An Investment Planning Model for a Battery Energy Storage System

- Considering Battery Degradation Effects

by

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ABSTRACT

As global energy demand has dramatically increased and traditional fossil fuels will be depleted in the foreseeable future, clean and unlimited renewable energies are recognized as the future global energy challenge solution. Today, the power grid in U.S. is building more and more renewable energies like wind and solar, while the electric power system faces new challenges from rapid growing percentage of wind and solar. Unlike combustion generators, intermittency and uncertainty are the inherent features of wind and solar. These features bring a big challenge to the stability of modern electric power grid, especially for a small scale power grid with wind and solar. In order to deal with the intermittency and uncertainty of wind and solar, energy storage systems are considered as one solution to mitigate the fluctuation of wind and solar by smoothing their power outputs. For many different types of energy storage systems, this thesis studied the operation of battery energy storage systems (BESS) in power systems and analyzed the benefits of the BESS. Unlike many researchers assuming fixed utilization patterns for BESS and calculating the benefits, this thesis found the BESS utilization patterns and benefits through an investment planning model. Furthermore, a cost is given for utilizing BESS and to find the best way of operating BESS rather than set an upper bound and a lower bound for BESS energy levels. Two planning models are proposed in this thesis and preliminary conclusions are derived from simulation results. This work is organized as below: chapter 1 briefly introduces the background of this research; chapter 2 gives an overview of previous related work in this area; the main work of this thesis is put in chapter 3 and chapter 4 contains the generic BESS model and the investment

planning model; the following chapter 5 includes the simulation and results analysis of this research and chapter 6 provides the conclusions from chapter 5.

To my wife,

Your encouragement and support

give me the strength to across the mountains.

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Sets

$BAT(i)$	Set of all batteries at bus i
BUS	Set of all buses
ES	Set of all BESSs
G	Set of all generators
G^{normal}	Set of all generators except slow startup generators
G^{slow}	Set of all slow startup generators
$GEN(i)$	Set of all generators at bus i
H	Set of BESS types

LINE	Set of all transmission lines
PV	Set of all photovoltaic stations
S	Set of all scenarios
SIZE	Set of BESS capacity sizes
SIZE_PE	Set of power electronic device capacity sizes
SOL(i)	Set of all photovoltaic stations at bus *i*
SOLAR	Set of all photovoltaic stations
T	Set of all time periods
π(,i)*	Set of all lines connected to bus *i* as "to bus"
π(i,)*	Set of all lines connected to bus *i* as "from bus"
Variables	
$ch_{b,h,t,s}$	BESS charging power variable
$dch_{b,h,t,s}$	BESS discharging power variable
I_h	BESS type selection variable
$I_{b,h,m}$	BESS selection variable
$I_{b,n,z}^{PE}$	Power electronic device selection variable
$I_{b,t}^{FC}$	Full charge variable
$P_{g,t,s}$	Generator power output variable
$P_{o,t,s}$	Photovoltaic station power output variable
$P_{k,i,j}$	Active power flow on line k from bus *i* to bus *j*
$Q_{k,i,j}$	Reactive power flow on line k from bus *i* to bus *j*
$r_{g,t,s}$	Spinning reserve provided by generators

$r_{b,t,s}$ Spinning reserve provided by BESS

$SOC_{b,h,t,s}$ BESS State-of-Charge variable

$u_{g,t,s}$ Generator status variable

$u_{g,t}$ Slow generator status variable

V_i Bus *i* voltage

$v_{g,t,s}$ Generator startup variable

$v_{g,t}$ Slow generator startup variable

$w_{g,t,s}$ Generator shutdown variable

$w_{g,t}$ Slow generator shutdown variable

$x_{b,h,t,s}$ BESS charging status variable

$\zeta_{b,h,t,s}$ BESS depth of discharge variable

$\zeta_{b,h,t,s,n}$ Piecewise linear function segment variable

$\theta_{i,t,s}$ Bus voltage angle variable

Parameters

B_k Susceptance of line *k*

C_g Generator operating cost

CAP BESS capital cost

CAP^{PE} Power electronic devices capital cost

$ch_{b,h}^{max}$ BESS maximum charging power

$dch_{b,h}^{max}$ BESS maximum discharging power

DT_g Generator minimum shut down time

G_k Conductance of line *k*

l_n	Piecewise linear function segment length
$L_{i,t}$	Load demand at bus *i* in time period *t*
$L_{i,t}^{P}$	Active power demand at bus *i* in time period *t*
$L_{i,t}^{Q}$	Reactive power demand at bus *i* in time period *t*
MAX_b^d	The maximum SOC level of BESS in day d
MIN_b^d	The minimum SOC level of BESS in day d
NL_g	Generator no load cost
P_g^{max}	Generator maximum power output
P_g^{min}	Generator minimum power output
PE^{max}	Power electronic devices maximum power rate
Q_g^{max}	Generator maximum reactive power output
Q_g^{min}	Generator minimum reactive power output
R_g^{+}	Generator maximum one hour ramp up rate
R_g^{SU}	Generator maximum start up ramp up rate
R_g^{-}	Generator maximum one hour ramp down rate
R_g^{SD}	Generator maximum shut down ramp down rate
RR_g^{+}	Generator maximum ten minutes ramp up rate
R_b^{+}	BESS maximum ramp up rate
R_b^{-}	BESS maximum ramp down rate
RR_b^{+}	BESS maximum ten minutes ramp up rate
S_k	Complex power on line *k*
SD_g	Generator shut down cost

SP_t	Spinning reserve requirement
SU_g	Generator startup cost
UT_g	Generator minimum start up time
V^{max}	Maximum bus voltage
V^{min}	Minimum bus voltage
$\alpha_{h,n}$	BESS penalty cost
$\alpha_{h,n}^0$	BESS fixed penalty cost
β	Constant
γ	Constant
$\eta_{b,h}^{dch}$	BESS discharging efficiency
$\eta_{b,h}^{ch}$	BESS charging efficiency
ρ_s	Scenario weight

CHAPTER 1

INTRODUCTION

In recent years, the penetration level of renewable energies such as wind and solar has dramatically increased with the improvement of renewable energy technologies. The industries and academics have paid more and more attention to renewable energies and proposed a new concept called microgrid. A microgrid is a small scale, local power system containing a variety of electric generators, loads and perhaps an energy storage system that normally connects to a main grid but can operate autonomously under urgent conditions. Microgrids are regarded as future solutions to meet the increasing power system load demand and the system stability requirement. Generally, a microgrid has many distributed electricity generation units such as rooftop solar panels, community photovoltaic stations, wind turbines, small gas turbines etc. When comparing to centralized resources, distributed resources are valuable in terms of losses and efficiency and they are very important for power systems reliabilities. Distributed resources give a microgrid the ability to operate autonomously, often referred as the island operating mode, as opposed to the grid-connected mode in which a microgrid is connected to a large power system. This kind of capability implies that a microgrid working at island model may survive under a huge system blackout like 2003 northeast blackout in U.S.

With the increasing demand for power systems, especially for microgrids, renewable energies are supposed to play a more and more important role in solving the future energy crisis. The incentive behind this fact is that renewable energies have several of their own advantages. Unlike fossil fuel energies have limited amount on earth, renewable energies have unlimited capacities which is a big advantage. Besides this advantage, renewable energies are also free to use and people generally assume that there is no operation cost for renewable energies. However, renewable energies also have big disadvantages, which are their inherent intermittency and uncertainty. Since wind turbines are driven by wind and solar panels are powered by the sun, they are easily affected by the local weather. For instance, a solar panel could be blocked by a cloud and then lose almost all of its power output; a wind turbine output may drop because the wind suddenly ceases. Another issue is their scheduling problem due to difficulties of weather forecast. Even the accuracy of wide area weather forecast today needs to be improved; it is very hard to forecast local weather accurately. Failing to forecast the local weather and the output of renewable energies will cause imbalance between power supply and demand. The imbalance between frequency regulation requirements and capabilities is an emerging concern for power systems caused by the increasing renewable portfolio standards in U.S. The fact that traditional thermal generators are replaced by renewable energy technologies loses frequency regulation capability while increasing the regulation requirements due to renewable energy technologies are generally unable to provide stable and consistent regulation power like most thermal and hydro plants [1].

A common way to deal with this issue is to have some backup resources in power systems, such as ancillary service from main grid, distributed fast response generators, energy storage systems etc. The main girds are often regarded as a huge power generation pool for microgrids operating in grid-connect mode and the main grids can provide enough backup resources to microgrids. Distributed fast response generators, like local gas turbines and energy storage systems are key equipment for microgrids operating in the island mode. Note that an energy storage system can not only provide backup resources but can also reduce the system cost by shifting the load demand from peak hours to off-peak hours through charging and discharging. This kind of capability is very valuable to a microgrid system since it is coordinated with the purpose of microgrids to reduce the power system operating cost.

Currently, many types of energy storage systems have been discussed. Some of them are commercialized and some of them are still in developing for commercial implementations. Those commercial and experimental types of energy storage systems including technologies like pumped hydro, Compressed Air Energy Storage (CAES), batteries, flywheels, supercapacitors and Superconducting Magnetic Energy Storage (SMES). In terms of capacity, pumped hydro type energy storage system is the most widely used technology. The pumped hydro unit is working like a dam but it can pump water up to its water reservoir. CAES is another choice of large scale energy storage technology; it can compress air to a tank and then uses stored air to increase the efficiency of the combustion generator and increases the output of the generator. Pumped hydro and CAES technologies are capable of storing large amount of energy but are deficient in their response speeds. There are several other energy storage technologies having relatively very fast response capabilities, like flywheels, supercapacitors and Superconducting Magnetic Energy Storage (SMES). Current implementations or demonstrations of these fast response technologies are mainly providing regulation service to the power grid by immediate reactions to grid disturbances. However, the current implemented capacities of fast response energy storages are relatively small and the ability to provide load shifting and load leveling services are therefore dimmed.

The battery energy storage systems (BESS) are able to combine the advantages of large scale energy storages, like pumped hydro and CAES, and fast response energy storage such as flywheels, supercapacitors and SMES. The BESS can afford enough capacity to shift or level the power grid loads and can respond to the system operator's command in a relatively short time. Therefore, this thesis would like to focus on BESS technologies and finds out its benefits in power systems.

In order to find the benefits of BESS, a modeling of BESS is required. BESS have many different types of battery technologies, like lead-acid, lithium ion and sodium sulfur etc. Current battery models focus on the electric characteristic of batteries, those models capture characteristics like battery voltage, battery internal resistance, effective capacity etc. Based on some common features of different battery types, this research proposes a battery model which captures the economical side of batteries. This proposed model gives a "degradation cost" to batteries, and then calculates the potential benefits of BESS through an investment planning model.

