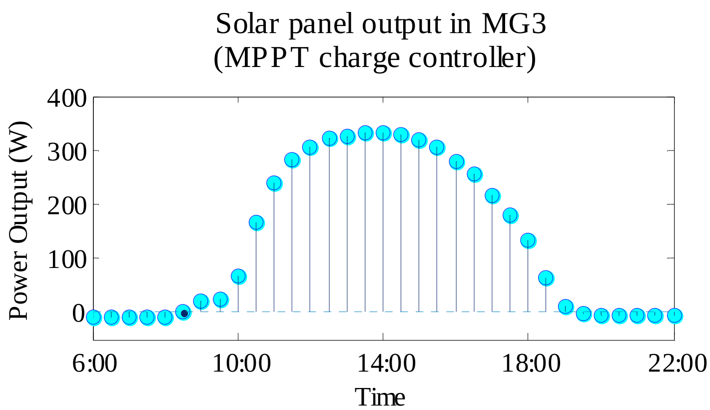


Figure 4-6 PV Panels Generation Curves (Test Date: 9/6/2012)

4.3.2.2 Texas Solar Rebates and Incentives

Though there is no official legislation in Texas that requires utilities to provide net metering to facilitate renewable energies, SB 20 launched a goal to achieve an additional 5880 MW renewable energy capacity by 2015; 500 MW are mandated to be non-wind resources, which indirectly promotes solar energy. A further target of additional renewable energy capacity is set to be 10000 MW by 2025 [56]. In order to encourage the installation of PVs, federal, state, local, and private incentives and rebates offer numerous economic stimuli such as tax credits, tax deductions, property tax relief, purchase incentives (rebates), production incentives, etc.. Among them, a significant portion is designed to benefit residential applications [57, 58]. In different cities, various incentives are offered to cut installation costs and to offer rebates per kWh of solar generation, making PV installation in households feasible. For example, the residential customer discussed in this part of the work took advantage of local and federal incentives, including a solar panel rebate of 3$/kW from the local utility; a rebate of 0.8$/kW for participation in a demonstration project; and a 30% federal tax incentive [59, 60]. Assuming a life time of 25 years for the solar panel system, the approximate daily cost for each kW installation is $0.04. Considering the fact that the electricity retail price will actually be higher than the wholesale price, there will be sufficient savings after installation to compensate for this daily cost. Another example can be found at UT Arlington: the installation of 384.93kW solar panels atop Park North and Park Central parking garages cost the university $368,000, but Oncor provided a $390,000 rebate [61]. From these two examples, the cost of PV installation can be reduced to a negligible level via incentives and rebate programs. Therefore, the solar panel installation cost is not considered in this study.

4.3.3 Energy Storage Device Selection

The day-night cycle causes extremely unevenly distributed PV output over the course of 24 hours. Energy storage devices offer possible solutions to improve the effective utilization of solar power by leveling peak demand and shifting excess energy to the time when electricity is needed and sunlight is not available. Nowadays, many types of storage devices are available, and several criteria such as application type, reliability, feasibility, power rating, storage capacity, electrical efficiency, lifetime, response time, and costs must be considered when making choices [62]. For residential usage, batteries are preferred since they can be located inside the building. The energy is stored in electro-chemical form, and the batteries are connected to the grid by compatible auxiliary devices, like power converters and inverters. Typically, the battery system has 60% to 80% cycling efficiency and its response time is approximately 20 ms [63].

Though batteries have good characteristics, their high cost presents a major obstacle to large-scale application. Ongoing research aims to enhance capacity and lower costs. New technologies under development include Li-based, sodium-sulfur, nickel-cadmium, nickel-metal hydride, and zinc-bromine batteries. [64, 65].

The primary goal of selecting storage devices in this study is market success. Thus the main objectives are to: 1) reduce cost; 2) increase performance; 3) reduce weight and volume; 4) increase tolerance to abnormal conditions. Li-based batteries have a wide range of uses such as powering electric vehicles and aerospace applications because of their high energy density. Li-based batteries also have a satisfactory energy-to-weight ratio, low charge loss, and no memory effect [29]. Therefore, Li-based battery is used for this study and the chosen model is currently under development, supported by the U.S. Department of Energy under American Recovery and Reinvestment Act cost-shared grants. The battery is expected to be available by 2014 [66]. The life span of the battery is expected to be 15 years with a cost of $3400 and a capacity of 11.6 kWh.

4.3.4 Financial Opportunities Analysis: Case Studies

In order to adopt the ideas of SB 1125 and reap the financial benefits, DR programs design in ERCOT is extended to residential customers for the studies. The financial benefits calculation in this work is based on daily information, so the cost of batteries is also scaled to daily intervals. By calculation, the battery cost per day per kWh is $0.053. This cost is a key factor when seeking optimal storage capacity.

Three case studies of implementing PV systems and Li-based batteries under ERCOT's demand response program's design for a household will be discussed in the following sections. The ultimate target of the studies is to explore financial opportunities in RTM. A typical Texas residential load profile and the LMP information of ERCOT's RTM are applied to calculate the battery capacity and total revenue.

4.3.4.1 ERCOT Real Time Market LMPs

The whole sale price information of the ERCOT real time market can be accessed through [67]. The price information of 7/24/2012 for a node called AUSTPL_ALL (near Austin) is shown in Figure 4-7 as an example. 7/24/2012 is a common summer day, with a temperature range between 77℉ and 96℉. From Figure 4-7, it is shown that the prices before 11 am and after 9 pm were relatively low, all less than 30$/MWh, while the peak price appeared at around 4 pm, reaching more than 80$/MWh. The prices varied more than 4 times within a single day.

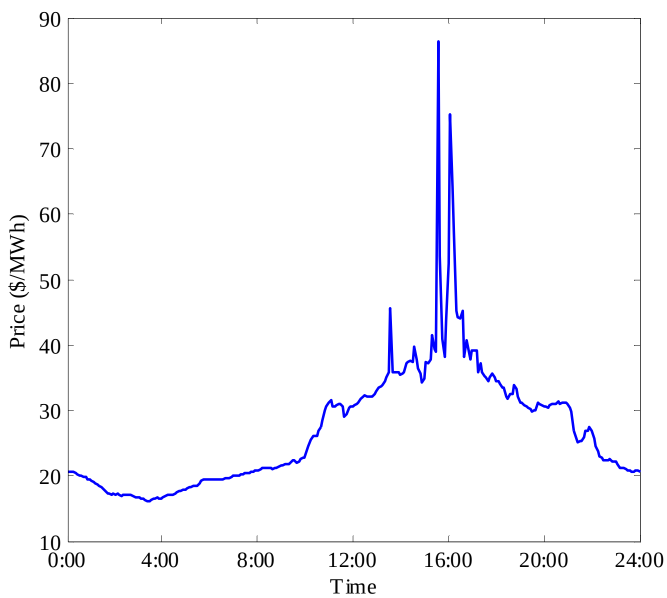


Figure 4-7 LMP in Real Time Market at Node AUSTPL_ALL (Date: 7/24/2012)

In a VLR program, load customers can request their REPs to provide the prices that ERCOT publishes during real time operations [52]. In customers' monthly electricity bills, the charges coming from the transmission and distribution service providers (TDSP) for operating and maintaining power facilities are included regardless of which REP is chosen; the TDSP charge usually costs several cents/kWh [68]. In this work, the main interest is to employ the fluctuations of the price signals. Thus, the electricity prices applied to the residential customers are assumed to be the wholesale electricity price without the TDSP and other charges, since they will not affect the prices variation patterns. The prices are assumed to remain constant for five minutes before new data are published.

4.3.4.2 Load Profile and PV Generation Curve

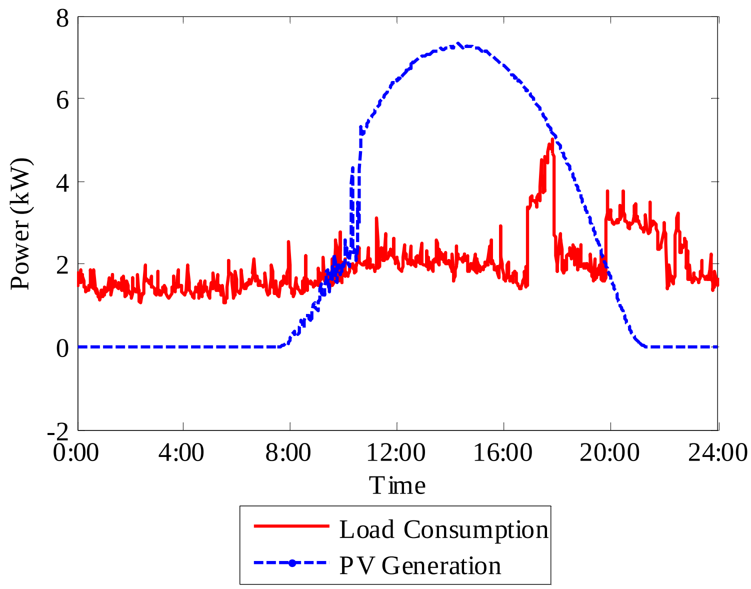


Figure 4-8 Load Consumption Curve and PV Generation Curve of a Typical Texas Household on 7/24/2014

The per minute load consumption and PV generation data within 24 hours on 7/24/2014 from a typical Texas household near node AUSTPL_ALL are used for the analysis in this dissertation, and the data are shown in Figure 4-77. With the nodal price at AUSTPL_ALL and load consumption data, the electricity cost C_0 for this single day can be calculated by

$$C_0 = \int_0^{1440} p_M(t) \cdot P_L(t) \cdot \frac{1}{60} dt \tag{4-1}$$

Where C_0 is the total cost; $p_M(t)$ is the LMP at node AUSTPL_ALL for each minute in \$/kWh; $P_L(t)$ is load consumption power in kW, and is assumed to be constant within each minute. C_0 is calculated to be \$1.8645.

This household has PVs installed, which provide power during daytime between 8 am and 9 pm. The demand is around 2 kW during most of the day before the peak hour around 5 pm. Since the output of PVs exceeds load consumption during most of the day, batteries might provide a solution to shift the excess part for night use. Because battery cost is an important factor, different scenarios involving PV and battery installation are discussed.

4.3.4.3 Case Studies

As previously mentioned, the cost of PV systems is not considered in this study. Several other assumptions for the battery systems are made: 1) perfect efficiency (for calculation purposes); 2) maintenance free; 3) no auxiliary devices (e.g. inverters) cost. In addition, in all the cases, electricity feeds back from user side to grid side is designed to be minimum and is not metered.

Scenario One: PV only

In this case, PVs are installed in the household while no batteries are included. When there is no output from PVs, electricity is imported from the grid; when PVs have power output, it will be consumed before grid power. The electricity cost C_1 for 7/24/2012 with PV installed can be calculated by using (4-2)

$$C_1 = \begin{cases} \int_0^{1440} p_M(t) \cdot [P_L(t) - P_{PV}(t)] \cdot \frac{1}{60} dt & (\text{when } \mathrm{P_L} > \mathrm{P_{PV}}) \\ 0 & (\text{when } \mathrm{P_L} < \mathrm{P_{PV}}) \end{cases} \tag{4-2}$$

Where $P_{PV}(t)$ is PV power generation in kW at each minute and is assumed to be constant for the whole minute. C_1 equals to \$0.8826 after calculation.

Compared to C_0, the electricity cost C_1 has been reduced by 53%, showing that installing PV is a cost effective solution if the cost of the PV can be compensated through incentive programs. This is because PV output covers most of the power consumption in the daytime, reducing the total energy imported from the grid, especially when the LMP is high during peak hours. Therefore, installing PV is a good solution for reducing electricity bills.

Scenario Two: Batteries Only

The main idea of this scenario is to install energy storage devices (batteries in this study) in a household and store the electricity in the batteries when the LMP is low. Instead of importing electricity from the grid during peak hours, energy in the batteries will be used to reduce the total cost. One key factor which influences overall revenue is the capacity of the battery system since the cost of batteries is still relatively high for large scale applications.

A threshold price that clarifies a boundary between the high price and the low price is defined to determine whether the batteries absorb or deliver electricity. A threshold factor k_b is also introduced. When the LMP reaches the threshold price LMP_{set}, batteries start to deliver electricity; LMP_{set} is defined by

$$LMP_{set} = LMP_{MAX} \cdot k_b \quad (0 < k_b < 1) \tag{4-3}$$

Where LMP_{MAX} represents the maximum price among the day in \$.In this study LMP_{MAX} is assumed to be well forecasted. For example, LMP_{MAX} in Figure 4-7 is 86.33 \$/MWh. When k_b is chosen to be 0.75, LMP_{set} is 72.25 \$/MWh. Thus when the LMP is higher than 72.25 \$/MWh, the batteries will support the load. For different values of k_b, different battery capacities will be required. A lower LMP_{set} value results in the need for larger battery capacity.

The total cost of batteries is calculated by the product of the cost per kWh and the total capacity. As mentioned before, the cost of the battery used in this dissertation is 0.053 $/kWh per day. A plot of the total electricity cost as a function of threshold factor k_b is shown in Figure 4-9; k_b changes from 0.3 to 1 for better visualization. When k_b is chosen to be a smaller value, the batteries start to absorb energy when the LMP is relatively low, thus a larger capacity is required; however, the cost saved by shifting PV output cannot compensate the investment for batteries, resulting in an invalid solution. As k_b increases, the cost varies slightly around $1.86. The minimum cost in this scenario, C_2, is acquired at $1.8558 when k_b is 0.45-0.57. Compared with C_0, there is not much improvement after installing the batteries because of their high cost. This scenario might become feasible as battery technology develops.