This thesis is organized in the following structure. Chapter 1 introduces the topic, followed by a literature review in chapter 2. In chapter 2, this thesis reviews past works in this area and proposes to aims of this thesis. The main work of this thesis is presented in chapter 3 and chapter 4, which include the battery degradation model and the investment planning model respectively. Chapter 5 illustrates the simulation results of this research. Conclusion and future work are given in chapter 6.

CHAPTER 2

LITERATURE REVIEW

Since electricity is extremely hard to store as electric energy for a long time, electricity is usually stored as other forms of energy such as magnetic energy or chemical energy. Batteries are the type of devices converting electricity energy to chemical energy for long time storing purpose. Generally, a battery consists of an anode, a cathode and chemical components between these two electrodes. According to the different chemical components, the batteries can be categorized as lead-acid, sodium sulfur (NaS), lithium ion (Li-ion), nickel cadmium (NiCd), nickel-metal hydride (NiMH) etc. as described in reference [1]. Among these diverse battery technologies, some of them are suitable for and have been implemented in power system today. This chapter briefly summarizes several battery technologies implemented in current power systems. A part of battery data comes from reference [3]-[7].

a. Lead-acid: the lead-acid battery, which is invented in 1859, is the most mature battery technology today and has been developed more than hundred years. It has been widely used in the daily life such as vehicle batteries. The majority of BESS in United States power systems are lead-acid batteries [10]. The high reliability and low capital cost ($150 – 400/kWh) are the main advantages of lead acid batteries. Depending on the design of lead acid batteries, their efficiency range from 70%-80%. However, the applications of lead-acid batteries are limited due to their drawback of short cycle life (1000-2000 cycles). Besides this, lead acid batteries have a low energy density about 30-50 Wh/kg because lead is a heavy metal. In extreme conditions, lead-acid batteries need a temperature management system since their performance will go down significantly at low working temperature. Lead-acid batteries can be grouped into two types: a) flooded type lead-acid battery and b) valve regulated lead-acid battery (VRLA). In recent decades, a more advanced type of lead-acid batteries, called the Advanced Lead-acid Battery, are implemented. In the Advanced Lead-acid Battery a supercapacitor electrode composed of carbon is combined with the lead-acid battery negative plate in a single cell to better regulate the flow (charge and discharge) of energy, thereby extending the power and life of the battery [8].

b. NaS: unlike the lead-acid battery consisting of solid electrodes and liquid electrolytes, the NaS battery is made up of two liquid-metal electrodes (molten sulfur is anode, molten sodium is cathode) and a solid electrolyte. The big advantage of NaS batteries is their fitness for large-scale power system applications due to their high energy density (150-240 Wh/kg), good cycle efficiency (75%-90%) and relatively long cycle life (>2500 cycles). Another advantage is that the major materials of NaS batteries are relatively inexpensive. Thus the cost of NaS batteries is lower when compared to other battery technologies (capital cost is about $350~/kWh). However, a main problem of NaS batteries is the safety issue: i) pure sodium will be instantaneously burnt when it contacts water or air and ii) the NaS battery has to operate at about 570K temperature to allow the chemical process happen and heating devices are generally needed. The NaS technologies are widely implemented and well demonstrated in Japan from over 30 sites.

c. Li-ion: Lithium ion batteries have very high energy density both in size (200-500 Wh/L) and weight (75-200 Wh/kg) and are widely used in portable applications such as cell phone batteries, laptop batteries etc. Also, the very high charge/discharge efficiency (>95%) of Li-ion batteries is another superiority. Li-ion batteries' high cycle life (>10000 cycle life) gives Li-ion batteries a wider range of power applications. Li-ion battery is regarded as the most valuable potential technology and the future solution for electricity energy storage. One main concern of the Li-ion battery today is its high capital cost (>$600/kWh) due to its special manufacturing cost, which stems its commercializing in power system. Many Li-ion battery system demonstration projects have built in U.S and are being tested by utilities.

d. NiCd: Nickel cadmium batteries have been invented for more than hundred years and they are very popular and mature as well as lead-acid batteries. NiCd batteries consist of cadmium hydroxide cathodes, nickel hydroxide anodes, separators and electrolytes [13]. The advantages of NiCd batteries are their high reliability and very low maintenance cost. NiCd batteries also have a high energy density (50-75 Wh/kg), a higher cycle life (2000-2500 cycle life) than lead acid batteries. These valuable features make NiCd batteries not only popular in daily life but also widely accepted in power system. However, their high capital cost (>$500/kWh) is a main drawback. Another well known phenomenon of NiCd batteries is their memory effect, which prevents partial discharging and charging NiCd batteries since NiCd batteries will remember previous partial discharging level and take the level as full-discharge level.

One large NiCd technology system with 27 MW for 15 min (40MW for 7 min) and 46 MVA capability has been established in Golden Valley, Alaska, USA [9][11][12].

TABLE I summarizes some battery technology projects implemented in power system today and introduces their designed roles in the power system based on the information provided by the Department of Energy (DOE) International Energy Storage Database [10].

TABLE I
BATTERY TECHNOLOGIES PERFORMANCES AND APPLICATIONS

BATTERY TYPE	**LARGEST CAPACITY**	**LOCATION**	**APPLICATIONS**
Lead-acid (the Advanced Lead-acid Battery)	36 MW/24 MWh	Goldsmith , TX, USA	Renewables Capacity Firming Electric Energy Time Shift Frequency Regulation
Sodium Sulphur	34 MW/23.8 MWh	Rokkasho, Aomori, Japan	Renewables Capacity Firming Renewables Energy Time Shift Electric Supply Reserve Capacity - Spinning
Lithium ion	8 MW/32 MWh	Tehachapi, CA, USA	Voltage Support Electric Supply Capacity Renewables Capacity Firming
Nickel Cadmium	27 MW/7.25 MWh	Fairbanks, AK, USA	Electric supply reserve capacity - spinning Grid-connected residential (reliability) Grid-connected commercial (reliability & quality)

Many of current implemented BESS are designed for improving power system reliability and power quality. Compared to generators, the BESS has a very faster response time, usually is less than one minute, to the system disturbance and outages. This feature of the BESS is very appropriate for providing regulations in the ancillary services and reserves in power systems. Depending on the requirements, a BESS with a proper designed power conversion system (PCS) can operate in four quadrants mode and provide adjustable active and reactive power to power systems.

As described in [14]-[16], there are several different types of battery models can be used: electrochemical model, electrical-circuit model, analytical model etc. The electrochemical model requires a lot of battery details, such as the thickness of electrodes and is inappropriate for investment planning purposes. The electrical-circuit model uses circuit elements to represent battery characteristics. Although electrical-circuit model is less complex than electrochemical model, electrical-circuit model still incorporates nonlinearity. For instance, electrical-circuit model uses a capacitor to represent the capacity of battery, which leads to a nonlinear mathematic formulation. Analytical model uses differential equations to represent the battery nonlinear characteristics, which is also hard to solve in an investment planning aspect.

A lithium-ion electrochemical model is presented in [33]-[35]. Six nonlinear, coupled differential equations are formed in this model. These equations give the battery voltage and current as a function of time; further details such as potentials in the electrolyte and electrode phases, salt concentration, reaction rate and current density in the electrolyte are also given by this model as functions of time. This model has a very high accuracy and it is often used in the comparison against other models. However, a detailed knowledge of battery is needed to set up more than 20 parameters for this model. Some of those parameters are much more detailed such as the thickness of the electrodes, the initial salt concentration in the electrolyte.

The electrical-circuit model can successfully describe the V-I characteristics of a battery. With more components added into the electrical-circuit model, this method can even include some external factors such as ambient temperature, depth of discharge etc. However, this type of method may not be suitable for large scale power system simulation because it is too complicated for a power system level calculation. For example, the present generator model in the power flow calculation is a voltage source with an internal impedance. This is a simple model and there are other complicated models which can represent generator characteristics more precisely. This simple generator model has been widely used in nowadays power flow calculation since the simplified model captures the main characteristic of a generator and it is easy to calculate. Considering that today's power system could contain thousands or ten thousands buses, it is a computational hazard if a more sophisticated generator model is used in the power flow calculation.

Analytical model is a very intuitive model and is similar to electrochemical model in order to describe the nonlinear effects of battery. Analytical model captures battery electric characteristics as well as electrochemical model but with less complexities and less detailed knowledge of battery. Instead of calculating the model parameters from the battery structures like electrochemical model, analytical model determines its parameters by experiments. The kinetic battery model [36]-[38] is the most well-known analytical model.

Although different kind of batteries have their own special characteristics, a common phenomenon is observed that a battery has finite charge/discharge cycles [29][30]. This finite number of cycles is highly related to the battery utilization pattern and the battery depth of discharge (DOD) is the main factor. The battery DOD is determined by the battery state-of-charge (SOC), reference [31] discusses about the SOC detecting method and noted that the accuracy of SOC detecting is very important in implementation of battery management system. The operating temperature is another important factor affecting the battery lifetime. In fact, since batteries are complex electric-chemical device, temperature has influence on almost every part of batteries through affecting chemical reactions. For example, a Li-ion battery's effective capacity will decrease in cold environment and recover in normal temperature. But the effects of temperature are often neglected because a consistent working temperature environment is provided by installing accessary equipment such as battery management system. Generally, the battery management systems are not just maintaining the temperature of batteries but are also equalizing the charge/discharge process for batteries. The difference between the battery pack and a single cell and the impact of unbalance charging/discharging are described in [31].

Reference [32] examines the profits of several types of BESS for three different applications, which are load leveling, control power and peak shaving. Reference [32] estimates the value of BESS in load leveling application by comparing the net present value of BESS costs with the net present value of revenues of load leveling application. A delay of investment for a potential transmission line upgrade is accounted for the application revenue in this reference. The BESS profits for control power application are revenues collected in the ancillary markets subtracting the BESS cost. Peak shaving application benefits are considered as the savings of electricity bill for end-users as owners of BESS. In [32] conclusions, BESS gain its highest value by supplying primary control power among those three different applications.