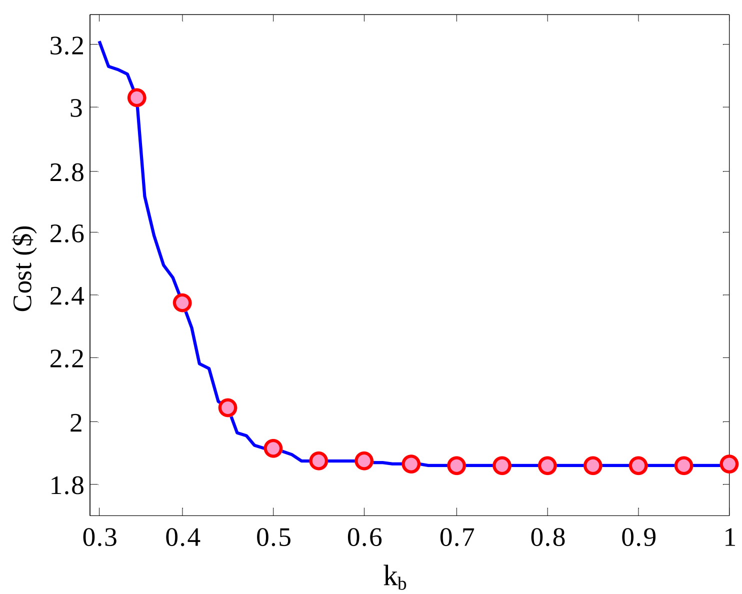


Figure 4-9 Electricity Cost for 7/24/2012 with Different Threshold Factor k_b

Scenario Three: PV and Batteries

With the installation of both PV and batteries, this scenario is designed to optimize the usage of solar power. The electricity generated by PVs has the priority to supply the load. When PV generation is greater than load consumption, the surplus portion is stored in the batteries; when generation is less than consumption, batteries supply the load before grid electricity is imported. The total cost of this case consists of two parts, electricity cost and battery cost. The total cost C_3 for 7/24/2012 can be achieved by (4-4)

$$C_3 = \int_0^{1440} p_M(t) \cdot [P_L(t) - P_B(t)] \cdot \frac{1}{60} dt + C_B(E) \tag{4-4}$$

Where $P_B(t)$ is the battery output power in kW; E is the battery capacity; and C_B is the battery cost per day in $ calculated from the product of battery capacity and cost per kWh. As the capacity varies, C_B will also change.

To maximize financial benefits, shared ESS are assumed when calculating the storage capacity since the actual value required for a single household may fall below the economic scale. The electricity cost as a function of storage capacity is plotted in Figure 4-10. As capacity increases, the total cost drops before reaching the bottom and then rising again. All the capacity choices which make the total cost less than C_0 are valid solutions. C_3 is chosen to be the minimum value, $0.7955. This result shows that by installing both PVs and batteries, the electricity cost can be reduced on the condition that a proper storage capacity is chosen.

The comparison of three different scenarios is shown in Table 4-3. In summary, installing PV is an effective method of cutting electricity bills, and implementing batteries together with PV system brings slightly better results. However, if only batteries are added, they do not significantly reduce the electricity bill. In general, PV installation does provide an alternative for supplying residential load, especially during peak hours in Texas. Customers are able to obtain some financial benefits by participating in DR programs. The LMP of wholesale market is used in this work since the variation of prices is the main interest; when retail price is implemented where prices are higher, the scenario with battery installation will have better results.

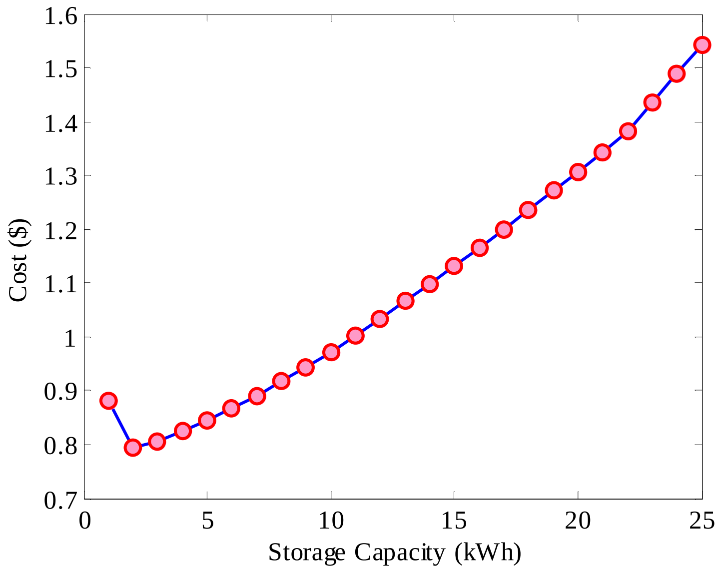


Figure 4-10 Electricity Cost When Different Storage Capacity Is Chosen

Table 4-3 Cost Comparison for Three Scenarios

Scenarios No.	Scenario Design	Total Cost (C)
0 *(Base Case)*	No PV nor Battery is installed, import electricity from the grid	C_0 = \$1.8645
1	Install PV only	C_1 = \$0.8826
2	Install battery only	C_2 = \$1.8558
3	Install both PV and battery	C_3 = \$0.7955

4.3.5 Conclusions

Since similar laws may be implemented in other markets in the future, this study uses ERCOT's demand response programs and SB1125 as an example to implement PV systems and Li-based batteries for a household to reap financial benefits. Three different scenarios have been studied. Based on the analysis results, following conclusions can be derived:

1) DR programs at the residential level are win-win policies that can benefit the load customers and relieve grid congestion during peak hours.
2) The financial benefits are largely dependent on customers' load profiles. Savings can be achieved when consumption habits are changed by shifting some non-time-sensitive load to the time when LMP is low.
3) For the locations with wider nodal price variation, the proposed approach in this dissertation becomes more attractive.
4) When rebates and incentives are available, installing renewable sources suitable for residential area applications like PV is a clean and cost effective option to fulfill home demand.
5) Due to its high cost, installing energy storage devices alone is of little benefit, but PV installation can work as an alternative method for supplying residential load in Texas, especially during peak hours.

4.4 Demand Response Program Participation for Aggregated Residential Appliances with Renewable Source and Storage Devices

Though the LMP in the wholesale market can change from one moment to another, for most residential customers, electricity bills are still charged monthly over a flat rate where the price does not reflect the actual electricity cost during usage [69]. Without market incentives, residential customers do not have any motivations to curtail their consumption to lower the peak demand or relief the supply shortage. The deficiency with flat rate on the one hand forces utilities to take the risks associated with price fluctuations for keeping electricity rate constant [70]; while on the other hand residential customers do not have opportunities to adjust their consumption patterns according to LMP variations to reduce electricity bills.

In addition, the growth of electricity demand and environmental concerns drive people to seek solutions from renewable energy. Therefore, this paper also proposes an idea to install a solar farm coupled with energy storage devices to supply the aggregated demand to further increase the financial benefits for all participants.

4.4.1 Residential Appliance Classification

In recent years, the widely deployment of smart meters, smart sensors and automatic control devices in distribution and residential levels has created a platform to control the operation of residential appliances in an intelligent way considering both household economic benefits and grid operational constraints [71]. With the vision that demand response may be expanded to residential customers, this dissertation presents approaches to aggregate a number of residential customers to shift the coincidental peak load by adopting different operation strategies for the most representative residential load types, including HVACs, clothes dryers, and refrigerators for possible system reliability improvement and financial benefits for all participating customers. An optimal operation schedule is able to make decisions for the appliances for switching on/off, cycling and shifting operating time while compromising the comfort and convenience of customers within a predefined tolerable range. The smart appliances can be classified into different categories according to appliance characteristics and consumption patterns.

The most common appliances account for different shares of residential electricity consumption [72], as shown in Figure 4-11 where air conditioning (AC) and space heating account for nearly half of the consumption. Water heating, refrigerators, lighting, clothes dryers also occupy significant parts of the electricity bills. Residential appliances can be classified according to their properties and criticality to daily life, making it possible to design operation strategies accordingly. The appliances are generally classified into noncontrollable appliances and controllable appliances, where controllable appliances are further classified into thermostatically controlled appliances and nonthermostatically controlled appliances; the classifications of major residential appliances are shown in Table 4-4 [71]. The noncontrollable appliances are the critical loads which are not suitable for rescheduling in DR programs. For controllable appliances, the thermostatic ones have thermal inertia which means the load consumption of the current moment is influenced by the consumption of the previous moment and will affect the next moment. For nonthermostatically load, there are flexibilities on their service time and can be deferred as needed. Being the most representative appliances in each category, AC/Heater, clothes dryer and refrigerator are chosen in this study to discuss the operation strategies for each type of appliances. By aggregating a number of appliances and shifting the coincidental peak load by certain amount of time, financial benefits can be achieved.

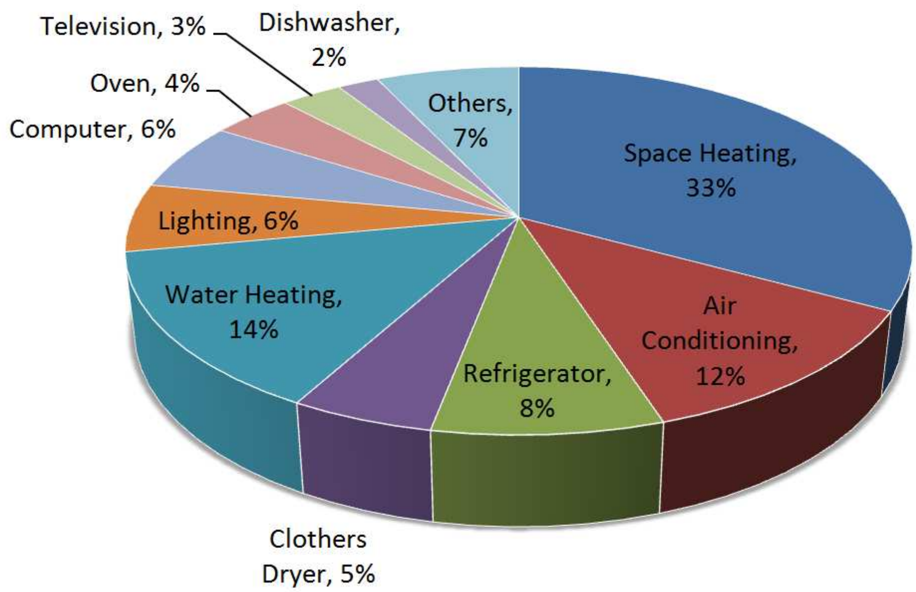


Figure 4-11 Residential Appliances Electricity Consumption Percentage

Table 4-4 Major Residential Appliance Category

Non-controllable Appliances	Controllable Appliances	
	Thermostatically Controlled	Nonthermostatically Controlled
Lightning	Air Conditioner	Clothes Washer
Refrigerator	Space Heater	Clothes Dryer
Television	Water Heater	Dish Washer

4.4.2 Aggregated Appliances Operation Strategy

4.4.2.1 AC/Heater Load Control – Steps of Temperature

It is common practice for most residential consumers to set the thermostat of AC/heater at a constant temperature set-point. This practice is inefficient and costly in a real-time electricity pricing environment since the AC/heater still operates at the same set-point even the LMP is high. On the other hand, when the price is low, this practice does not take advantage of that low price to operate AC/heater at the coldest/hottest allowable temperature to reserve the thermal energy for the subsequent periods.

The thermodynamics of AC/heater systems located at the end user is modeled as in [73]. It is assumed that the system is equipped with smart controls that manage the power consumption during the day in response to price signals, while at the same time maintaining the inside temperature within preset comfort limits. Equation (4-5) is used to simulate the indoor temperature of the next time frame [74].

$$T^{in}(k+1) = \epsilon T^{in}(k) + (1+\epsilon)\left(T^{out}(k) \pm \eta_{COP}\frac{P(k)}{A}\right) \tag{4-5}$$

$$(+: heating, -: cooling)$$

Where

$T^{in}(k)$	Inside temperature in period k
$T^{out}(k)$	Outside temperature in period k
$P(k)$	Power consumption in period k
η_{COP}	Coefficient of performance
ϵ	Factor of inertia (0.96)
A	Overall thermal conductivity ($0.14\ kW/°\mathrm{F}$)

Further, it is assumed that the smart control maintains the inside temperature within certain limits, which is around the user defined temperature set-point. Thus,

$$T^{min} \leq T^{in}(k) \leq T^{max}, \forall k \tag{4-6}$$

Where

T^{set}	User defined temperature set-point
ΔT	Maximum deviation from set-point ($2°\mathrm{F}$)
T^{min}	Minimum inside temperature ($T^{set} - \Delta T$)
T^{max}	Maximum inside temperature ($T^{set} + \Delta T$)

For the operation strategy, it is considered that the AC/heater operates within the ASHRAE comfort zones [75]. Comfort zones are seasonal: the summer zone is separated from the winter zone. As shown in, both zones cover approximately $6°\mathrm{F}$.

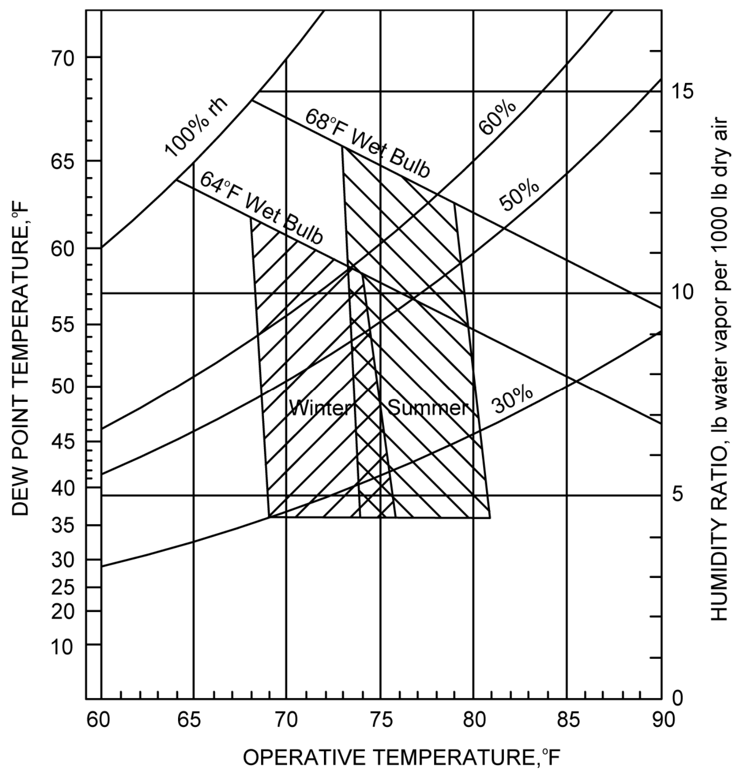


Figure 4-12 ASHRAE Summer and Winter Comfort Zones [75]

Outdoor temperature data of the year 2011 are obtained from [76] for a node in central Texas for simulation purposes. Figure 4-13 shows the temperature data of the entire year. Figure 4-14 shows the outdoor temperature data on a hot summer day while

Figure 4-15 shows outdoor temperature data on a cold winter day for illustration purpose. These data are used for AC/heater load control simulations together with the LMP of the same year at the same node.

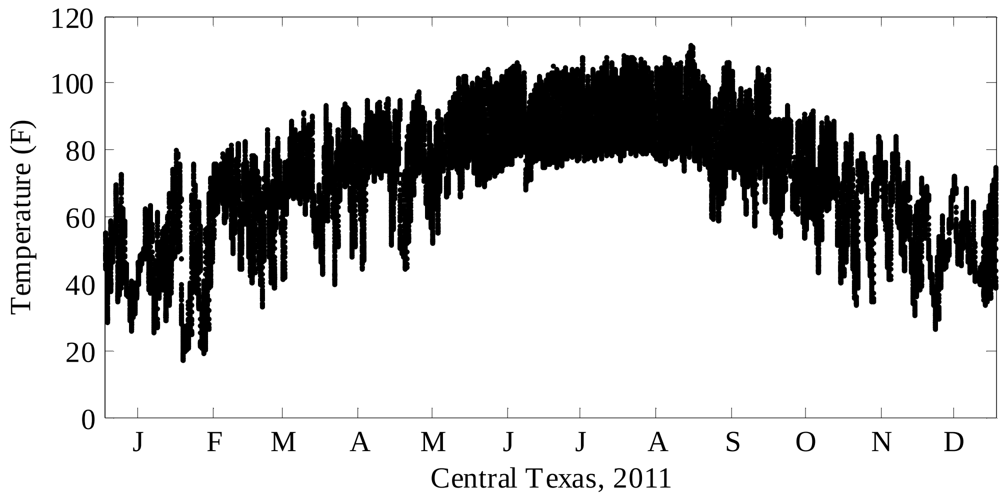


Figure 4-13 Annual Temperature of a Node in Central Texas in 2011(F°)

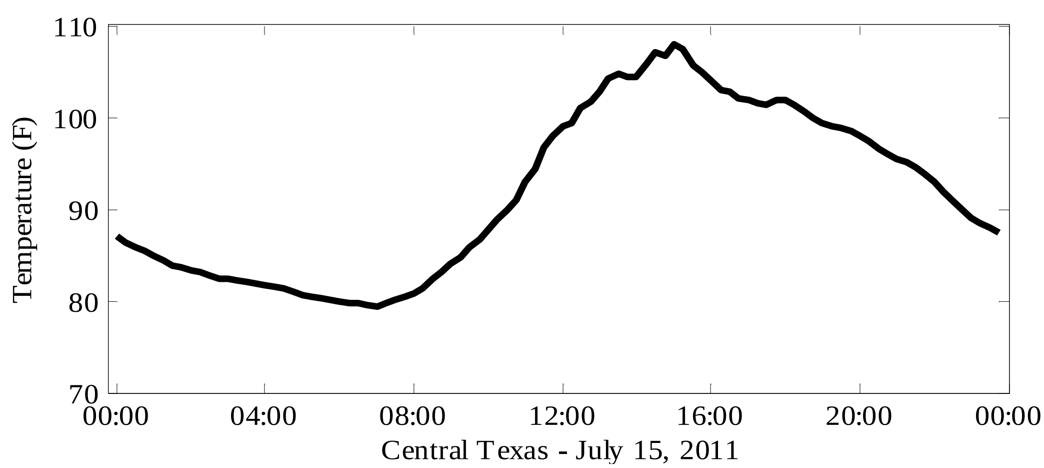


Figure 4-14 Temperature at a Node in Central Texas on a Summer Day (F°)

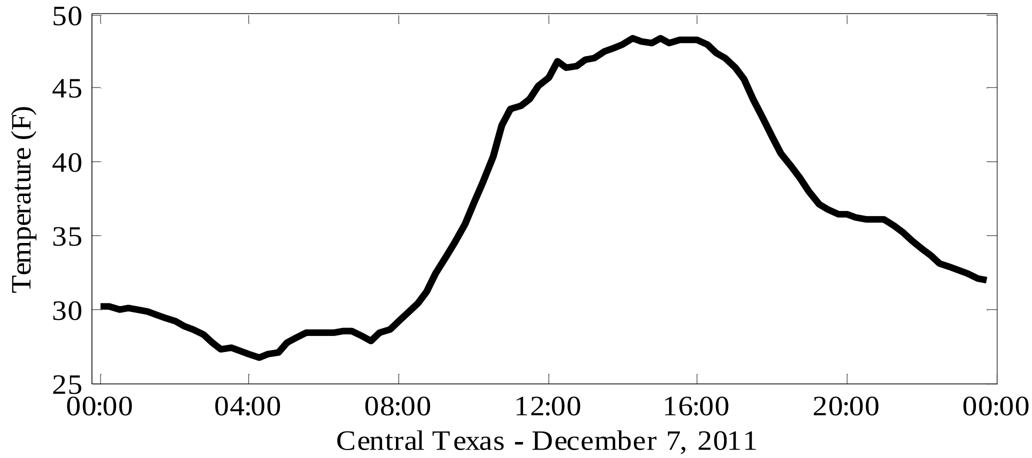


Figure 4-15 Temperature at a Node in Central Texas on a Winter Day (F°)

Five LMP breaking points are chosen as demonstrations for establishing the Steps of Temperature based load control. The first point is 0 \$/MWh, and the rest points are selected as the percentiles of 2.5^{th}, 25^{th}, 50^{th}, and 75^{th} of the annual LMP data which are 14 \$/MWh, 23 \$/MWh, 26 \$/MWh and 35 \$/MWh respectively. The AC is operated the coolest possible (near the lower boundary of the ASHRAE summer comfort zone, e.g. 75°F) when the LMP is lower than the predefined value (e.g. 14 \$/MWh). On the other hand, the AC load is operated the hottest (near the upper boundary of the ASHRAE summer comfort zone, e.g. 79°F) when the LMP is higher than the predefined value (e.g. 35 \$/MWh). The AC is operated between these two boundaries depending on the real-time electricity prices. This strategy is called the "Steps of Temperature Preferences" or the "Steps of Temperatures"[77]. Consumers can easily adjust and balance the price and temperature settings according to their preferences while still maintain their comfort from the saving.

The strategy to control the heater follows a similar approach. The heater is operated the hottest possible (near the upper boundary of the ASHRAE winter comfort zone, i.e. 73°F) when the LMP is lower than the predefined value (e.g. 14 \$/MWh). On the other hand, the heater load is operated the coolest (near the lower boundary of the ASHRAE winter comfort zone, i.e.$69\ ^{\circ}\mathrm{F}$) when the LMP is higher than the predefined value (e.g., 35 $/MWh). The heater is operated between these two boundaries depending on the real-time LMP.

4.4.2.2 Clothes Dryer – Price Naming

The control strategy of Price Naming, as presented in [78], is a suitable strategy to be exploited for nonthermostatically controlled residential appliances such as clothes dryers. This is a familiar operation mode in the online discount reservation in [79] or in the auto insurance in [80] and it is adopted as load control strategy. An operator of the aggregated load can “name” his/her own electricity purchasing price for the load controller to send the control command to operate an appliance when the LMP drops below the desired price threshold [78]. By shifting the aggregated load usage to subsequent cheaper LMP timeframes, the overall consumption is not reduced and the desired missions are accomplished, but the benefits can be substantial.

For modeling the clothes dryer consumption, a one-year worth of statistically averaged usage pattern of this end-use appliance is utilized. For the purpose of this study, the load data obtained as part of the End-Use Load and Consumer Assessment Program are used that have been made publicly available in [81]. The average yearly consumption (kWh/year) of clothes dryers can be expressed as follows [82]:

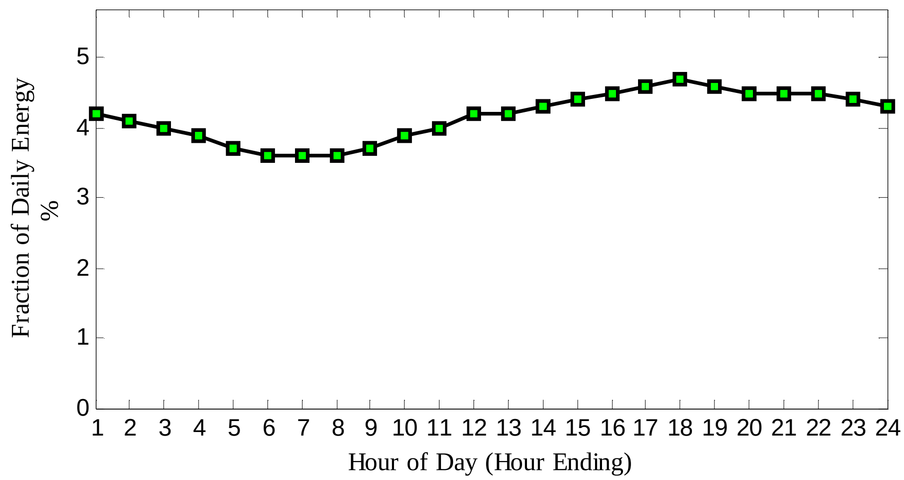
$$538.2 + 179.4 \times N_{br} \tag{4-7}$$

Where

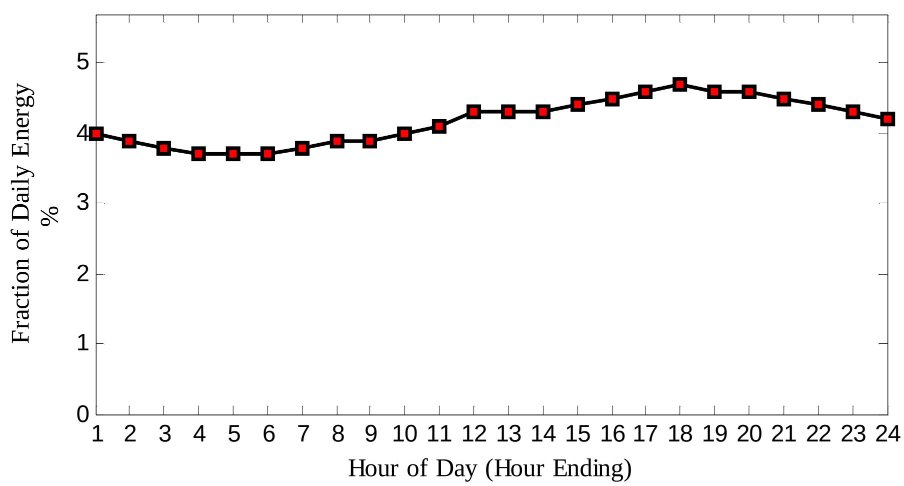
N_{br} Number of bedrooms ($N_{br} = 3$ in this study)

4.4.2.3 Refrigerator

Similarly, a one-year worth of statistically averaged usage pattern of this end-use appliance is utilized from the ELCAP data [81]. The average annual consumption (kWh/year) of a refrigerator is 434kWh/year. Refrigerator is classified as non-controllable appliance; therefore its original consumption pattern will not be modified. The hourly electricity consumption by a refrigerator on an average winter and summer day is shown in Figure 4-16 (a) and (b) respectively.



(a) Winter (Oct - Mar)



(b) Summer (Apr - Sep)

Figure 4-16 ELCAP - Refrigerator Load Shape for an Average Day

(a) Winter Day (b) Summer Day

4.4.3 Solar Power and Energy Storage

4.4.3.1 PV and Energy Storage Systems Integration

Texas is rich in solar resource. With the advantages of emission-free, long life-span and low maintenance requirement, PV is a preference for harvesting solar energy in this study. The incentives and rebates from federal, state and local levels make the PV installation feasible.

The day-night cycling causes the output of PV to be extremely unevenly distributed. Typically, the maximum PV output in a single day appears around 2pm while the peak hours of the demand are between 4pm – 7pm, which is usually when LMP increase dramatically. To effective utilize PV output, energy storage systems (ESS) are implemented in this collaborative system to store the excess energy when the PV generation is higher than load consumption. The stored energy is used to supply load when PV power cannot fulfill the load and it can also be used to mitigate possible price spikes or sags. Several PV and energy storage hybrid projects are built across the world to mitigate the intermittence of the renewable energy. Meanwhile, the importance and benefits of installing ESS are realized more and more in recent years, for example, in California, the Public Utilities Commission requires 1.3GW of battery installation by 2020 [83]. The selection and sizing of ESS are beyond the reach of this study; it is assumed that ESS is preinstalled. Therefore, this study defines the operation strategies while both PV and ESS are available and their sizes are fixed.