CHAPTER 3

BATTERY DEGRADATION MODELING

3.1 Background information

This thesis figures out the benefits of BESS in power systems. BESS has its unique feature, which is different to generators and even different to other energy storage technologies. BESS does not have fuel cost because it stores energy produced by other units and send energy back to the grid later on. A common misunderstanding of BESS operating cost is that the cost associated with BESS stored energy is treated as BESS operating cost; however, this is not correct. The cost associated with the amount of stored energy has already been reflected in production cost of other resources. Take a single bus system as an example and assume this single bus system contains a generator and a BESS. If the BESS has charged 80 MWh energies with 80% efficiency then the generator must produce 100 MWh energies and, of course, there is a 100 MWh generator production cost. It is obvious that the generator production cost has contained the cost of 80 MWh energies in the BESS. For this example, someone may argue that the 36 MWh (100 - 80×80%) losses are the BESS operating cost; however, this argument is also not correct. In this single bus system example, although the generator could reduce its production by 64 MWh due to the BESS discharges 80 MWh with 80% discharge efficiency, the generator is producing 100 MWh more energy when the BESS is charging. There are additional 36 MWh of the generator production as comparing cases with and without BESS implemented. Therefore, the losses cost is already included in the generator production cost. Other types of energy storage like pumped hydro units have this same feature and pumped hydro units are often modeled as generators with zero operating cost. The lifetime of pumped hydro units is generally not determined by its DOD level. However, the BESS lifetime will be dramatically decreased when its cycling DOD level is high. Therefore, giving BESS a zero cost is not very appropriate. Instead of giving a zero cost for BESS, this thesis proposes a cost for BESS associated with its lifetime. This cost, called degradation cost, is about to reflect the extra cost of replacing the BESS earlier. With implementing the degradation cost, BESS profits are calculated through an investment planning model which will be described in details in chapter 4.

3.2 Battery degradation cost

For a battery long-term investment planning model, there are two main factors should be considered: one is the battery degradation and another one is the time value of money. Battery degradation is a phenomenon that the residual life of a battery is highly relevant to its utilization. Generally, the heavy utilizing a battery will reduce its lifetime significantly. This phenomenon is caused by many different factors and incorporated with a lot of non-linearity due to the nonlinear battery chemical reaction process. Right now, there is no single model includes every capacity degradation factors due to the nonlinearity and the non-convexity. If every detail of the battery chemical reaction process is incorporated, then the degradation model for a battery will be highly nonlinear and non-convex. Such complexity will make the model difficult to solve a large-scale investment planning model for BESS. As a result, this thesis proposes an approach that approximates the degradation of the battery's lifecycle. In terms of time value of money, this thesis assumes a fixed interest rate over the study periods. This is a common approach to calculate the time value of money in long-term, for example, 10 years or more.

Battery is a complicated electrochemical process device, which makes it hard to be modeled and be predicted precisely in terms ofbattery's lifecycle. However, it is important to consider the degradation of the battery's lifecycle because, otherwise, the utilization of the battery may cause substantial economic losses and lead to inaccurate investment decisions. This thesis will provide an approach to approximate battery's lifecycle by capturing the major stress factors in order to calculate the substantial economic losses. Many stress factors affect battery life, such as DOD, charging/discharge rate, temperature, charging regime, dwell time at low and high states-of-charge (SOC), current ripple [17] etc. The most important factors are depth-of-discharge, discharge rate and temperature. SOC is the percentage of battery energy left versus battery capacity. DOD is the amplitude of SOC changed in two continuous periods. How DOD impacts battery cycle life is illustrated in Fig.1 below. The effect of DOD on battery cycle life is widely observed by many references [17][22][24][45][46] on lead-acid battery, Li-ion battery, NiCd battery, NaS battery etc. Battery manufactures also have widely recognized this phenomenon and generally provide the curve of DOD vs. cycle life [47][48]. Typically, the data curve is obtained by experiments. The number of charge/discharge cycles are counted when the battery is continuously cycling at certain DOD level until it fails. Although a battery is possible to cycle at different DOD levels, the influence of combining different DOD levels on a battery cycle life has not been well investigated. Therefore, assuming the number of cycle life for different DOD levels is independent is a practical approach so far. Details about this assumption are discussed in the following paragraphs.

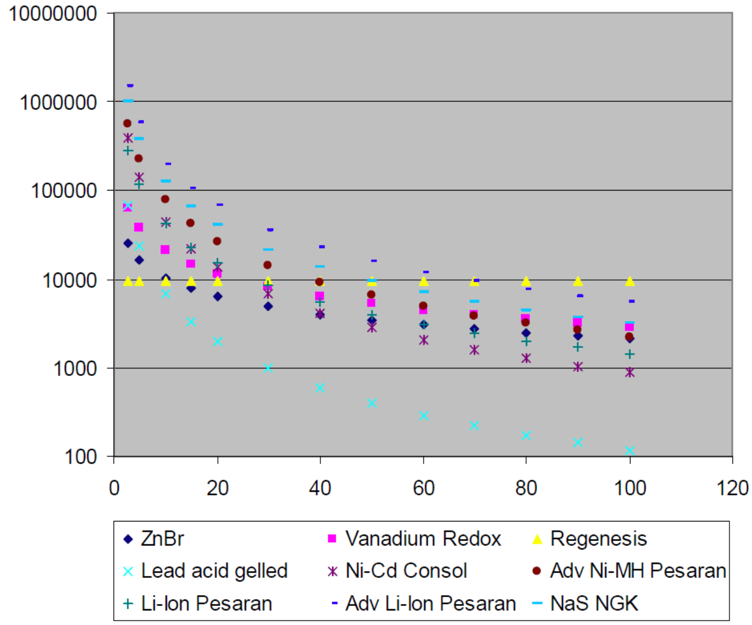

Fig. 1 Batteries cycle life vs. DOD [18]

As shown in Fig.1, the number of total possible cycles is a function of SOC level:

$$N^{max} = f(SOC) \tag{3.1}$$

Equation (3.1) is based on the assumption that the battery is recharged to its full capacity after each discharge [19]. This assumption is not always valid since such a protocol may not be enforced in power system operations. Such a protocol inhibits optimal utilizing of the energy storage asset. For instance, there could be a situation that an expensive generator has to start up to charge a battery to its full capacity before next discharge cycle. In fact, there are two main stress factors affect a battery life: one is DOD and another one is the initial SOC of a discharge cycle. The DOD has larger influence on the battery life than the initial SOC. The battery capacity is known to be reduced over its lifetime with discharge and charge cycles. The evaluation method of the battery ageing effect is first introduced by Facinelli [20]. Facinelli observes that cycling damage to a battery is primarily a function of the depth of discharge (and corresponding recharge) to which the battery is subjected. For example, going from 10% to 30%

discharge and back was seen to be approximately the same as from going from 50% to 70% and back [21]. That is saying that a full charge is not necessary after a discharge and before a next cycle. Therefore, equation (3.1) can be revised. It is easy to conclude that when a full charge is ensured after each discharge, the first stress factor can be replaced by SOC, which means equation (3.1) is a simplification of the battery model under microgrid operation. But right now there is no such complicated battery model available, the practical way to model battery characteristics is to revise equation (3.1) to approximate the actual model. The revised model uses DOD in equation (3.1) instead of SOC, that is:

$$N^{max} = f(DOD) \tag{3.2}$$

The equation (3.2) can be derived from battery-life-test data sheet provided by battery manufacture at certain test condition, which is under constant temperature and constant charging/discharging rate. Discharge rate impacts have not been addressed in equation (3.2). However, in a multiple time periods study, the impact of discharge rate is partially captured. For instance, a battery depleting itself in a single period or in ten periods evenly will represent different discharge rates. The two different discharge rate can be captured by different DOD levels, that is, a single period with a DOD level versus ten periods with a DOD/10 level for each. However, how charging/discharging rate affects battery life is not quite clear so far since the lack of data.

Equation (3.2) reveals the relationship between battery cycle life and DOD, however, power system operators concern more about battery life time than battery cycle life. Typically, battery manufactures do not provide data sheets describe the relationship between lifetime and DOD. So, in order to obtain this relationship, a rain-flow-counting method [22] is used in this thesis. Facinelli's Miner's Rule method is originally developed for discrete, non-overlapping cycles, which typically be found in photovoltaic based battery charging system as Facinelli described. The cycle counting method used is known as rainflow counting method [23]. The substance of rain-flow-counting method is to calculate the reduction of battery lifetime rather than expected lifetime. Several assumptions need to be made before using this method as described in [24]:

The cycle life lost in each period is small;

The cycle life lost in each period is unrelated to previous cumulative loss;

The cycle life lost in each period is independent;

The cycle life lost in each period is caused by single discharging procedure.

The first assumption is appropriate since a single study period (one hour) is relatively small to several years of a battery lifetime.

For the second assumption, a same discharge cycle, for instance a full-cycle, will pay a higher opportunity cost at the end of a battery's life than at the beginning of a battery's life based on battery characteristics. In other words, the loss of cycle life is related to previous period. However, this is a progressive process; the cost difference in two consecutive periods is relatively small. Thus, it is reasonable to assume the opportunity costs are unchanged in a short time.

The third assumption actually has two parts: one is the loss of cycle life is related to previous periods and another one is that the initial SOC of one period is related to previous period. According to the second assumption, the cycle life lost is independent from cumulative losses. And since the magnitude of the cycle was found to be more important than the initial state of the cycle [24], therefore, it is reasonable to assume the cycle life lost is independent of the initial SOC. Thus, the third assumption is appropriate.

The last assumption is ensured when the investment planning model only allows a single procedure to happen in each period. In other words, charging and discharging are not allowed in the same period.

Rain-flow-counting method assumes that a battery is dead when the number of cumulative cycles over all periods is equal to the number of total possible cycles. That is, for a certain DOD level, a battery reaches its end of life when below function is held:

$$n_{DOD} = N_{DOD}^{max} \tag{3.3}$$

Where, n_{DOD} is the cumulative number of cycles at DOD level, N_{DOD}^{max} is the maximum number of cycles at DOD level. If n_{DOD} is a portion of N_{DOD}^{max}, then the battery is been cycled n_{DOD}/N_{DOD}^{max} of its total life. For instance, if a battery cycles 100 times at 100% DOD level and 500 times at 50% DOD level. Then cycle the battery at 100% DOD level 50 times will leave half its life, which allows the battery cycles another 250 times at 50% DOD level. Thus, for operating at different DOD level, the criterion of the battery life ending is:

$$\sum_{\forall DOD} \frac{n_{DOD}}{N_{DOD}^{max}} = 1 \tag{3.4}$$

Based on those four assumptions above, each same DOD level cycle will cost the same amount of battery life. Then, if assuming a battery lifetime is L at DOD level, the reduction of lifetime (RoL) for a single cycle at DOD level is:

$$RoL(DOD) = L/N_{DOD}^{max} \tag{3.5}$$

By introducing a reference battery lifetime at a reference DOD level, the reduction of lifetime at DOD levels can be easily represented by:

$$RoL(DOD) = RoL(DOD^{ref}) - \Delta RoL(DOD) \tag{3.6}$$

Where,

$$\Delta RoL(DOD) = L^{ref}/N_{DOD^{ref}}^{max} - L/N_{DOD}^{max} \tag{3.7}$$

Therefore, the estimate lifetime of battery over all periods, that is, battery lifetime model is:

$$L = L^{ref} - \sum_{\forall t} \Delta RoL(DOD^t) \tag{3.8}$$

Equation (3.8) builds a connection between a battery life time and its DOD, which reflects the battery utilization. Next, this thesis finds out the relationship between the battery cost and the battery utilization. Since batteries do not consume fossil fuel like generators, this thesis thinks that the battery cost is not an actual cost, instead, it is an opportunity cost; an opportunity cost represents the cost of replacing batteries earlier than designed life as well as the savings from postponing batteries replacement.

Assuming the battery replacement cost is a, then the time value of money for replacing the battery every L^{ref} years over infinite time is:

$$a(1+i)^{-L^{ref}} + a(1+i)^{-2L^{ref}} + a(1+i)^{-3L^{ref}} + \cdots$$

$$= a(1+i)^{-L^{ref}} \sum_{n=0}^{\infty} (1+i)^{-n \cdot L^{ref}}$$

$$= a(1+i)^{-L^{ref}} / \left[1 - (1+i)^{-L^{ref}}\right] \tag{3.9}$$

Where, $a = C_b^{cap} \cdot SOC_b^{\max}$, which represents the battery replacement cost.

The time value of money for replacing the battery at L years in the first time, and then replacing the battery at L^{ref} years over infinite time is:

$$a(1+i)^{-L} + a(1+i)^{-L-L^{ref}} + a(1+i)^{-L-2L^{ref}} + \cdots$$

$$= a(1+i)^{-L} \sum_{n=0}^{\infty} (1+i)^{-n \cdot L^{ref}}$$

$$= a(1+i)^{-L} \Big/ \left[1-(1+i)^{-L^{ref}}\right] \tag{3.10}$$

The extra cost is equation (3.9) substracting equation (3.10):

$$a \cdot \left[(1+i)^{-L} - (1+i)^{-L^{ref}}\right] \Big/ \left[1-(1+i)^{-L^{ref}}\right] \tag{3.11}$$

If battery energy system operation sticks to the reference DOD level, that is, the battery lifetime will be the same as the reference lifetime, then the battery energy system should have no penalty cost. This is shown in function (3.10), when $DOD = DOD^{ref}, L = L^{ref}$, the extra cost is zero.

Substitute equation (3.8) into equation (3.11):

$$a\,(1+i)^{-L^{ref}}\left[(1+i)^{\sum_{\forall t}\Delta RoL^{t}} - 1\right] \Big/ \left[1-(1+i)^{-L^{ref}}\right] \tag{3.12}$$

Equation (3.12) indicates that, the penalty cost for ΔRoL^t in time period t is related to previous cumulative loss of lifetime and this is called aging effect. This means that the penalty cost is higher when cumulative loss is growing

Like in the discussion about the third assumption, here in the model, this thesis will divide one ten-year period into ten one-year periods, then every one-year period has its own opportunity cost. Although it is not necessary to run an investment planning model for 10 years, which is also hard to do that; our model brings the idea that at different year, a battery may have a different opportunity cost in the model based on estimated cumulative lifetime loss.

From equation (3.12), it is easy to find that the total degradation cost consists of two parts: one is DOD and another one is battery utilization ($\sum_{\forall t}\Delta RoL^{t}$). The opportunity cost is proportional to DOD, and is a function of battery utilization. By assuming a lead-acid battery's capital cost is $330/kWh and its reference life is 10 years, the degradation cost can be calculated from equation (3.12) and plotted in Fig. 2.

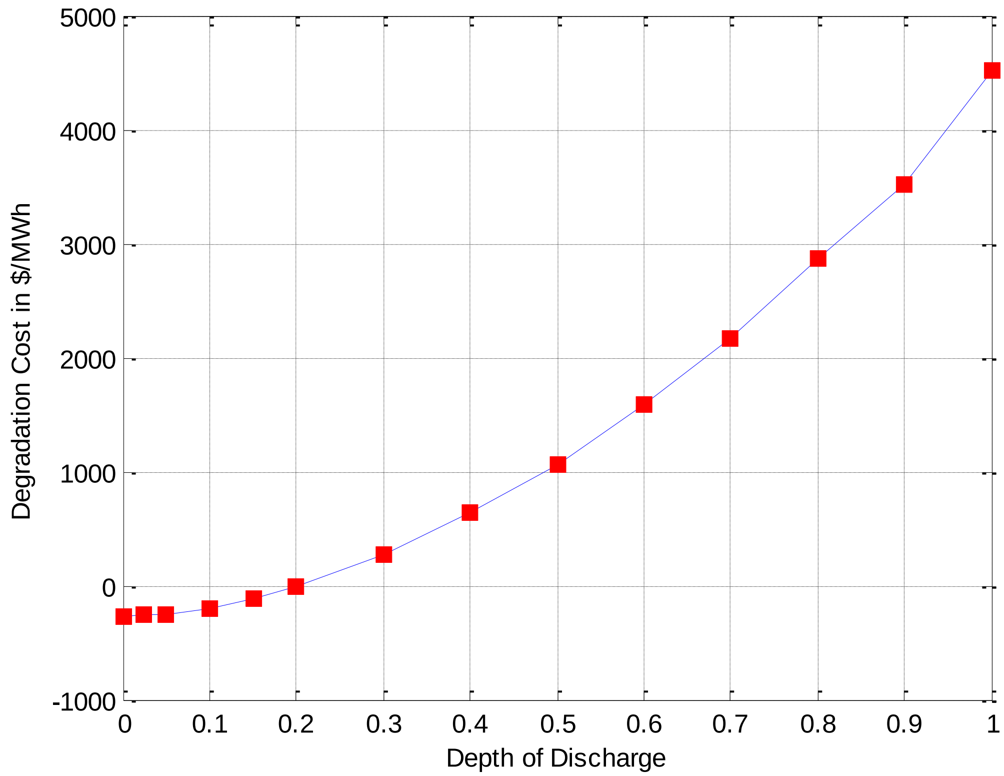

Fig. 2 Lead-acid battery degradation cost

3.3 Battery degradation model

From Fig. 2 it can be see that the opportunity cost (OPC) is a nonlinear function of DOD, this nonlinear function is linearized to a piecewise linear function below.

$$OPC = \alpha_0 + \sum_{n=1}^{N} \alpha_n \cdot DOD_n \tag{3.13}$$

Subject to,

$$0 \leq DOD_n \leq DOD; \; n = 1,2, \dots, N \tag{3.14}$$

$$\sum_{n=1}^{N} DOD_n = DOD \tag{3.15}$$

In this thesis, DOD is calculated on a daily basis, that is, DOD is the value of maximum SOC subtracting minimum SOC within 24 hours. This is an approximation technique because the batteries life time is mainly determined by major charge/discharge cycles, which is the largest DOD cycle occurs in a certain time period according to reference [22]. Giving ζ^t represents the amount of energy cycled in *t* period, then DOD will be given by $DOD = \zeta^t / SOC_b^{max}$ and the overall cost in *d* days is represented by:

$$cost = OPC \cdot SOC_b^{max} = \alpha_0 \cdot SOC_b^{max} \cdot d + \sum_{\forall d} \sum_{\forall b} \sum_{n=1}^{N} \alpha_n \zeta_{b,n}^d \tag{3.16}$$

Subject to,

$$0 \leq \zeta_{b,n}^d \leq l_n \cdot SOC_b^{max};\ n = 1,2,\dots,N \tag{3.17}$$

$$\sum_{n=1}^{N} \zeta_{b,n}^d = \zeta_b^d \tag{3.18}$$

$$\zeta_b^d \geq MAX_b^d - MIN_b^d \tag{3.19}$$

$$MAX_b^d \geq SOC_{b,t}\ \forall b, \forall t \in \{\, 24(d-1)+1, \dots, 24d \mid d = 1,2,\dots \} \tag{3.20}$$

$$MIN_b^d \leq SOC_{b,t}\ \forall b, \forall t \in \{\, 24(d-1)+1, \dots, 24d \mid d = 1,2,\dots \} \tag{3.21}$$

Battery operations also subject to some physical rules, which result in these constraints below:

$$SOC^{min} \leq SOC_{b,t} \leq SOC^{max} \tag{3.22}$$

$$SOC_{b,t} = SOC_{b,t-1,} + \eta_b^{ch} ch_{b,t} - \frac{1}{\eta_b^{dch}} dch_{b,t} \tag{3.23}$$

$$dch_{b,t} - dch_{b,t-1} + ch_{b,t-1} - ch_{b,t} \leq PE^{max} \tag{3.24}$$

$$dch_{b,t-1} - dch_{b,t} + ch_{b,t} - ch_{b,t-1} \leq PE^{max} \tag{3.25}$$

Constraint (3.22) is the battery capacity constraint. In (3.22), the lower bound is using SOC^{min} instead of using 0 because a battery may not be fully utilized due to the battery design. When discharging a battery beyond the lower bound limit, the battery may be ruined or cannot recharge anymore. Therefore, using SOC^{min} rather than 0 is more logical. In fact, SOC^{min} can set to be 0 if a battery does not have a lower bound. Constraint (3.23) is SOC transition constraint, η_b^{ch}, η_b^{dch} are charging and discharging efficiencies. Constraint (3.24) and (3.25) are the battery charge and discharge ramping rate constraints.

As mentioned in chapter 2, one of BESS's applications is to provide ancillary service. Constraints (3.26)-(3.28) describe characteristics of BESS for providing spinning reserves.

$$0 \le r_{b,t} \le PE^{max} \tag{3.26}$$

$$0 \le r_{b,t} \le ch_{b,t} + PE^{max} - dch_{b,t} \tag{3.27}$$

$$0 \le r_{b,t} \le \eta_b^{dch} \cdot SOC_{b,t} \tag{3.28}$$

3.4 Charging and discharging status variables

In practice, a battery cannot charge and discharge at the same time. However, in mathematics, a battery may charge and discharge at the same time while keeping the same output characteristic. For example, a battery charging at 1unit is mathematically equal to charging at 2 units and discharging at 1unit or charging at 3 units and discharging at 2 units etc. Since this obeys the actual process, constraints (3.26), (3.27) are needed to prevent charge and discharge to happen at the same time:

$$0 \le ch_{b,t} \le PE^{max} x_{b,t} \tag{3.29}$$

$$0 \le dch_{b,t} \le PE^{max}(1 - x_{b,t}) \tag{3.30}$$

This thesis thinks that (3.29) and (3.30) are not necessary in some cases. Because the model of this thesis penalizes DOD (the change of SOC) and the model will minimize the change of SOC. This thesis find that a situation with charging and discharging a battery at the same time will have a larger change of SOC and then will result in diseconomy for a battery. In this situation, (4.1) and (4.2) could be relaxed without loss of model accuracy. Later part of this section will give some examples and then proves it.