4.4.3.2 Energy Storage Systems Operation Strategy

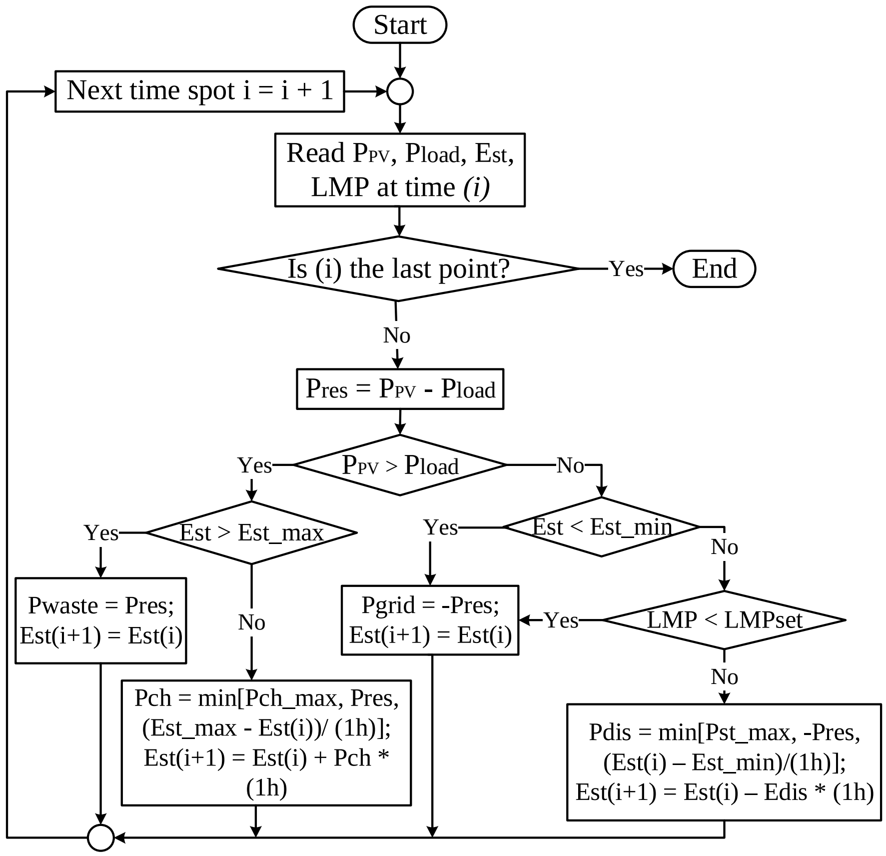


Figure 4-17 Dispatch Algorithm of PV Power and Energy Storage Devices

The operation strategy is designed to choose the power sources for supplying customer appliances, which can be PV output, ESS or grid. The control strategy is illustrated in Figure 4-17. At each time step i, PV output P_{PV}, load consumption P_{load}, ESS energy status E_{st} and LMP are read. The residue power P_{res} is calculated by

$$P_{res} = P_{PV} - P_{load} \tag{4-8}$$

If $P_{res} > 0$, the residue power will be either used to charge ESS when the storage is not fully charged or dumped which leaves E_{st} unchanged. When $E_{st} \geq E_{st\_max}$, the wasted power (which is either consumed in heat or curtailed) P_{waste} and E_{st} are calculated as

$$P_{waste} = P_{res} \quad (4\text{-}9)$$

$$E_{st}(i+1) = E_{st}(i) \quad (4\text{-}10)$$

When $E_{st} < E_{st\_max}$, the storage devices can be charged, and the charging power P_{ch} is limited by the physical limits of the inverters P_{ch_max}, P_{res}, and the ESS energy status. P_{ch} and E_{st} are calculated as

$$P_{ch} = \min\,[P_{ch\_max}, P_{res}, (E_{st\_max} - E_{st}(i))/(1\text{h})\,] \quad (4\text{-}11)$$

$$E_{st}(i+1) = E_{st}(i) + P_{ch} \times (1h) \quad (4\text{-}12)$$

If $P_{res} \le 0$, PV output is not enough to cover the load consumption. If E_{st} is smaller than or equal to the minimum limit E_{st_min}, E_{st} will not be changed, and the power imported from the grid, P_{grid} will compensate the shortage of PV power.

$$P_{grid} = -P_{res} \quad (4\text{-}13)$$

$$E_{st}(i+1) = E_{st}(i) \quad (4\text{-}14)$$

On the other hand, if $E_{st} > E_{st\_min}$, a threshold price, LMP_{set}, is chosen to avoid over cycling of the ESS but still reduce purchasing electricity from grid if the LMP is high. In this study, LMP_{set} is the 75th percentile of the whole year LMP. When $LMP < LMP_{set}$, buying electricity from the grid is acceptable. ESS energy status will be unchanged. P_{grid} and $E_{st}(i+1)$ can also be calculated from (4-13) and (4-14). But when LMP goes beyond the threshold value, the discharge power from the storage devices, P_{dis}, will be limited by the discharging capability of the inverters, the shortage between load consumption and PV output ($-P_{res}$), and the status of ESS. P_{dis} and E_{st} are calculated in (4-15) and (4-16) respectively.

$$P_{dis} = \min\,[P_{dis\_max}, -P_{res}, (E_{st}(i) - E_{st\_min})/(1h)] \quad (4\text{-}15)$$

$$E_{st}(i+1) = E_{st}(i) - P_{dis} \times (1h) \quad (4\text{-}16)$$

4.4.4 Simulation Results

Several conditions and assumptions are made to obtain a more realistic simulation:

1) The aggregation of 1,000 households is considered. The simulation is developed for the entire year of 2011.
2) Recently a number of major appliance companies have invested in the production of smart appliances which are capable of supporting the proposed control strategies. It is assumed that a smart appliance has the ability to automatically schedule its operation based on real time pricing and also allow remote control by customers via smart phones or across the Internet [84].
3) The LMP at a node in central Texas is used for the aggregated load for billing purposes.
4) A distribution level solar farm with ESS is assumed to be available and supplies electricity for the 1,000 customers.

Three case studies are implemented for comparison. The study results for a typical summer day (7/20/2011) and a typical winter day (12/7/2011) are shown as examples for the control of AC/heater. The study result for a summer day with price spikes (7/15/2011) is chosen to show the control strategy of the clothes dryer.

4.4.4.1 No Load Control

In this case, the AC/heater will always operate at the preset temperature regardless of LMP variations. As shown in Figure 4-18 and Figure 4-19, the AC works at 77^{o}F while the heater works at 71^{o}F. The clothes dryer will operate without any load control either, as shown in Figure 4-20.

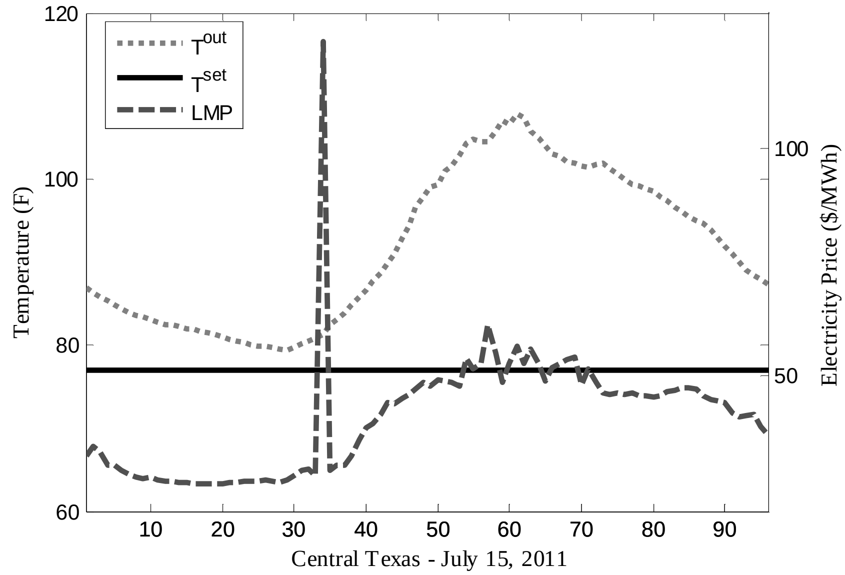


Figure 4-18 Outside Temperature, Temperature Setting and LMP as Seen from a Residential Customer in Central Texas on 7/5/2011

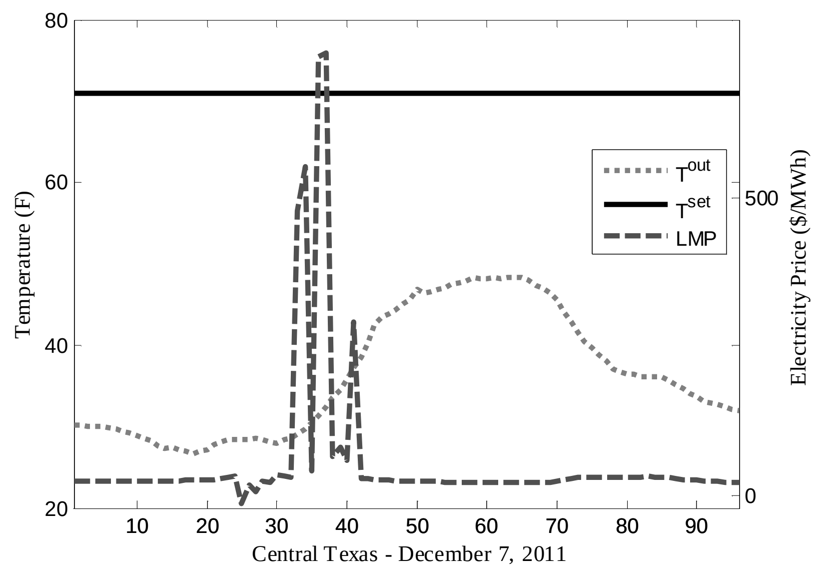


Figure 4-19 Outside Temperature, Temperature Setting and LMP as Seen from a Residential Customer in Central Texas on 12/7/2011

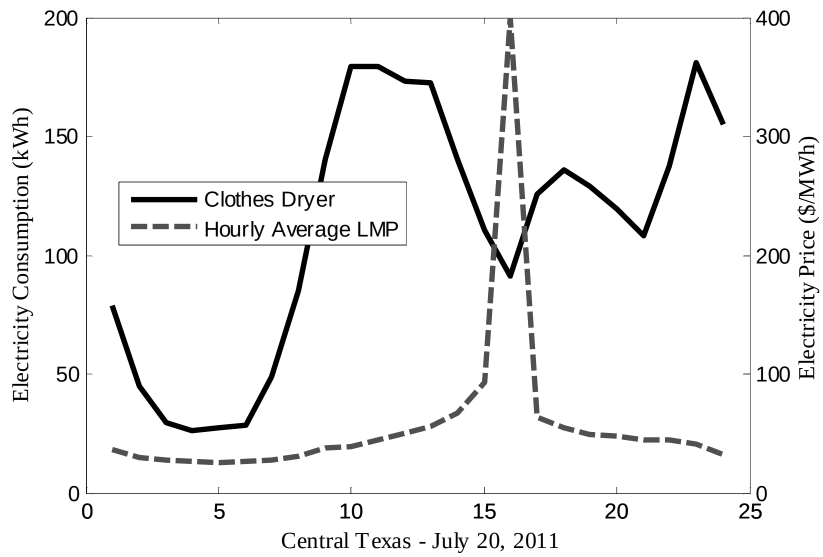


Figure 4-20 Total Clothes Dryer Electricity Consumption for the 1,000 Customers without Load Control and Hourly Average LMP in Central Texas on 7/20/2011

4.4.4.2 Load Control – Steps of Temperature and Price Naming

The ACs and heaters will operate according to the Steps of Temperature control algorithm as seen in Figure 4-21 and Figure 4-22 respectively. It can be noticed that the temperature setting will change depending on the real time LMP.

On the other hand, the clothes dryer will operate following the Price Naming strategy. In this case, the price which lies 97.5th percentile of the LMP (70$/MWh) has been set as the threshold for operation, as shown in Figure 4-23.

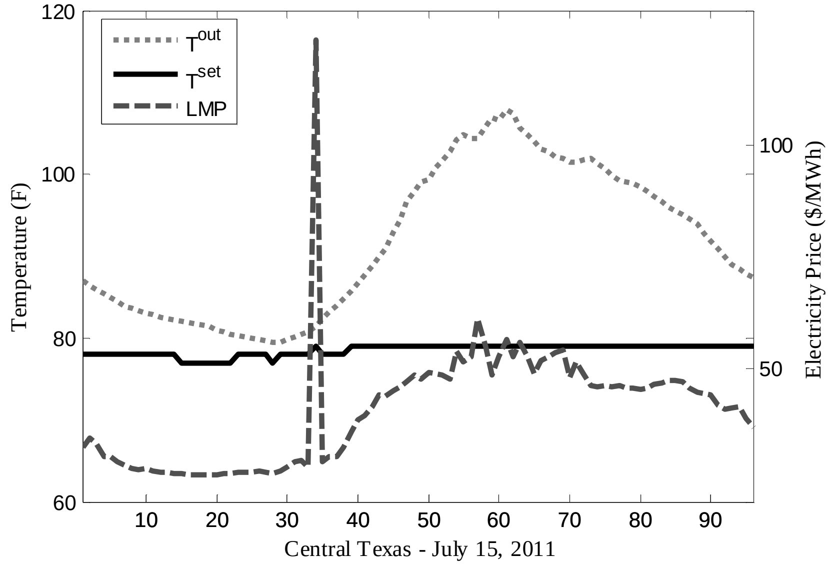


Figure 4-21 Outside Temperature, Temperature Setting and LMP as Seen from a Residential Customer in Central Texas on 7/15/2011 under the Steps of Temperature

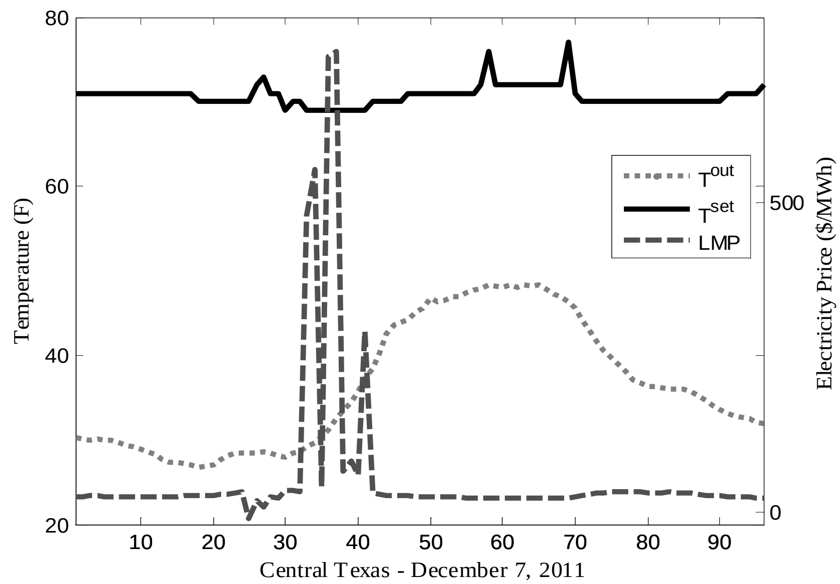


Figure 4-22 Outside Temperature, Temperature Setting and LMP as Seen from a Residential Customer in Central Texas on 12/7/2011 under the Steps of Temperature