TABLE II
EXAMPLE CASES FOR DIFFERENT CHARGE AND DISCHARGE RATE

$\eta^{ch} = 0.5,\ \eta^{dch} = 0.5$							
Case #	1	2	3	4	5	6	7
The battery external characteristics	Charging at 1 unit			Charging at 0.4 unit	Discharging at 1 unit		Do nothing
Internal combinations of ch&dch	ch=1, dch=0	ch=1.2, dch=0.2	ch=4/3, dch=1/3	ch=0.4, dch=0	ch=0, dch=1	ch=1, dch=2	ch=0, dch=0
DOD	0.5	0.2	0	0.2	-2	-3.5	0

TABLE II shows that even two different charging/discharging situations have the same external characteristic, they will have different DOD. For example, case 1 and case 2 are both charging at 1 unit but case 1 has a 0.5 unit DOD while case 2 only have a 0.2 unit DOD. TABLE II also implies that a battery will gain less energy or lose more energy if it is charging and discharging at the same time. Take case 1 and case 2 as an example again, a battery gain only 0.2 unit increment of SOC in case 2; however, case 1 with the same charging power as case 2 has a 0.5 unit increment of SOC; case 2 gains 0.3 unit less of energy than case 1. Below paragraphs demonstrate that above conclusions are general and *x* variables with associated constraints can be relaxed.

Proof:

For charging process, assume that the battery is charging at *x*. Then the real case (the battery is only charging) is $ch = x\ (x > 0), dch = 0$. According to State-of-Charge equation,

$\Delta SOC = \eta^{ch} \cdot x$

Considering any unreal case (the battery is charging and discharging), for instance, $ch = y, dch = z, where\ y - z = x$. In this situation,

$\Delta SOC' = \eta^{ch} \cdot y - z/\eta^{dch}$

Then take the difference of ΔSOC and $\Delta SOC'$:

$\Delta SOC - \Delta SOC' = \eta^{ch}(x - y) + z/\eta^{dch}$

$= \eta^{ch}(x - y) + (y - x)/\eta^{dch}$

$= (\eta^{ch} - 1/\eta^{dch})(x - y)$

Because $0 < \eta^{ch} < 1, 0 < \eta^{dch} < 1$, so

$(\eta^{ch} - 1/\eta^{dch}) < 0$

Since $x, y, z > 0$, then

$(x - y) < 0$

Therefore,

$\Delta SOC - \Delta SOC' > 0$,

Which means a battery will gain less energy if it is charging and discharging at the same time.

For discharging process, assume that the battery is discharging at x.

Then the real case (the battery is only charging) is $ch = 0, dch = x\ (x > 0)$. According to State-of-Charge equation:

$\Delta SOC = -x/\eta^{dch}$

Considering any other unreal case (the battery is charging and discharging), for instance, $ch = y, dch = z, where\ z - y = x$. In this situation,

$\Delta SOC' = \eta^{ch} \cdot y - z/\eta^{dch}$

Then take the difference of ΔSOC and $\Delta SOC'$:

$\Delta SOC - \Delta SOC' = -\eta^{ch}y + (z - x)/\eta^{dch}$

$= -\eta^{ch}y + (x + y - x)/\eta^{dch}$

$= (1/\eta^{dch} - \eta^{ch})y$

Because, $0 < \eta^{ch} < 1, 0 < \eta^{dch} < 1$, so,

$(1/\eta^{dch} - \eta^{ch}) > 0$

Since $x, y, z > 0$, then

$\Delta SOC - \Delta SOC' > 0$ and $|\Delta SOC| < |\Delta SOC'|$

Which means a battery will lose more energy if it is charging and discharging at the same time.

Proof over.

The above proof shows that fictitious cases, a batter charging and discharging at the same time, are uneconomical in terms of battery energy; this proof also indicates that model is unlikely to choose fictitious cases. This inference is valid for discharge process since the penalty cost of fictitious case is larger than the penalty cost of the real case (a battery only charge or discharge at a time). The higher cost is due to the absolute change of SOC in fictitious case is greater than it in real case. As for charging process, someone may argue that since this thesis associated a penalty cost for the absolute change of SOC, the model will choose fictitious cases in order to reduce the penalty cost. For example, someone may argue that the model will choose case 2 instead of case 1 in TABLE II because case 2 has less penalty cost. However, this thesis finds that the above inference is suit for both charging and discharging process.

For the charging process, if the model is going to choose case 2 instead of case 1 to reduce the penalty cost by allowing the battery charge and discharge at the same time, then the model will just simply choose case 3 instead of case 2 in TABLE II. Because the change of SOC in case 3 is zero and then, consequently, the penalty cost is zero, which is the lower bound of the penalty cost. However, when case 3 compares to the case 5 in TABLE II, a battery in case 3 will need 1 more unit of charging power from the grid.

Even though the penalty costs are zero for both case 3 and case 5 but the power grid in case 3 has a higher generation cost than it in case 5 and the overall system cost of case 3 is higher. Obviously, case 3 is less attractive for the model than case 5. On the other hand, when comparing case 2 and case 4, it is obvious that case 4 is a more efficient solution than case 2. The battery in case 4 only uses 0.4 unit of charging power (comparing to 1 unit of charging power in case 2) and gains the same amount of energy in case 2. Since case 2 consumes more energy from the main grid and result in a higher overall system cost, consequently, case 4 is the optimal solution if the model is going to choose between case 2 and case 4. This outcome implies that fictitious cases (like case 2) are not good choices when a certain amount of energy is needed for a battery.

Therefore, fictitious cases are not likely to be selected by the minimization model unless there is over generation in the system or a negative locational marginal price (LMP) is observed at the BESS location.

When there is over generation occurs in a power system, the model will choose fictitious case to meet the node balance constraint. For instance, a battery with 50% charging and discharging efficiency in a microgrid, which has 3MW over generations, will charge at 3MW and discharge at 1MW to absorb this 3MW over generations while keeping SOC unchanged. At this time, the battery behaves as an artificial load. This type of problem is typically caused by uncertainty of renewable energies like wind and solar. Due to uncertainties of renewable energies, it is possible that the real time power output of a renewable energy like wind is larger than the forecasted power output. Generally, two methods are implemented to take care of this issue: one is reducing power outputs from other generation units and another one is curtailing the extra amount of power outputs of renewable energies. Here, this thesis uses the second method to deal with over generation problem by assuming that wind and solar energy can be cut off immediately in any time by any amounts. Such that this thesis could relax x variable for taking care of over generation issue and reduce the model complexity and computational time.

Another situation is when the battery location bus has a negative LMP. The model may choose fictitious cases and let the battery behave as an artificial load such that the total system cost could be decreased. However, the chance of having negative LMPs in the system is very low. Negative LMPs situation is unlikely to occur and, therefore, x variable can be relaxed in most situations. Furthermore, in this thesis, a two-step method is going to take care of this issue. Since it is unlikely that the model will choose to have the energy storage device to charge and discharge at the same time this thesis initially solves the problem with neglecting the binary variable x and then check to see if there is a violation. In other words, this thesis is going to check to see if there is a period where the energy storage asset is said to be charging as well as discharging. If no such situation exists, then the resulting solution is the global optimal solution to the original formulation that includes the binary variable. If the resulting solution has charging and discharging occurring for the energy storage device during the same hour, then the model is re-solved by then enforcing the binary variable in order to get the true global solution.

CHAPTER 4

INVESTMENT PLANNING MODEL

The investment planning model is about to answer two types of questions: a) what kind of BESS should be placed in what location in a power grid; b) what are the benefits of this BESS. Considering that it is extremely hard to answer these two questions within one model, this thesis proposes an investment planning model containing two different parts and finds the type, size, location and benefits of BESS in the power grid.

First of all, the type, size and location of BESS are needed before accurate calculating the benefit of BESS. In chapter 2 literature reviews, many researches just analyze the benefits of BESS but do not give specified solutions for investment planning decision. For example, reference [32] discusses the value of BESS in power system and gives an analysis of its benefits. But [32] does not give the answer that what type of BESS should be chosen and where should it be located. Moreover, [32] do not consider the power system network topology; the results are basically derived from a single bus point of view and pre-determined BESS operations. Pre-determined BESS operations assign a peak hour discharging and off-peak hour charging cycle for arbitrage activities and average market price is used to calculate BESS benefits. However, this thesis believes that the BESS benefits analysis with considering the power system network topology should be more trustworthy. Therefore, the investment planning model proposed in this thesis takes the power system network topology into consideration. In order to answer the questions that what are the type, location and size of BESS and find the proper operation schedule for the grid, binary variables are incorporated in this model. For example, binary variables with BESS type, location and size indexes are used for deciding the appropriate BESS type and location. Typically, 1 is interpreted as 'chosen choice' and 0 is interpreted as 'ignored choice'. The idea of BESS type and location options are modeled as binary variables are very straightforward. Although BESS size options are generally considered as continuous variables, this thesis models these options as binary variables. One reason o model BESS size options as binary variables is that continuous variables will create a lot of nonlinearities and will cause a lot of computational burdens. Another reason is that manufacturers usually only provide finite options of commercial products. Even though discrete BESS size sets may result in a suboptimal solution when compared to continuous sets and loss of the accuracy, the accuracy of result can be improved by increasing the number of discrete BESS options. In fact, he discrete set of BESS size is a trade-off between the model accuracy and the computational efficiency.

The first part of the investment planning model, called the decision planning model, is a mixed integer linear program (MILP) due to those binary variables mentioned in the paragraph above. Generally, a MILP is very hard to solve in a relatively short time. Ideally, an investment planning analysis is expected to take consider of all time periods in the overall time window but, in practice, this is impossible for current solver. This thesis proposes a method called daily cycle method to take care of this issue. The basic idea of the daily cycle method is to estimate the longtime overall cost through a small number of days, more details are explained in section 4.1.

After determining the BESS type, size and location in the decision planning model, the production cost model, which is the second part of investment planning model, will find out the annual benefit of BESS in a grid. Although the decision planning model can give a total operating cost of a grid, the result is not accurate enough because the daily cycle method only uses a small amount of days to represent a long period like a year. This thesis believes that a good evaluation of the BESS annual benefits should take all days in a year into consideration. Remember that an important reason behind using daily cycle method in the decision planning model is that many binary decision variables of BESS are incorporated. However, since the production cost model can gain information about the BESS type, size and location from the result of the decision planning model those BESS binary decision variables are no longer needed for the production cost model. In order to include all days in the model and gain results in a reasonable time, further approximations and simplifications are needed because the decision planning model still cannot handle the job of evaluating the BESS annual benefits with considering all days in a year; even after the decision planning model neglects BESS binary decision variables and associated constraints. Therefore, the production cost model further neglects binary variables such as generator status variables, generator startup variables and generator shut-down variables (though startup/shut-down variables are not modeled as binary variables in this thesis but they are typically modeled as binary variables) and makes the production cost model a LP model such that the production cost model is able to run on a 365-day period. In here, costs like generator no load cost and startup/shut-down cost are neglected. Even though the benefits of BESS may be underestimated by neglecting no load cost and startup/shut-down cost, the estimation result is still trustworthy since the major part of generation cost is generator fuel cost, which is not neglected. To estimate the overall benefits in a BESS total life, it is not necessary to run the model for every single year. A common way to estimate the overall benefits for a transmission planning in industry today is to calculate the annual savings of several selected years and then estimate the annual savings of other years by extrapolating. This thesis calculates the savings on year 1, 3, 5 and 10 first and then interpolates those points on the graph to estimate the remaining years' savings. In the production cost model, the capital cost of BESS is not modeled. Since all generators are committed and constraints like minimum up/down time are relaxed in the production cost model, each modeled year is relatively independent. Therefore, solving the production cost model for each year separately is potentially equal to solving 10 years together. This means that the BESS benefits of year 1, 3, 5 and 10 are unlikely influenced by calculating them separately and they are substantially the same as the results of year 1, 3, 5 and 10 from calculating 10 years together. An advantage of this estimation method for BESS annual benefits is that less computational resources are required. The drawback of this method is that a potential loss of accuracy exists. Further details of the production cost model can be found in section 4.2.

4.1 Decision planning model

The decision planning model is the first part of the investment planning model. The decision planning model is meant to find the optimal type, location and size of BESS, the overall benefits of BESS will be estimated in the production cost model. But, even a day-ahead stochastic UC is a computational hard problem due to today's computation capability, let alone solve a stochastic UC model over a long time window. Scenarios in stochastic UC model are the primary reasons cause computational difficulties. Scenarios largely increase the size of the model and make the model spend a lot of time, like days, to solve it or even become unsolvable. Therefore, this thesis proposes a daily cycle method to reduce the size of the model and make it solvable in a reasonable time without or with little loss of accuracy.

This daily cycle method comes from the idea of periodic waves, whose whole characteristics can be found in one period since wave characteristics in each period are identical. Another foundation of this method is the similarity of load curves. Although a load curve in summer peak day may very different from a load curve in spring peak day, but a load curve changes relatively small from day to day in a short period. These two facts provide a way to capture the main characteristic of annual load profile by a small amount of days. In this daily cycle method, 365 days of annual load profile are grouped into some characteristic days, like summer day, summer peak day, winter day, winter peak days etc. After grouping all 365 days into several day types, the annual cost are calculated through those characteristic days.

As explained above, generator outputs and generator statuses of two identical and consecutive days are the same. Therefore, for instance, generator power outputs and generator statuses of the second day are obtained once the UC problem of the first day is solved. Fig.3 illustrated the idea of this method.

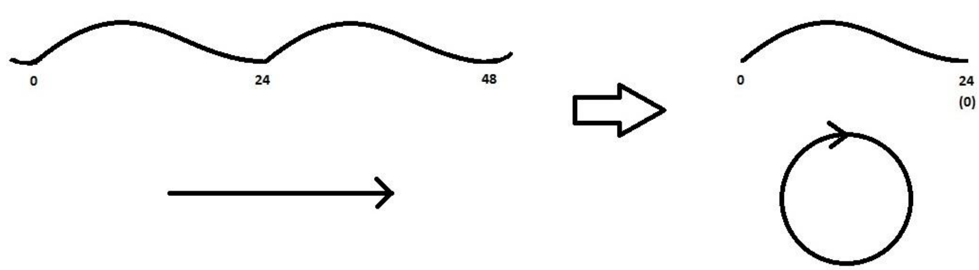

Fig. 3 Daily cycle

Instead of calculating two days UC problem, one day UC problem has been calculated. Because the solutions for these two days are exactly the same with assuming that the initial and end status of these two days are the same. Note that a previous day's last hour status is the initial status of the next day and a started up (or shut down) generator in the last day may remain "on" (or "off") in the next day due to the minimum up (or minimum down) time constraint. By properly setting the initial and end status constraints and the generators minimum up or down time constraints, the solution for this one day UC (daily cycle) will be the same as the solution for consecutive two or more days. Thus, instead of running the model over several consecutive same days, this method solves the model for just one day and multiplies the result by the number of days to get the savings. For instance, 365 days are grouped into spring day, summer day, fall day, winter day with n_1, n_2, n_3, n_4 days respectively, then the annual savings are: n_1×spring day savings+n_2×summer day savings+n_3×fall day savings+n_4×winter day savings. Obviously, this method is a trade-off between computational time and model accuracy and can be adjusted due to different requirement. It is easy to find that the accuracy of this method is getting higher when the number of characteristic days is increasing, but the computational time is also increasing.

The decision planning model and detailed explanations are illustrated below:

$$\min\Big\{\sum_{\forall s}\sum_{\forall t}\rho_s\Big[\sum_{\forall g}\big(C_g P_{g,t,s} + NL_g u_{g,t,s,} + SU_g v_{g,t,s} + SD_g w_{g,t,s}\big) + \sum_{\forall b}\sum_{\forall h}\sum_{\forall n}\big(\alpha_h^0 \sum_{\forall m} SOC_{h,m}^{max} I_{b,h,m} + \alpha_{h,n}\zeta_{b,h,t,s,n}\big)\Big] + \sum_{\forall b}\sum_{\forall h}\sum_{\forall m} CAP_h SOC_{h,m}^{max} I_{b,h,m} + \sum_{\forall b}\sum_{\forall h}\sum_{\forall z} CAP_h^{PE} PE_{h,z}^{max} I_{b,h,z}^{PE}\Big\} \quad (4.1)$$

Equation (4.1) is the objective function of the decision planning model. This contains generators cost, battery degradation cost and capital cost of battery and power electronics.

$$P_{k,t,s} - B_k\big(\theta_{i,t,s} - \theta_{j,t,s}\big) = 0; \forall k, i \in from\_bus(k), j \in to\_bus(k) \quad (4.2)$$

Equation (4.2) is the line flow constraint.

$$\sum_{\forall k\in\pi(i,*)} P_k - \sum_{\forall k\in\pi(*,i)} P_k + L_{i,t} = \sum_{\forall g\in GEN(i)} P_{g,t,s} + \sum_{\forall b\in BAT(i)}\left(dch_{b,h,t,s} - ch_{b,h,t,s}\right) + \sum_{\forall o\in SOL(i)} P_{o,t,s}\,; \forall i, \forall h, \forall t, \forall s \qquad (4.3)$$

Equation (4.3) is the load balance constraint.

$$P_g^{min} u_{g,t,s} \le P_{g,t,s} \le P_g^{max} u_{g,t,s}; g \in G^{normal}, \forall t, \forall s \qquad (4.4)$$

Equation (4.4) is the generators output constraint.

$$P_k^{min} \le P_k \le P_k^{max}; \forall k \qquad (4.5)$$

Equation (4.5) is the transmission line constraint.

$$v_{g,t,s} - w_{g,t,s} = u_{g,t,s} - u_{g,t-1,s};\ \ \forall g, \forall s, t \in \{2,3,\dots,T\} \qquad (4.6)$$

$$v_{g,1,s} - w_{g,1,s} = u_{g,1,s} - u_{g,T,s};\ \ \forall g, \forall s \qquad (4.7)$$

Equation (4.6) and (4.7) are the generators status transition constraints. (4.7) is the initial generators status transition constraint because the last time period status is the initial status of the first time period in the daily cycle method.

$$u_{g,t,s} \in \{0,1\};\ \forall g, \forall t, \forall s \qquad (4.8)$$

$$0 \le v_{g,t,s} \le 1;\ \forall g, \forall t, \forall s \qquad (4.9)$$

$$0 \le w_{g,t,s} \le 1;\ \forall g, \forall t, \forall s \qquad (4.10)$$

Equation (4.8), (4.9), (4.10) are the generator status variables constraints.

$$\sum_{q=t-UT_g+1}^{t} v_{g,q,s} \le u_{g,t,s}\,;\ \forall g, \forall s\,, t \in \{UT_g, \dots, T\} \qquad (4.11)$$

$$\sum_{q=T-UT_g+t+1}^{T} v_{g,q,s} \le u_{g,t,s};\ \forall g, \forall s, t \in \{1, \dots, UT_g - 1\} \qquad (4.12)$$

Equation (4.11) and (4.12) are the generators minimum up time constraints. (4.11) and (4.12) ensure the minimum up time works in the daily cycle model. Take $T=7$, $UT_g=4$ as an example, if a generator start up at t=6 then this generator needs to be on at t=6, 7, 8, 9. Since a daily cycle model is implemented in this thesis, t=8, 9 of previous day are t=1, 2 in the next day in fact. In this case, (4.11) ensures that t=6, 7 must be on and (4.12) ensures that t=1, 2 (t=8, 9) must be on.

$$\sum_{q=t-DT_g+1}^{t} w_{g,q,s} \leq 1 - u_{g,t,s}\ ;\ \forall g, \forall s, t \in \{DT_g, \dots, T\} \tag{4.13}$$

$$\sum_{q=T-UT_g+t+1}^{T} w_{g,q,s} \leq 1 - u_{g,t,s};\ \forall g, \forall s, t \in \{1, \dots, DT_g - 1\} \tag{4.14}$$

Equation (4.13) and (4.14) are similar to (4.11) and (4.12), but equation (4.13) and (4.14) force generators to be off instead of on.

$$P_{g,t,s} - P_{g,t-1,s} \leq R_g^{+} u_{g,t-1,s} + R_g^{SU} v_{g,t,s}; \forall g, \forall t, \forall s \tag{4.15}$$

$$P_{g,t-1,s} - P_{g,t,s} \leq R_g^{-} u_{g,t-1,s} + R_g^{SD} w_{g,t,s}; \forall g, \forall t, \forall s \tag{4.16}$$

Equation (4.15) and (4.16) are generators ramping up & down constraints. When a generator is on, the ramping capability of this generator is restricted by R^{+} (R^{-}). If a generator is switched from off to on, the ramping capability of this generator is restricted by R^{SU} (R^{SD}).

$$SP_t \geq P_{g,t,s} + r_{g,t,s};\ g \in G^{normal}, \forall t, \forall s \tag{4.17}$$

$$SP_t \geq\ \beta \sum_{\forall o \in SOLAR} P_{o,t,s} + \gamma \sum_{\forall i} L_{i,t}\ ; \forall t, \forall s \tag{4.18}$$

$$SP_t - \sum_{\forall g \in G} r_{g,t,s} - \sum_{\forall b \in ES} \sum_{\forall h \in H} r_{b,h,t,s} \leq 0;\ \ \forall t, \forall s \tag{4.19}$$

Equations (4.17) to (4.19) are the system spinning reserves constraints. This thesis do not consider slow start up generators as spinning reserves providers as presented in (4.17), where G^{normal} is the set of all generators except slow start up generators. (4.18) specifies the requirement of overall spinning reserves which is a percentage of the sum of total load and installed solar capacities. BESS is considered to provide spinning reserves in this research as illustrated in (4.19), which requires the total spinning reserves provided by generators and BESS should be larger than the requirement of overall system spinning reserves.