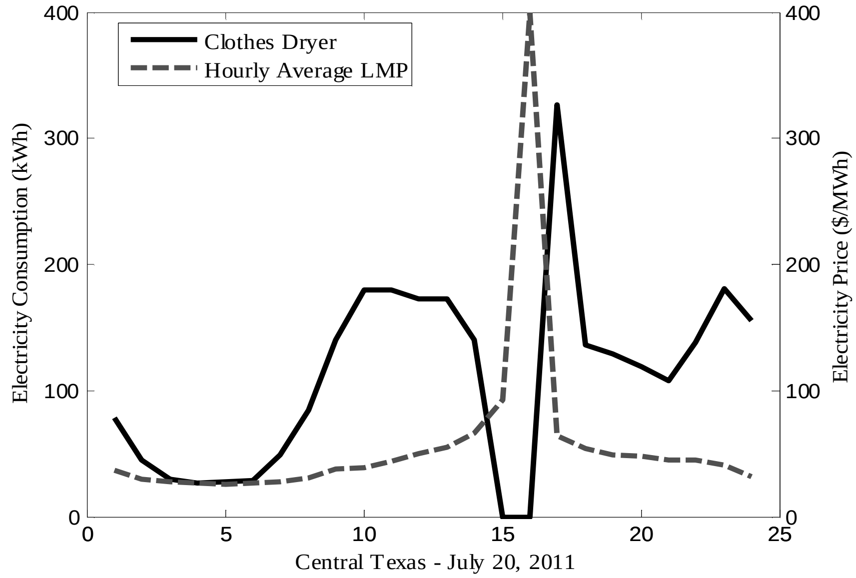


Figure 4-23 Total Clothes Dryer Electricity Consumption for the 1,000 Customers with Price Naming Load Control and Hourly Average LMP in Central Texas on 7/20/2011

4.4.4.3 Load Control with PV and Energy Storage

The operation strategy introduced in Section 4.4.3 is implemented. ESS storage status and LMP are considered for the operation of PV and ESS. The actual hourly output curve of a Texas PV farm in the year 2011 is used for simulation. The energy capacity of the ESS is assumed as 3 times of the average hourly customer total load consumption. The state of charge of the ESS is set between 20% and 80%.

The total load consumption and the powers supplied by PV farm are shown in Figure 4-24. The ESS energy status and LMP variations of a week in July is shown in Figure 4-25 for demonstration purposes. It is shown that the ESS is charged before high LMP period, and discharge during the peak hours.

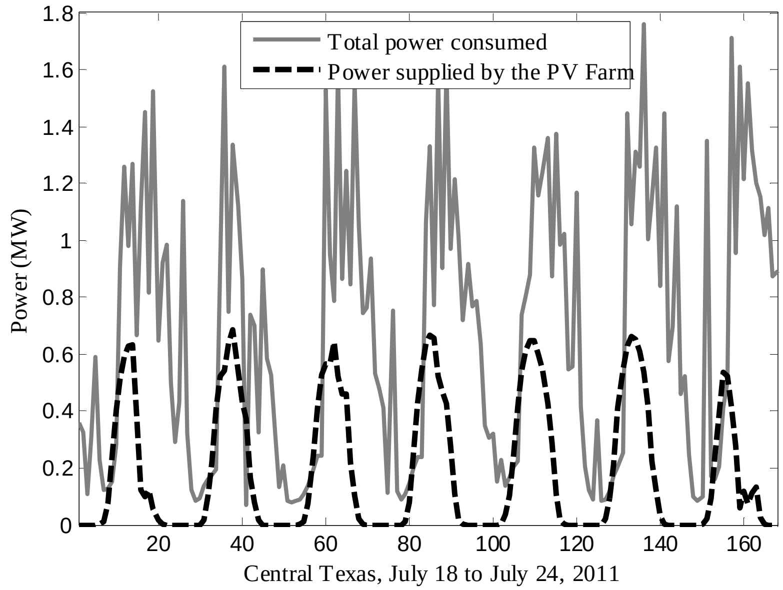


Figure 4-24 Total Load Consumption and Power Supplied by PV Farm

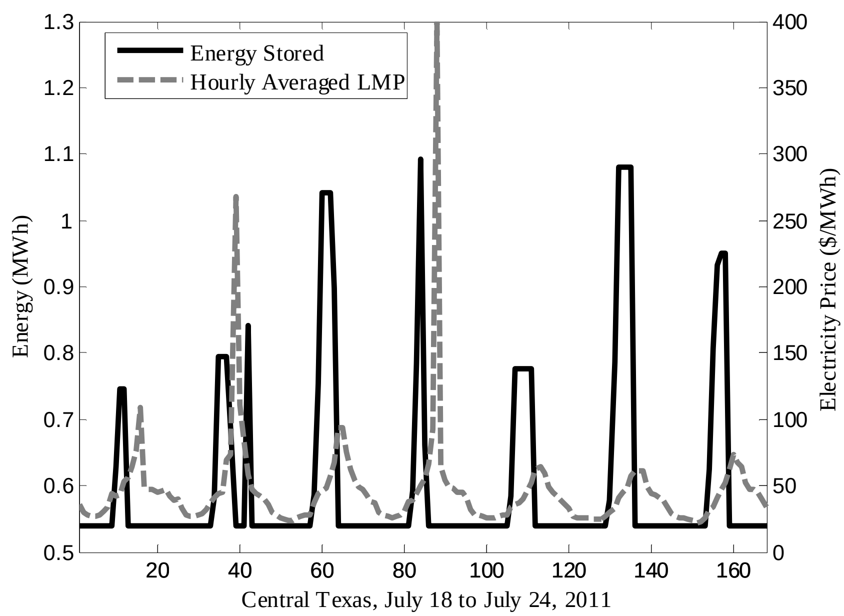


Figure 4-25 Energy Stored in ESS and LMP

The operation strategy is simulated for the whole year of 2011. In summary, when no load control is performed during one year operation, 1,000 customers will consume 7,183 MWh which represents a cost of 0.42 million of dollars. After implementing the load control strategies of Steps of Temperature for the ACs/heaters, and the Price Naming for the clothes dryers, the annual consumption is 7,067 MWh with a cost of 0.38 million of dollars.

Finally, when the group of customers utilizes renewable resources to meet its load through the PV power and ESS coupled with the load control strategies, they will consume from the grid 4,939 MWh which in turn represents 0.30 millions of dollars. This simulation results are summarized in Table 4-5.

Table 4-5 Results of the Simulations

Strategy	Annual Electricity Consumption Drawn from the Grid (MWh)	Total Cost (Millions of $)
No Load Control	7183.3671	0.4205
Load Control: Steps of Temperature, Price Naming	7067.0862	0.3826
Load Control with PV Power and Energy Storage	5994.7382	0.3145

4.4.5 Conclusions

While sustaining the reliability and maintaining the operation efficiency of the grid are the principal missions of ERCOT, DR programs provide a new way to ensure that sufficient resources are committed in electricity market. SB 1125 proposes the expansion of DR programs to residential and commercial customers while the reliability standards are maintained. With the vision that DR will be expanded to residential customers in the foreseeable future, an idea of aggregating a number of residences to shift the coincidental peak load by adopting different operation strategies is proposed. This study develops different operation strategies for the most representative residential load types, including ACs/heaters, clothes dryers, and refrigerators.

When real time LMP information are taken into consideration, by grouping the residential appliances into controllable and uncontrollable loads and designing corresponding operation strategies for each load type, savings can be made for customers, and the load profiles are adjusted to facilitate system reliability.

With the utilization of solar power and ESS, PV output is used both for supplying load demand and saving energy to the ESS. The operation strategies are simulated for a whole year and the annual costs are calculated and compared in this study. The results show that participating DR programs by doing load control and utilizing renewable resources, the total electricity cost can be reduced effectively, which suggests the effectiveness of the proposed approaches.

Chapter 5

Wind Farm Dispatch Scheduling with Hybrid Energy Storage Based on Wind and LMP Forecasting

Wind power, as a promising renewable energy resource for supporting continuously growing electricity demand, bears the disadvantages of non-controllable variability and partial unpredictability, which present challenges for large-scale integration into power system [85]. Energy storage systems (ESS) may work as a solution to shape the variable wind generation to follow certain production plans which benefits both system operation and market participation [86]. Currently, it requires significant financial commitment for a large scale ESS. Accurately forecasted wind power and LMP information can reduce the required capacity and make it financially feasible for the ESS to perform desired functions. This part of the dissertation focuses on the operation of wind farm with appropriate ESS installation.

Wind power forecasting methods can be generally classified into two groups: physical methods and statistical methods [87-89]. Physical methods employ meteorological data and physical laws to forecast the wind speeds and directions, and feed the results into wind turbine power curves to calculate the corresponding power outputs [90]. Statistical methods attempt to develop models using historical wind power data [91]. Hybrid approaches that combine both methods are also proposed to improve forecasting accuracy [92, 93]. Various algorithms have been proposed to develop wind forecasting models, including autoregressive models [94, 95], ANN [96, 97], support vector machines [98, 99], and fuzzy logic [100, 101], etc.

On the other hand, LMP forecasting in competitive electricity markets is critical for any decision-making process of market participants. Different candidates may impact LMP including system load profile, fuel price, transmission congestion, and generation facility behaviors [102]. LMP carries a nonlinear relationship with historical values and the forecasted values of the influencing factors [103]. ANN [104-106] techniques are one of the most commonly used methods for LMP forecasting.

With day-ahead wind power and LMP forecasting results, a wind farm with ESS is able to optimize its operation schedule to obtain maximum financial benefits. Researches have been done to optimize wind farm and ESS operations by forecasting wind power and designing operation strategies accordingly [86, 107]. However, the gap between the predicted and actual wind power is rarely considered.

In this study, the day-ahead wind power and LMP information are forecasted by ANN, and the forecasting results are used to dispatch the primary ESS to store wind power when the LMP is low, and delivers electricity during peak hours when LMP is high. Due to the required response speed, the mismatch between the forecasted wind power and actual wind power is adjusted by a second set of ESS in real-time operation to enhance the performance.

5.1 ANN Based Wind Power and LMP Forecasting

ANNs are massively parallel distributed processors consisted of simple computing units, called neurons, to mimic the learning processes that brain performs by constructing input-output mapping of the given examples [97, 108]. The complex non-linear relationship between input and output variables can be used to make future predictions.

The general structure of three-layer feed-forward ANNs which are composed of an input layer, a hidden layer, and an output layer is shown in Figure 5-1. It has been stated that as long as enough neurons are chosen, one hidden layer is enough to estimate any continuous function for application [97, 109]. This dissertation utilizes forward heuristic simulation to decide the proper number of hidden units. The training process starts with a small number of hidden units and increases the unit number by one until no significant improvement is achieved to avoid overfitting issues.

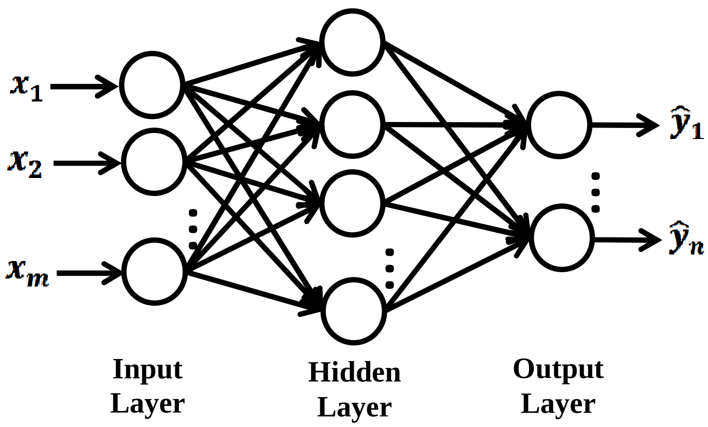


Figure 5-1 Structure of Three Layer Feed-Forward ANNs Model

The selection of input variables is problem-dependent; both influencing factors and historical data may affect the accuracy of the forecasting results. The forecast performances are evaluated by the mean absolute percentage error (MAPE) defined in (5-1), which is the ratio between absolute forecast errors and the actual values.

$$MAPE = \frac{1}{M}\sum_{i=1}^{M}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{5-1}$$

Where

M	total number of data points
y_i	i^{th} actual value
$\hat{y}_i$	i^{th} forecasted value

The forecasting of wind power and LMP information are discussed respectively in the following sections.

5.1.1 Wind Power Forecasting

The hybrid forecasting method is adopted in this study where both numerical weather prediction (NWP) data and historical wind farm power outputs are used to predict the wind power for the next day in 15-min time step. The available data are 9-month power output of a wind farm in West Texas, with a total installation capacity of 160MW. The weather information of the weather station located in the wind farm of the same year can be accessed from [76] and used as NWP data. Based on correlation coefficient analysis defined in (5-2), time indices (hour, quarter) and several meteorological data are used as ANN inputs including temperature, pressure, sine and cosine for wind direction, wind speed and humidity of the forecasting day.

$$\rho_{x,y} = \frac{Cov(X,Y)}{\sigma_x \sigma_y} = \frac{\sum (x-\mu_x)(x-\mu_y)}{\sqrt{\sum (x-\mu_x)^2 \sum (y-\mu_y)^2}} \tag{5-2}$$

Where

$\rho_{x,y}$	correlation coefficient between X and Y;
σ_x, σ_y	standard deviation of X and Y;
μ_x, μ_y	mean of x and y

Autocorrelation function defined in (5-3) is applied for selecting the appropriate lagged values for the power output data. The last 6-hour of day-ahead power outputs in 15-min time-step are chosen as inputs.

$$r_k = \frac{\sum_{t=k+1}^{T} (y_t - \mu_y)(y_{t-k} - \mu_y)}{\sum_{t=1}^{T} (y_t - \mu_y)^2} \tag{5-3}$$

Where

r_k	autocorrelation coefficient between y_t and y_{t-k}
T	length of time series
μ_y	mean of y

Therefore, the networks shown in Figure 5-1 is composed of three layers for wind power forecasting, while the input layer has 32 neurons, the output layer has 1 neuron (power output), and the hidden layer is calculated to have 20 neurons. The hyperbolic tangent activation function is employed with the networks and Levenberg-Marquardt method is used to train the model. The data from January to June are used to train the network and the data from July to September are used for testing. The MAPE of the model is calculated to be 10.24%. The actual and forecasted wind power of a week in July is plotted in Figure 5-2 as an example. The results of the ANN forecasting is accurate enough to forecast the day-ahead wind power, and the results will be used for day-ahead wind and hybrid ESS system operation optimization in Section 5.5.