$$0 \le r_{g,t,s} \le RR_g^{+} u_{g,t,s};\ g \in G^{normal}, \forall t, \forall s \tag{4.20}$$

$$r_{g,t,s} \le\ P_g^{max} u_{g,t,s} - P_{g,t,s};\ g \in G^{normal}, \forall t, \forall s \tag{4.21}$$

Spinning reserves provided by generators are limited by constraints (4.20) and (4.21). These two constraints indicate that the capability of providing spinning reserves for a generator is limited by the generator 10 minutes ramping rate and the margin power output.

$$u_{g,t} = u_{g,t,s};\ g \in G^{slow}, \forall t, \forall s \tag{4.22}$$

$$v_{g,t} = v_{g,t,s};\ g \in G^{slow}, \forall t, \forall s \tag{4.23}$$

$$w_{g,t} = w_{g,t,s};\ g \in G^{slow}, \forall t, \forall s \tag{4.24}$$

$$u_{g,t} \in \{0,1\};\ g \in G^{slow}, \forall t \tag{4.25}$$

$$0 \le v_{g,t} \le 1;\ g \in G^{slow}, \forall t \tag{4.26}$$

$$0 \le w_{g,t} \le 1;\ g \in G^{slow}, \forall t \tag{4.27}$$

Equation (4.22)-(4.27) are slow generators constraints. Note that the left-hand-side variables don't have scenario index s. As described in [27], a generator status may be on or off in different scenarios and this is not practical for slow start up generators since they cannot switch on and off immediately. Therefore, (4.22) to (4.24) enforce status of slow start up generators unchanged among different scenarios.

$$0 \le ch_{b,h,t,s} \le \sum_{\forall z} PE_{h,z}^{max} x_{b,t,s}\,; \forall b, \forall h, \forall t, \forall s \tag{4.28}$$

$$0 \le dch_{b,h,t,s} \le \sum_{\forall z} PE_{h,z}^{max} (1 - x_{b,t,s})\,; \forall b, \forall h, \forall t, \forall s \tag{4.29}$$

Equation (4.28) and (4.29) are similar to equations (3.29) and (3.30) in section 3.4. Except (4.28) and (4.29) use $\sum_{\forall z} PE_{h,z}^{max}$ instead of PE^{max} in (3.29), (3.30), where z is a size index for power electronic devices. When *x* equals to 1, the battery discharge output *dch* is restricted to 0 and charging power *ch* can vary between 0 and $\sum_{\forall z} PE_{h,z}^{max}$. On the contrary, *ch* is equal to 0 while *dch* can be greater than 0 when x equals to 0.

$$0 \leq ch_{b,h,t,s} \leq \sum_{\forall z} PE_{h,z}^{max} I_{b,h,z}^{PE} \,;\forall b, \forall h, \forall t, \forall s \tag{4.30}$$

$$0 \leq dch_{b,h,t,s} \leq \sum_{\forall z} PE_{h,z}^{max} I_{b,h,z}^{PE} \,;\forall b, \forall h, \forall t, \forall s \tag{4.31}$$

Equations (4.30) and (4.31) are charging and discharging output limit constraints. At the right hand side of these two constraints, I^{PE} is a binary variable as the selection of power electronic device size.

$$dch_{b,h,t,s} - dch_{b,h,t-1,s} + ch_{b,h,t-1,s} - ch_{b,h,t,s} \leq \sum_{\forall z} PE_{h,z}^{max} I_{b,h,z}^{PE} \,;\forall b, \forall h, \forall s, t \in \{2 \ldots T\} \tag{4.32}$$

$$dch_{b,h,t-1,s} - dch_{b,h,t,s} + ch_{b,h,t,s} - ch_{b,h,t-1,s} \leq \sum_{\forall z} PE_{h,z}^{max} I_{b,h,z}^{PE} \,;\forall b, \forall h, \forall s, t \in \{2 \ldots T\} \tag{4.33}$$

$$dch_{b,h,1,s} - dch_{b,h,T,s} + ch_{b,h,T,s} - ch_{b,h,1,s} \leq \sum_{\forall z} PE_{h,z}^{max} I_{b,h,z}^{PE} \;;\forall b, \forall h, \forall s \tag{4.34}$$

$$dch_{b,h,T,s} - dch_{b,h,1,s} + ch_{b,h,1,s} - ch_{b,h,T,s} \leq \sum_{\forall z} PE_{h,z}^{max} I_{b,h,z}^{PE} \;;\forall b, \forall h, \forall s \tag{4.35}$$

Equations (4.32)- (4.35) are the battery ramping rate constraints.

$$0 \leq r_{b,h,t,s} \leq \sum_{\forall z} PE_{b,h,z}^{max} I_{b,h,z}^{PE} \,;\forall b, \forall h, \forall t, \forall s \tag{4.36}$$

$$0 \leq r_{b,h,t,s} \leq ch_{b,h,t,s} + \sum_{\forall z} PE_{b,h,z}^{max} I_{b,h,z}^{PE} - dch_{b,h,t,s}; \forall b, \forall h, \forall t, \forall s \tag{4.37}$$

$$0 \leq r_{b,h,t,s} \leq \eta_{b,h}^{dch} \cdot SOC_{b,h,t,s}; \forall b, \forall h, \forall t, \forall s \tag{4.38}$$

Equations (4.36)-(4.38) are the BESS spinning reserve constraints.

$$0 \leq SOC_{b,h,t,s} \leq \sum_{\forall m} SOC_{h,m}^{max} I_{b,h,m} \,;\ \forall b, \forall h, \forall t, \forall s \tag{4.39}$$

Equation (4.39) is the battery capacity constraint. SOC^{max} is a parameter and $I_{b,h,m}$ is a binary variable for picking up the appropriate size of the BESS.

$$SOC_{b,h,t,s} = SOC_{b,h,t-1,s} + \eta_{b,h}^{ch} ch_{b,h,t,s} - \frac{1}{\eta_{b,h}^{dch}} dch_{b,h,t,s}; \forall b, \forall h, \forall s, t \in \{2 \dots T\}$$

(4.40)

$$SOC_{b,h,1,s} = SOC_{b,h,T,s} + \eta_{b,h}^{ch} ch_{b,h,1,s} - \frac{1}{\eta_{b,h}^{dch}} dch_{b,h,1,s};\ \forall b, \forall h, \forall s \tag{4.41}$$

Equation (3.2.37) and (3.2.38) are the BESS SOC transition constraints.

$$MAX_{b,h,s}^{d} \geq SOC_{b,h,t,s}\ \ \forall b, \forall h, \forall s, \forall t \tag{4.42}$$

$$MIN_{b,h,s}^{d} \leq SOC_{b,h,t,s}\ \ \forall b, \forall h, \forall s, \forall t \tag{4.43}$$

$$\zeta_{b,h,t,s}^{d} \geq\ MAX_{b,h,t,s}^{d} - MIN_{b,h,t,s}^{d}; \forall b, \forall h, \forall t, \forall s, \forall k \tag{4.44}$$

$$\sum_{n=1}^{N} \zeta_{b,h,t,s,n}^{d} = \zeta_{b,h,t,s}^{d}; \forall b, \forall h, \forall t, \forall s, \forall k \tag{4.45}$$

$$0 \leq\ \zeta_{b,h,t,s,n}^{d} \leq l_n \cdot \sum_{\forall m} SOC_{h,m}^{max} I_{b,h,m}\, ; n = 1,2, \dots, N \tag{4.46}$$

Equations (4.42)-(4.46) are similar to equations (3.17)-(3.21).

$$\sum_{\forall h} \sum_{\forall m} I_{b,h,m} \leq 1; \forall b, \forall h, \forall m \tag{4.47}$$

$$\sum_{\forall b} \sum_{\forall h} \sum_{\forall m} I_{b,h,m} \geq 1; \forall b, \forall h, \forall m \tag{4.48}$$

$$\sum_{\forall z} I_{b,h,z}^{PE} = \sum_{\forall m} I_{b,h,m}\, ; \forall b, \forall h, I_{b,h,z}^{PE} \in \{0,1\} \tag{4.49}$$

$$SOC_{b,h,t,s} \geq \sum_{\forall m} SOC_{h,m}^{max} I_{b,h,m} - M \cdot (1 - I_{b,t}^{FC}); \forall b, \forall h, \forall t, \forall s \tag{4.50}$$

$$\sum_{\forall t} I_{b,t}^{FC} = \sum_{\forall h} \sum_{\forall m} I_{b,h,m}\, ,; \forall b, \forall h, \forall m,\ I_{b,t}^{FC} \in \{0,1\} \tag{4.51}$$

Equation (4.47) and (4.48) ensure that the whole system has at least one BESS while each bus has at most one BESS. Power electronic devices selection constraint is described as (4.49), which promise that a bus with BESS must have one power electronic device. Equations (4.50) and (4.51) are the BESS full charge constraints, which ensure that the BESS will be fully charged at least once in a day.

4.2 Production cost model

Production cost model is the second part of the investment planning model. After the decision planning model determines the BESS location, size and battery type, the production cost model will calculate the estimate annual savings of the BESS. The production cost model is based on the DCOPF model. Some variables and constraints are relaxed in order to form a LP model such that this model is suitable for long term calculation. For instance, generator status variables and their constraints are not included in this production cost model compared to the decision planning model. Generally speaking, the nonlinear parts of the decision planning model are neglected or linearized in the production cost model; the BESS location, size and battery type are fixed in the production cost model. Also, the capital cost of batteries and power electronic devices are excluded from calculating the operating cost of the system with BESS. As described in the beginning of section chapter 4, annual savings of 1st, 3rd, 5th and 10th year are calculated first and then the annual savings of other years can be found by interpolating. The production cost model is stated and explained in below:

$$\min\left[\sum_{\forall t}\sum_{\forall g}\left(C_g P_{g,t}\right) + \sum_{\forall b}\sum_{\forall t}\sum_{\forall n}\left(\alpha_b^0 SOC_b^{max} + \alpha_{b,n}\zeta_{b,t,n}\right) + \sum_b\sum_t \lambda\left(Deg \cdot SOC_b^{max} - SOC_{b,t}\right)\right] \tag{4.52}$$

(4.52) is the production cost model's objective function, including generators linear cost, the battery degradation cost and the battery full-charge penalty cost. The first two terms are similar to what described in above section 4.1. The last term $\lambda(Deg \cdot SOC_b^{max} - SOC_{b,t})$ is the battery full-charge penalty cost, which is a fictitious cost in order to penalize that the BESS is not in fully charged status. λ is the full-charge penalty price, a positive number. *Deg* is a parameter which represents the battery capacity degradation process. Ignoring the parameter *Deg* first, ($SOC_b^{max} - SOC_{b,t}$) represents the gap between the BESS SOC and the BESS capacity, this term is always positive and when this gap times the full-charge penalty price the result are also positive. Since the production cost model is a minimization model, the production cost model will try to minimize the BESS gap with considering the generators operating cost and the battery degradation cost. A very big number will fix the BESS SOC at the maximum capacity while a very small number will not have a significant impact on the BESS SOC. In this research, λ is set to be about \$0.1/MWh, this value is gained by test. *Deg* is a battery capacity degradation parameter. As discussed in chapter 2, the capacity of a battery will decrease when cycle it. In this research, the capacity of the BESS is supposed to degrade at a constant rate, for example 2%. That is, the capacity in the first year is 100%, then 98% in the second year and then 96.04% in the third year etc.