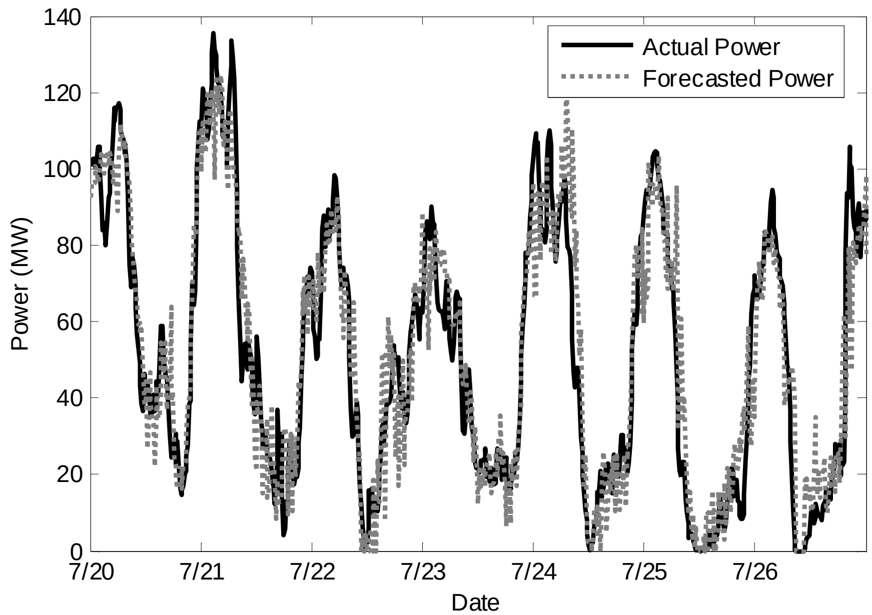


Figure 5-2 Actual and Forecasted 15-min Wind Power of a Sample Week in July

5.1.2 LMP Forecasting

In nodal market, LMP is the cost to provide the next MW of power at given node; it includes marginal generation cost, marginal loss cost and marginal transmission congestion cost [43]. In ERCOT, wind generation is not required to submit offers in the day-ahead market like other qualified scheduling entities. Wind generation resources are allowed to generate according to the wind condition, and it usually participates the real-time market as a price-taker [110]. Thus, the day-ahead LMP forecasting provides essential information for optimizing the wind-hybrid ESS dispatch schedule. Since LMP does not fluctuate as frequently as wind power output, the time-step of LMP forecasting is chosen at 1-hour.

ANN technique is applied for the day-ahead hourly LMP forecasting in this dissertation. The hourly LMP and load profile of ERCOT real-time market are used for the study. Based on correlation coefficient and autocorrelation coefficient analysis discussed in Section 5.1.1, the variables feeding the input layer are: day of the week, hour, whether or not holiday, forecasted temperature, system load and the lagged values of LMP_{t-k}, corresponding to the indices k = 24, 25, 26, 48, 49, 50, 72, 73, 74, 96, 97, 98, 120, 121, 122, 144, 145, and 146. For LMP forecasting, the input layer has 23 neurons, the hidden layer is calculated to have 18 neurons, and the only output neuron is LMP.

The annually 15-min LMP data from ERCOT are available and the hourly LMP data feeding into the ANN are the average value of each hour at the node nearest to the wind farm. The data from January to June are used to train the network and the data from July to September are used for testing. The actual and forecasted hourly LMP of the same sample week as wind power is plotted in Figure 5-3. The MAPE is calculated to be 17.38%. The majority of the forecasting errors come from the price spikes.

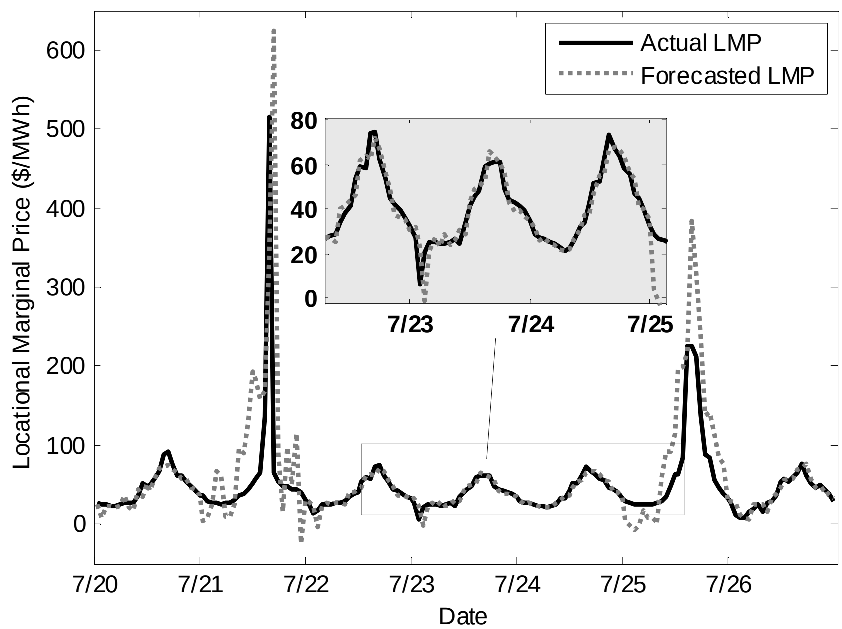


Figure 5-3 Actual and Forecasted Hourly LMP of a Sample Week in July

Two price spikes can be observed in the weekly LMP curve in Figure 5-3. The price spikes are possibly caused by either transmission congestions or dispatching of expensive peaking units to compensate the insufficient system level wind power output, which was forecasted by the system operators to plan for generation schedule. From Figure 5-3, LMP forecasting for an operation day without price spike can reflect the price variations more accurately, as shown by the magnifying window. However, when LMP spikes happen, as in July 21 and July 25, the mismatches between actual and forecasted LMP become quite large.

It can be observed from Figure 5-2 and Figure 5-3 that the wind farm has higher output in the early morning and at late night while the LMP has higher values, even spikes, during the peak hours, typically in the afternoon. Therefore, the application of hybrid ESS can optimize the production plan of the wind-storage system according to LMP variations to realize financial benefits from the power markets.

5.2 Hybrid ESS Technology Selection

The Hybrid ESS is composed of two set of ESS in this study. The primary ESS is utilized for optimizing wind-storage system production with day-ahead forecasting data. Different types of technologies have been adopted for bulk energy storage in power system, while several studies suggest that pump hydroelectric storage (PHS) is the most widely used large-scale ESS because of technology maturity, large storage capacity, long storage period, high round-trip efficiency and relatively low capital cost per unit energy [10, 86, 111]. Therefore, PHS is chosen as the primary ESS in this study where the pump will elevate the water to an upper reservoir during off-peak hours and a turbine will generate electricity when the water is released during peak hours.

In real-time operation, the forecasting errors are addressed by a secondary ESS. With a smaller operation time-step (15-min is chosen), the secondary ESS reacts to the actual wind power and LMP data and adjusts the total production schedule accordingly.

Compared with the primary ESS, the secondary ESS requires smaller installation capacity and faster response time. Being highly modular and having low standby losses, rechargeable batteries can respond very rapidly to smooth out load changes and co-generated power. Various rechargeable batteries are available nowadays, among which sodium sulfur (NaS) battery is preferred in this study due to its very high electrical efficiency, long cycle life and potential low cost [10].

5.3 Day-Ahead Wind-ESS Optimization

For wind-ESS operation optimization with day-ahead wind power and LMP forecasting data, the available wind power can be: 1) directly delivered to the grid; 2) stored to the primary/secondary ESS and redeliver to the grid later; 3) dissipated by dump load or wind curtailment, as shown in Figure 5-4.

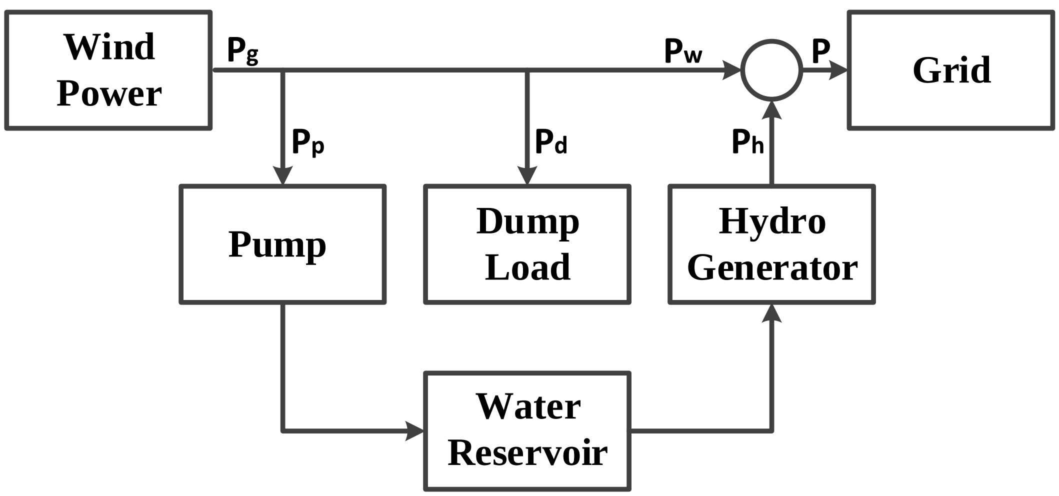


Figure 5-4 Day-ahead Operation of Wind Farm and the Primary ESS

To decrease the wear and tear costs of hydro units, the dispatch is scheduled for each hour. The daily operation optimization function is defined as

$$\max_{P^{(i)},P_p^{(i)}} \sum_{i=1}^{24} (P^{(i)} \times LMP^{(i)} - P_p^{(i)} \times C_p) \tag{5-4}$$

Where the objective is to maximize the total daily revenue, *(i)* is the number of time interval, *P* is the power delivered to the grid based on forecasting, LMP is the locational marginal price P_P is the power consumed by pump system and C_P is the cost of pump system. The revenue is calculated from the sale of wind power in different hour at different LMP subtracting the cost of operating the pump system.

The optimization is subject to the following constraints.

1) Power Balance Constraints:

$$P^{(i)} = P_w^{(i)} + P_h^{(i)} \tag{5-5}$$

$$P_g^{(i)} = P_w^{(i)} + P_p^{(i)} + P_d^{(i)} \tag{5-6}$$

Where P_W is the wind power delivered to the grid directly, P_h is the power generated by hydro unit, P_d is the power dissipated by dump load, and P_g is the forecasted total available wind power.

2) Delivered Wind Power Constraints:

$$P_w^{(i)} \geq 0 \tag{5-7}$$

This constraint limits that the power consumed by the pump system can only be supplied by the wind farm.

3) Dump Load Constraints:

$$P_d^{(i)} \geq 0 \tag{5-8}$$

4) Pump Output Constraints:

$$P_p^{\min} \leq P_p^{(i)} \leq P_p^{\max} \tag{5-9}$$

Where P_p^{min} and P_p^{max} are the maximum and minimum pump system power consumption limits.

5) Hydro Unit Output Constraints:

$$P_h^{\min} \leq P_h^{(i)} \leq \min\left(P_h^{\max}, \eta_h \frac{E_R^{(i)}}{1h} \right) \tag{5-10}$$

The output of the hydro unit is limited by its own power limits and the available energy stored in the upper water reservoir. P_h^{min} and P_h^{max} are the maximum and minimum hydro unit power generation limits. E_R is the available water reservoir energy, and η_h is hydro unit efficiency.

6) Water Reservoir Energy Constraints:

$$E_R^{(i+1)} = E_R^{(i)} + \left(\eta_p P_p^{(i)} \times (1h) - \frac{P_h^{(i)}}{\eta_h} \times (1h) \right) \tag{5-11}$$

$$0 \le E_R^{(i)} \le E_R^{\max} \tag{5-12}$$

$$E_R^{(1)} = E_R^{(24)} = E_R^{\max} \times k \tag{5-13}$$

Where η_p is pump system efficiency and E_R^{max} is the maximum available water reservoir energy.

The energy stored in the water reservoir at the beginning of each hour is determined by the initial energy of the previous hour and the output of both pump system and hydro generation units during the previous hour. To make the operation strategy available for longer time span, the initial and final energy levels of an operation day are predefined by an energy level factor k as shown in (5-13).

5.4 Real-Time Wind-ESS Dispatch

In real-time operation, the primary ESS system is dispatched based on the optimal schedule developed from day-ahead forecasting information. While the actual wind power output may differ from forecasted value, the secondary ESS either compensates the power mismatches or exploits the excess wind power concerning its energy and power limits. In real-time power market, ERCOT publishes the settlement price for each node 5-min ahead of the operation time. The prices of at 0, 15, 30 and 45 minutes of each hour are used as actual LMP, and are used for price comparison for the next 15 minutes. The actual LMP is compared with a threshold price (LMP_{thr}), which is determined according to LMP forecasting to reduce unnecessary or uneconomic battery cycling. The algorithm of dispatching the secondary ESS is shown in Algorithm 5-1.

Algorithm 5-1 Secondary ESS dispatch

For each time interval (i)

  if $P_g^{act(i)} > P_g^{(i)}$ (P_{mis} is positive)

    if $LMP^{(i)} < LMP_{thr}$

      (charge battery until E_B^{max}; deliver rest power to grid)

      $P_{ch}^{(i)} = \min[P_{ch}^{max}, P_{mis}, \eta_{bch} \cdot (E_B^{max} - E_B^{(i)}) / t]$

      $P^{act(i)} = P^{(i)} + P_{mis}$

      $E_B^{(i+1)} = E_B^{(i)} + P_{ch}^{(i)} \times t$

    else ($LMP^{(i)} > LMP_{thr}$)

      (deliver wind power and battery energy to grid)

      $P_{dch}^{(i)} = \min[P_{dch}^{max}, \eta_{bdch} \cdot (E_B^{(i)} - E_B^{min}) / t]$

      $P^{act(i)} = P^{(i)} + P_{mis} + P_{dch}^{(i)}$

      $E_B^{(i+1)} = E_B^{(i)} - P_{dch}^{(i)} \times t$

    end if

  else **(**$P_g^{act(i)} < P_g^{(i)}$, P_{mis} is negative)

    if $LMP^{(i)} < LMP_{thr}$

      (deliver less wind power to grid; charge reservoir)

      $P^{act(i)} = P^{(i)} + P_{mis}$

      $E_B^{(i+1)} = E_B^{(i)}$

    else ($LMP^{(i)} > LMP_{thr}$)

      (discharge battery; deliver energy to grid)

      $P_{dch}^{(i)} = \min[P_{dch}^{max}, \eta_{bdch} \cdot (E_B^{(i)} - E_B^{min}) / t]$

      $P^{act(i)} = P^{(i)} + P_{dch}^{(i)} + P_{mis}$

      $E_B^{(i+1)} = E_B^{(i)} - P_{dch}^{(i)} \times t$

      $E_R^{(i+1)} = E_R^{(i+1)} + \eta_p P_{mis}$

    end if

  end if

Where P_g^{act} is the actual total available wind power, P_{mis} is the actual and forecasted wind power mismatch, LMP_{thr} is the LMP threshold for secondary ESS operation, P_{ch}, P_{dch} and η_{bch} are battery charge power, discharge power and charging efficiency respectively, and E_B is the available battery capacity.

In each 15-min time interval, when the actual wind power exceeds the forecasted value, real-time LMP will be compared with LMP_{thr} to determine the strategy to use the surplus wind power. The secondary ESS will be charged until its maximum capacity when LMP is lower than LMP_{thr} to shift the power to peak hours; when LMP surpasses LMP_{thr}, the extra wind power will be directly delivered to the grid to gain financial benefits.

On the contrary, when the actual wind power fails to reach the forecasted level, if real-time LMP is less than LMP_{thr}, instead of being delivered to the grid, wind power is consumed by the pump system to elevate water to the upper reservoir; if real-time LMP is greater than LMP_{thr}, the energy stored in the secondary ESS will be discharged and sent to grid to take advantage of the high LMP. At the same time, the output of the primary ESS will be used to accommodate possible deficits of the wind power.

5.5 Application Results and Discussion

Numerical simulation results of sample cases are used to illustrate the benefits of the proposed dispatch method.

5.5.1 Assumptions and Parameters Selection

ESS can contribute to grid reliability needs, defer transmission and distribution upgrade investments as well as integrate renewable generation resources. The advantages of implementing ESS have been realized in recent years and the installation of ESS starts to become mandatory. For example, in October 2013, the California Public Utilities Commission sets an energy storage goal for utilities of installing 1.3 GW batteries by 2020 [83]. Since the main goal of this part of the dissertation is to design the operation strategy of wind farm with hybrid ESS, the installation and maintenance costs of the ESS are not considered in the calculation.

The total available primary storage capacity is defined as 80% of 2-hour wind farm installation capacity, which is 256MWh. The efficiency of pump system and hydro unit are both set at 87%, with a round-trip efficiency $\eta_r = \eta_p \times \eta_h = 75.7\%$. The power output limits of the hydro units are defined as 10MW and 50MW for minimum and maximum respectively, and pump system can consume from 0MW to 50MW. The operation cost of pump system is set as 2$/MWh. The energy level factor k of the primary ESS is set as 50%.

For the secondary ESS, NaS battery has a high charge/discharge efficiency (85+%) [112]. Therefore, the charge and discharge efficiency are both set as 93% with a round-trip efficiency of 86.5%. Being secondary ESS, the energy capacity of the battery system is smaller since it is designed to adjust mismatches between forecasted and actual wind power. The total energy capacity is set as 2-hour of average wind power mismatches, (a forecasting error of 10.78% is this study), which is 18MWh. The limits for the state of charge are defined between 20% and 80% of the energy capacity, and the maximum charge and discharge power are both defined as 2MW. The LMP threshold (LMP_{thr}) is set as 75 percentile of the forecasting results to avoid unnecessary cycling.

5.5.2 Case Studies

As discussed in Section 5.1.2, the accuracy of LMP forecasting becomes worse when price spikes happen. The dispatch strategy of two typical summer days, July 24th (without LMP spikes) and July 25th (with LMP spike) are used as examples to calculate the financial revenues respectively.

To solve the optimization problem, CVX, a package for specifying and solving convex programs is used *[113, 114]*. The dispatch results of the wind farm and ESS for

July 24th, when no LMP spikes happen, are shown in Figure 5-5 to Figure 5-8. In Figure 5-5, the total forecasted wind power and the scheduled deliverable wind power are plotted to the left axis. The LMP are plotted to the right axis. A large portion of the wind power generated between 5am and 9am when the LMP is low (shown in Figure 5-5) are shifted to the peak hours between 3pm to 6 pm as shown by the solid curve which represents the total scheduled wind power in Figure 5-8. The charge and discharge process of both primary ESS and secondary ESS are plotted in Figure 5-6 and Figure 5-7. The total actual output of the wind-storage system is plotted by the dash line in Figure 5-8. The total revenue of this case is $45832, while the original revenue without optimization is $39898.

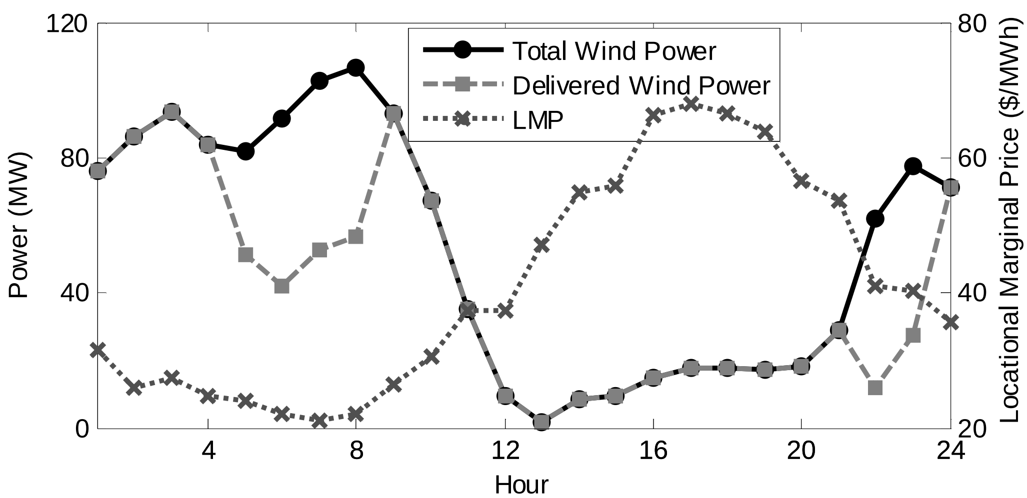


Figure 5-5 Total Wind Power, Delivered Wind Power (Left-Axis) and LMP (Without Price Spikes, Right-Axis) for July 24th

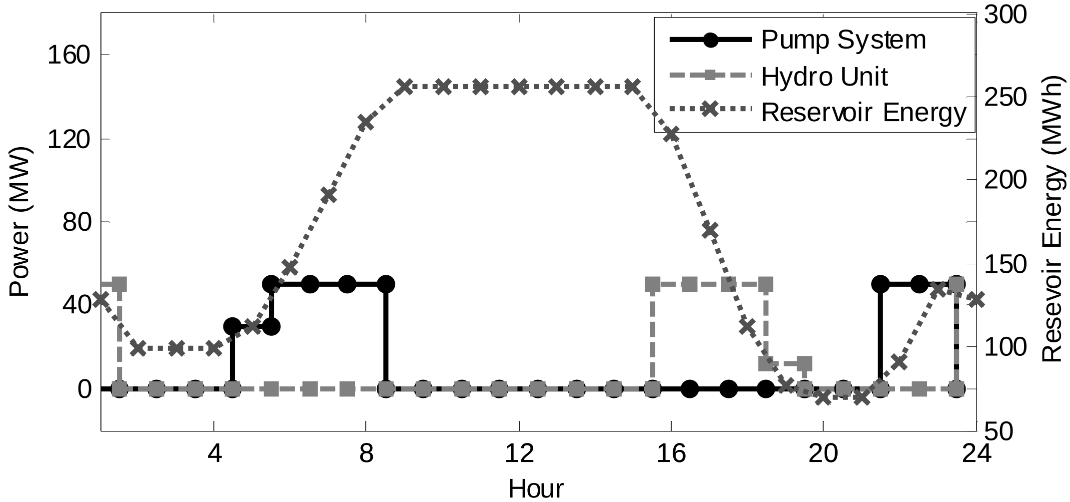


Figure 5-6 Pump System Consumption, Hydro Unit Output (Left-Axis) and Water Reservoir Energy Level (Right-Axis) for July 24th

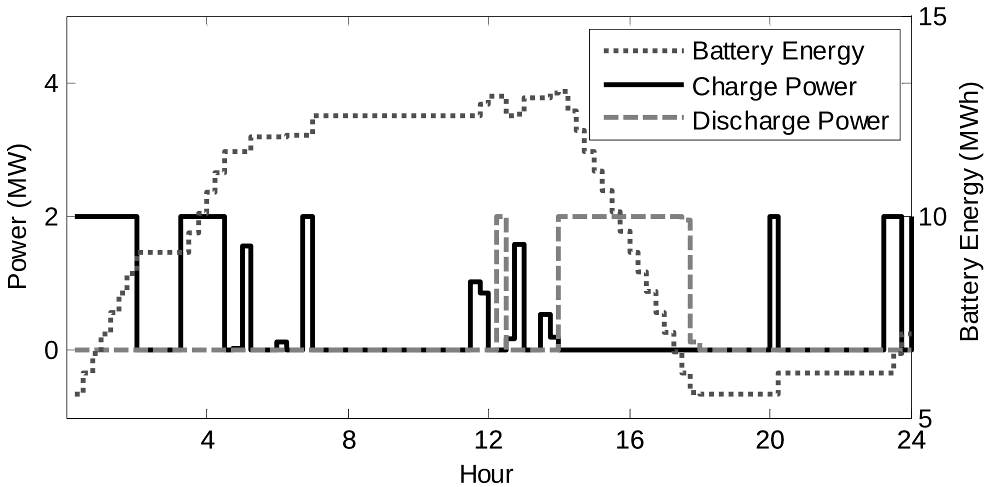


Figure 5-7 Battery Charge and Discharge Power (Left-Axis) and Battery Energy (Right-Axis) for July 24th

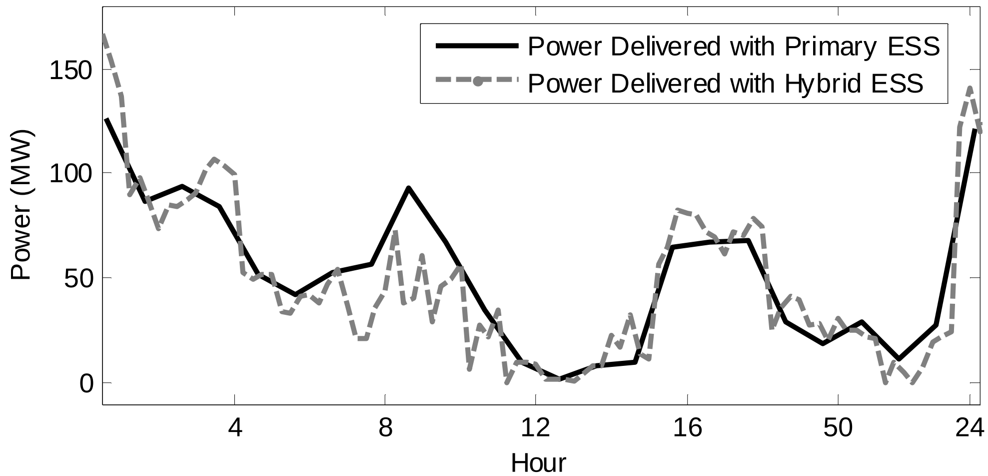


Figure 5-8 Scheduled Power Delivered with Primary ESS and Actual Power Delivered to the Grid with Hybrid ESS for July 24th

The dispatch results for July 25th, when LMP spikes happen are shown in Figure 5-9 and Figure 5-12.

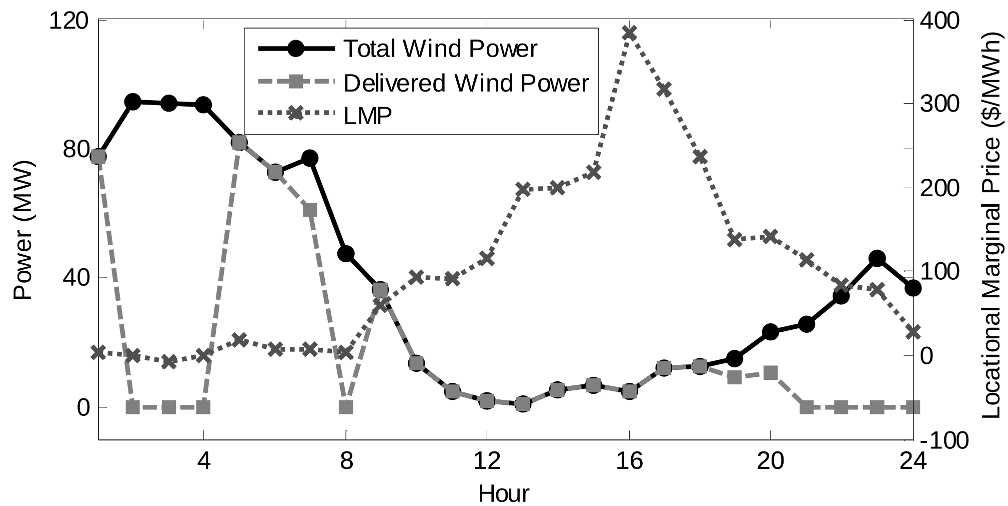


Figure 5-9 Total Wind Power, Delivered Wind Power (Left-Axis) and Lmp (With Price Spikes, Right-Axis) for July 25th

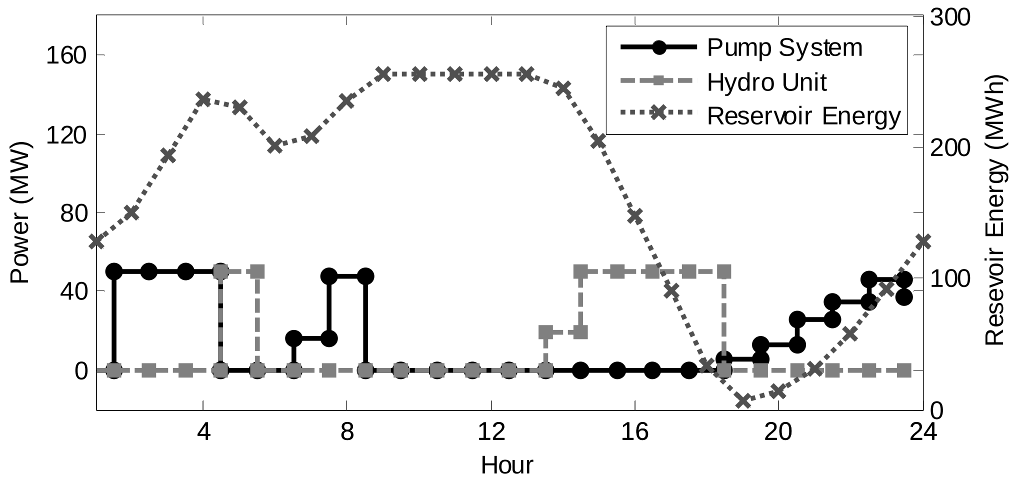


Figure 5-10 Pump system consumption, hydro unit output (left-axis) and water reservoir energy level (right-axis) for July 25th

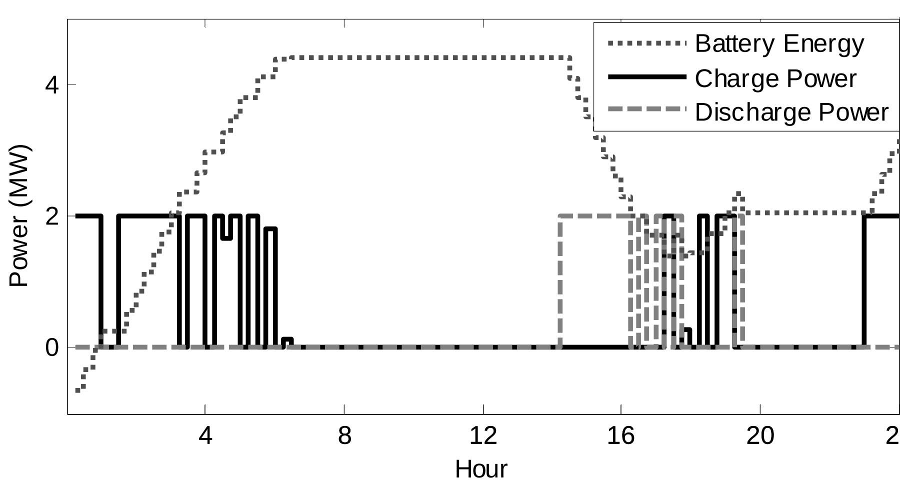


Figure 5-11 Battery charge and discharge power (left-axis) and battery energy (right-axis) for July 25th

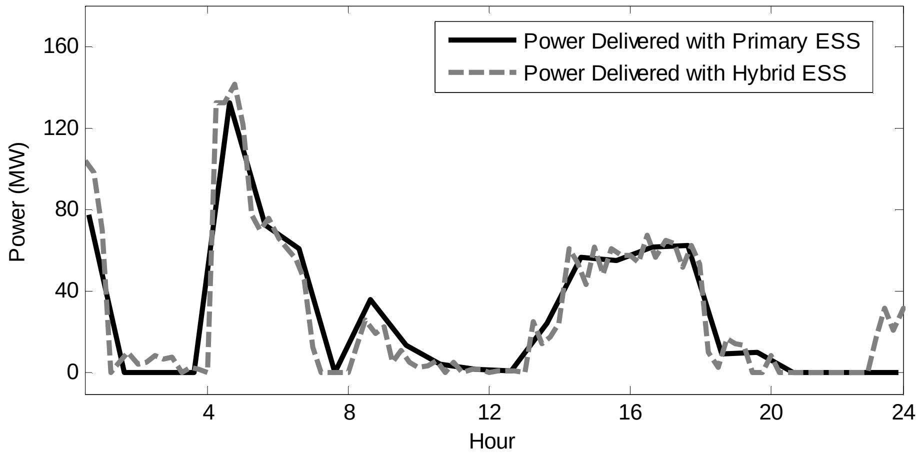


Figure 5-12 Scheduled power delivered with primary ESS and actual power delivered to the grid with hybrid ESS for July 25th

When comparing the dispatch results with non-spike case, it can be observed that when there are LMP spikes, more wind power are stored into ESS and discharged when the price is considered high, and less wind power are directly delivered to the grid, as shown in Figure 5-9. To take advantage of the tremendous LMP variations, both primary ESS and secondary ESS are cycled more often than the operation day without LMP spikes, as shown in Figure 5-10 and Figure 5-11. The total actual output of the wind-storage system is plotted by the dash line in Figure 5-12. The total revenue of this case is \$61085, while the original revenue without optimal scheduling is \$30761.

The dispatch results are compared and summarized in Table 5-1. With hybrid ESS, the total revenue of the wind farm has satisfactory improvement for both operation days with and without LMP spikes. The revenue increase for July 24th is about 15.11%; the revenue increase for July 25th, when the price cap goes up to 400 \$/MWh, is as high as 98.49%. Therefore, with accurately forecasted wind power and LMP information, the dispatch of the wind farm with hybrid ESS system works as a profitable strategy in the deregulated electricity market.

Table 5-1 Dispatch and Original Revenue Comparison

Date	Original Revenue ($)	Dispatch Revenue ($)	Increase (%)
July 24th (no LMP spikes)	39898	45925	15.11
July 25th (LMP spikes)	30761	61059	98.49

5.6 The Impacts of Forecasting Accuracy

To achieve optimal dispatch results, accurately forecasted wind power and LMP information play important roles. With wind power and LMP information, the hybrid ESS is able to plan ahead to store wind power and consume the stored energy based on electricity price signals. Moreover, well-forecasted wind power can enhance system stability and reduce economic uncertainty. On the other hand, well-forecasted LMP information is able to reduce network congestion and generate electric power by more efficient units. However, both wind power and LMP information are affected by various factors. For wind, factors including temperature, pressure, wind direction, wind speed, humidity and so on; all these factors have impacts on the actual wind power outputs of a wind farm. For LMP information, uncertainties contain generators operation plan, season, weather, network congestions, outage plans, etc. Though historical data and other related information are available, there is an ongoing research in the energy forecasting community to improve the forecasting accuracy of wind and LMP to achieve better results.

To study the impacts of forecasting accuracy on the hybrid ESS dispatch results proposed by this dissertation, pseudo hourly wind power and 15-min LMP day-ahead forecasting data for the peak season (from July to September) are used to study the relationship between dispatch revenue and forecasting accuracy. The peak season is chosen because the LMP usually experience more price spikes during this period, so the ESS can make better financial revenue. The MAPE of wind power forecasting is from 10% to 20%, with a rough step of 3%, while the MAPE of LMP forecasting is from 17.73% to 26.39% with a rough step of 3%. The MAPE of the pseudo wind power and LMP Forecast data used for the study are summarized in Table 5-2.

Table 5-2 The MAPE of the Pseudo Wind Power and LMP Forecast Data

	MAPE			
Wind Power	10.76 %	13.21 %	16.23 %	20.07 %
LMP	17.73 %	20.09 %	23.72 %	26.39 %

Different cases are studied with each pair of wind power and LMP MAPE. The total revenues of the months from July to September are calculated, and the comparisons of the revenue are shown in Figure 5-13.

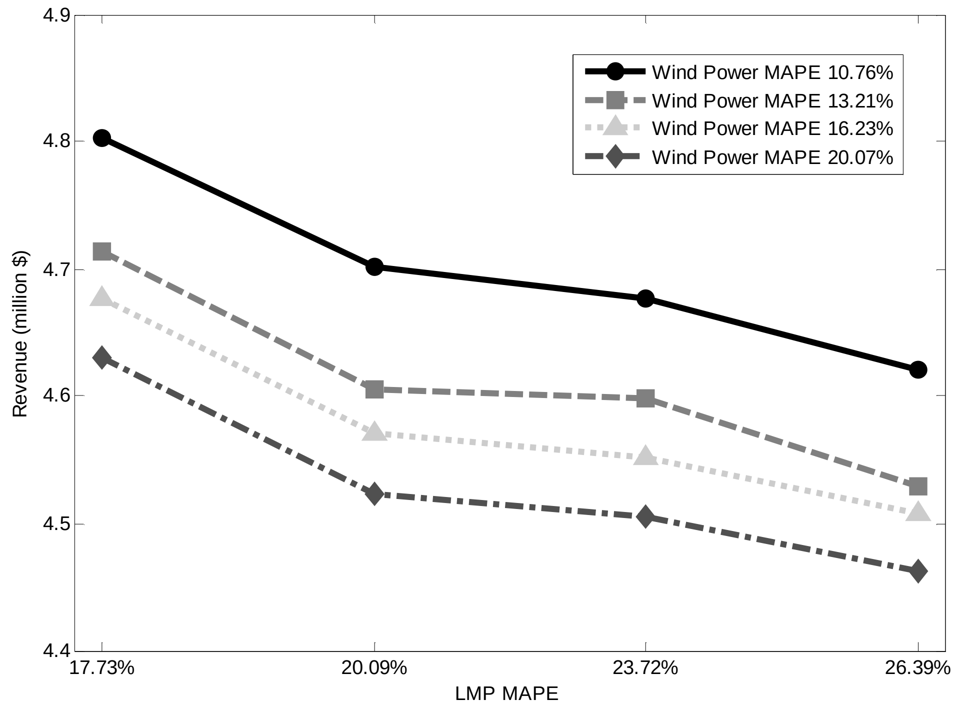


Figure 5-13 Comparison of Total Revenue for Different Wind Power and LMP MAPE Cases

It can be shown from the comparison results that the total revenue drops as the forecasting accuracy decreases. An approximately 10% drop from both LMP forecasting MAPE and wind power forecasting MAPE will reduce the total revenue about 4%. Therefore, increasing forecasting results is crucial for improving the total dispatch revenue.

5.7 Summary

In this study, the dispatch strategy for a wind farm with hybrid ESS is developed based on day-ahead wind power and LMP forecasting information. In general, the outputs of the wind generation resources are based upon wind conditions, and they participate in the electricity market as price-takers. While the potential benefits of large-scale ESS are recognized nowadays, some states have passed regulations about energy storage installation requirements. In this dissertation, a hybrid ESS with primary ESS and secondary ESS is designed to dispatch the total output of wind-storage system according to LMP signals. The primary ESS is designed to optimize system revenue according to day-ahead wind power and LMP forecasting, while the secondary ESS is applied to adjust the mismatches between actual values and forecasted values in real-time operation. Two-case studies for two typical summer operation days, one with LMP spikes and one without LMP spikes, are included to show the potential financial benefits of the dispatch strategy. The calculation results show that large financial benefits can be achieved by the proposed dispatch strategy, especially for days with LMP spikes. Improving both, wind power and LMP forecasting, is a crucial method of improving the total revenue.

Chapter 6

Conclusions and Future Work Directions

6.1 Conclusions

As an alternative to conventional power plants, renewable energy draws more and more attention to fulfill the growing electricity demand owing to its sustainable nature. However, the non-dispatchable output of renewable energy presents significant challenges for power systems, especially for large-scale integration. Being a bridge between renewable resources and the grid, ESS could shape the variable renewable generation to follow certain production plans which benefits both system operation and market participation. Furthermore, ESS can contribute to grid reliability needs, defer transmission and distribution upgrade investments as well as integrate renewable generation resources.

This dissertation presented several studies covering the utilization of ESS for seamless integration of renewable energy under ERCOT nodal market design to pursue financial revenue for both renewable generation side and end-use customer side:

For renewable generation side, by creating a hybrid renewable power plant, it was shown that the intermittent output of wind and solar PV generation could compensate each other. With the help of ESS, the hybrid generation profile could follow the ERCOT load profile, which can benefit system reliability and increase the dispatchability of renewable resources.

Another study focused on the operation dispatch of a wind farm. In this study, the day-ahead wind power and LMP information were forecasted by ANN, and the forecasting results were used to dispatch the primary ESS to store wind power when the LMP is low, and to deliver electricity during peak hours when LMP is high. In real-time operation, the mismatch between the forecasted wind power and actual wind power was adjusted by a second set of ESS to enhance its performance. Since the mismatch may be either positive or negative, the secondary ESS either compensated the power mismatches and/or exploited the excess wind power concerning its energy and power limits. With this hybrid ESS design, financial benefits can be achieved for the wind farm.

For end-user customer side, different scenarios were designed and studied for demand response program participation. The participation of Voluntary Load Response program is studied for residential customers, and the application of renewable energy resources at distribution level with ESS are studied. At aggregated level, the appliances are classified into different groups according to their criticality to human lives, and different control algorithms were designed to allow the aggregated load to participate in demand response programs for financial benefits.

6.2 Future Work Directions

Currently, the high capital costs of the ESS are still the main obstacles preventing it from large-scale industrial application. Sizing the ESS and selecting suitable ESS technology and corresponding auxiliary devices for each specific renewable power plant site is of great value before implementation.

In addition, the forecasting method used in this dissertation is the ANN, which is a relatively mature method for wind power and LMP forecasting. Some other forecasting algorithms might be studied for wind power and LMP forecasting to improve the forecasting results, and different forecasting results could be fed into the optimization models to compare the final results.

Finally, the optimization model used in this dissertation was a deterministic model, where the output of the model was fully determined by the parameters and the initial conditions. Solving the problems with stochastic models considering the randomness in power system operation may be conducted in future research.

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