The production cost model constraints are listed below:

$$P_{k,t} - B_k(\theta_{j,t} - \theta_{i,t}) = 0; k \in Line, i \in from\_bus(k), j \in to\_bus(k) \tag{4.53}$$

$$\sum_{\forall k \in \pi(i,*)} P_k - \sum_{\forall k \in \pi(*,i)} P_k + L_{i,t} = \sum_{\forall g \in GEN(i)} P_{g,t} + \sum_{\forall b \in BAT(i)} (dch_{b,t} - ch_{b,t}) + \sum_{\forall o \in SOL(i)} P_{o,t}\,;\ i \in BUS, t \in T, s \in S \tag{4.54}$$

$$P_g^{min} \le P_{g,t} \le P_g^{max}; \forall g \in G, \forall t \in T \tag{4.55}$$

$$P_k^{min} \le P_k \le P_k^{max}; k \in LINE \tag{4.56}$$

$$P_{g,t} - P_{g,t-1} \le R_g^{+};\ \forall g \in G, \forall t \in T \tag{4.57}$$

$$P_{g,t-1} - P_{g,t} \le R_g^{-};\ \forall g \in G, \forall t \in T \tag{4.58}$$

$$SP_t \ge P_{g,t} + r_{g,t};\ \forall g \in G, \forall t \in T \tag{4.59}$$

$$SP_t \ge \beta \sum_{\forall o} P_{o,t} + \gamma \sum_{\forall i} L_{i,t}\,; \forall o \in PV, \forall t \in T, \forall i \in BUS \tag{4.60}$$

$$SP_t - \sum_{\forall g \in G} r_{g,t} - \sum_{\forall b \in ES} r_{b,t} \le 0;\ t \in T \tag{4.61}$$

$$0 \le r_{g,t} \le RR_g^{+};\ \forall g \in G, \forall t \in T \tag{4.62}$$

$$r_{g,t} \le\ P_g^{max} - P_{g,t};\ \forall g \in G, \forall t \in T \tag{4.63}$$

Equation (4.53)-(4.56) are similar to constraints (4.2)-(4.5). Equations (4.57)-(4.63) are similar to constraints (4.15)-(4.21).

$$0 \le ch_{b,t} \le PE_b^{max}; \forall b \in ES, \forall t \in T \tag{4.64}$$

$$0 \le dch_{b,t} \le PE_b^{max}; \forall b \in ES, \forall t \in T \tag{4.65}$$

$$dch_{b,t} - dch_{b,t-1} + ch_{b,t-1} - ch_{b,t} \le PE_b^{max}; \forall b \in ES, \forall t \in T \tag{4.66}$$

$$dch_{b,t-1} - dch_{b,t} + ch_{b,t} - ch_{b,t-1} \le PE_b^{max}; \forall b \in ES, \forall t \in T \tag{4.67}$$

$$0 \le SOC_{b,t} \le Deg \cdot SOC_b^{max};\ \forall b \in ES, \forall t \in T \tag{4.68}$$

$$SOC_{b,t} = SOC_{b,t-1} + \eta_b^{ch} ch_{b,t} - \frac{1}{\eta_b^{dch}} dch_{b,t}; \forall b \in ES, \forall t \in T \tag{4.69}$$

$$MAX^d \ge SOC_{b,t}; \forall b \in ES,\ \forall t \in \{\, 24(d-1), \dots, 24d \mid d = 1,2, \dots \} \tag{4.70}$$

$$MIN^d \le SOC_{b,t}; \forall b \in ES,\ \forall t \in \{\, 24(d-1), \dots, 24d \mid d = 1,2, \dots \} \tag{4.71}$$

$$0 \le r_{b,t} \le PE_b^{max}; \forall b \in ES, \forall t \in T \tag{4.72}$$

$$0 \le r_{b,t} \le ch_{b,t} + PE_b^{max} - dch_{b,t}; \forall b \in ES, \forall t \in T \tag{4.73}$$

$$0 \le r_{b,t} \le \eta_b^{dch} \cdot SOC_{b,t,}; \forall b \in ES, \forall t \in T \tag{4.74}$$

$$\textstyle\sum_{n=1}^{N} \zeta_{b,n}^d = \zeta_b^d; \forall b \in ES, \forall d \tag{4.75}$$

$$0 \le \zeta_{b,n}^d \le l_n \cdot Deg \cdot SOC_b^{max};\ \forall b, \forall n, \forall t, \forall d \tag{4.76}$$

$$\zeta_b^d \ge MAX^d - MIN^d;\ \forall b, \forall d \tag{4.77}$$

Equation (4.64)-(4.77) are battery related constraints. Most of them are similar to battery constraints of the decision planning model, but there are some differences. For instance, since the BESS size and power electronic device size are already found by decision planning model, the right hand sides of (4.64)-(4.67) become PE^{max} and the right hand sides of (4.68) become SOC^{max}. Besides, the parameter *Deg* are added into (4.68) and (4.76).

4.3 Model implementation for distribution networks

This section briefly discusses about the implementation of the proposed model on distribution levels. The discussion will briefly describe the differences between transmission levels and distribution levels. More detailed discussions about distribution level applications are left to future work. The proposed investment planning model is developed base on DCOPF, which is suited for high voltage transmission or sub-transmission networks. The proposed formulation may become inappropriate for distribution networks since the assumptions of DCOPF may not be hold in distribution networks.

One assumption is that the DCOPF is a lossless model, which is assuming that line resistance is negligible, that is, $R<<X$. The R/X ratio in distribution networks is generally higher than the ratio in transmission level and, thus, the lossless line assumption is not as valid for distribution networks.

Another assumption of DCOPF is that the system is a 3-phase balanced system and this is also the base of ACOPF. In a 3-phase balanced system, 3-phase calculation can be modeled as a single phase calculation. However, this assumption of balanced 3-phase operation is barely valid in distribution levels. Distribution networks may 1, 2 or 3 phase loads and load for each phase is to be determined. Therefore, 3-phase power flows cannot be calculated by a single phase model.

Besides previous two assumptions, the DCOPF assumes that bus voltages are one per unit. Because in transmission levels, bus voltages are typically around one per unit within a small range. Thus, for simplicity, DCOPF assumes that bus voltages are equal to one. While voltage drop becomes larger in distribution networks, bus voltages will deviate one per unit in a much larger range. In ACOPF, this bus voltage assumption is relaxed. Bus voltages are not set to one per unit and AC power flows take bus voltages into consideration. The general formulations of ACOPF are listed in below.

$$\min \sum_{\forall g} c_g P_g$$

$$P_{kij}^2 + Q_{kij}^2 \le S_k^2, \forall k \tag{4.78}$$

$$P_{kji}^2 + Q_{kji}^2 \le S_k^2, \forall k \tag{4.79}$$

$$V_i^2 G_k + V_i^2 G_{ik} - V_i V_j \left[G_k \cos(\theta_i - \theta_j) + B_k \sin(\theta_i - \theta_j) \right] - P_{kij} = 0, \forall k \tag{4.80}$$

$$V_j^2 G_k + V_j^2 G_{nk} - V_j V_i \left[G_k \cos(\theta_j - \theta_i) + B_k \sin(\theta_j - \theta_i) \right] - P_{kji} = 0, \forall k \tag{4.81}$$

$$V_i^2 B_k + V_i^2 B_{ik} + V_i V_j \left[G_k \cos(\theta_i - \theta_j) - B_k \sin(\theta_i - \theta_j) \right] - Q_{kij} = 0, \forall k \tag{4.82}$$

$$V_j^2 B_k + V_j^2 B_{jk} - V_j V_i \left[G_k \cos(\theta_j - \theta_i) - B_k \sin(\theta_j - \theta_i) \right] - Q_{kji} = 0, \forall k \tag{4.83}$$

$$\sum_{k \in \pi(i,*)} P_{kji} - \sum_{k \in \pi(*,i)} P_{kij} - \sum_{g \in GEN(i)} P_g + L_i^P = 0, \forall i \tag{4.84}$$

$$\sum_{k \in \pi(i,*)} Q_{kji} - \sum_{k \in \pi(*,i)} Q_{kij} - \sum_{g \in GEN(i)} Q_g + L_i^Q = 0, \forall i \tag{4.85}$$

$$P_g^{min} \le P_g \le P_g^{max}, \forall g \tag{4.86}$$

$$Q_g^{min} \le Q_g \le Q_g^{max}, \forall g \tag{4.87}$$

$$-\theta^{max} \le \theta_i - \theta_j \le \theta^{max}, \forall k \tag{4.88}$$

$$V^{min} \le V_i \le V^{max}, \forall i \tag{4.89}$$

The last several paragraphs briefly talk about the assumptions of DCOPF and introduce the general ACOPF formulations. This is not saying that the ACOPF has to be adopted for distribution networks. Depending on specific purposes, the DCOPF can also be applied for distribution level investment planning. For instance, if the voltage regulation is not the main purpose of the BESS, the DCOPF is still a very attractive investment planning model approach for distribution networks not facing severe voltage drop and 3-phase unbalance. In this situation, after carefully modeling the losses, the DCOPF will not suffer much loss of accuracy but get lots of benefits in solution time. Furthermore, distribution networks are typically overbuilt, which means congestions seldom happen. The DCOPF problem could be further simplified as economic dispatch problem as long as system losses are properly calculated. Correspondingly, the ACOPF could handle situation where voltage drops are considered, like investigating BESS voltage regulation performances. How to deal with 3-phase unbalance is also situational based. Unbalanced 3-phase OPF problem can be solved through 3-phase analysis or some approximation approaches like in reference [51] [52] [53].The general ACOPF is a non-convex problem, which is considered as very hard to solve. Reference [50] proves that the ACOPF problem can be solved by the convex dual problem with zero duality gaps in tree networks, which are very common in distribution level power grids. In this section, the implementation of proposed model on tree structure distribution networks is discussed; mesh distribution networks are left for future work. Reference [50] provides a very useful tool to solve the ACOPF for radial distribution networks and can also be applied to this thesis's model. Considering that, in distribution networks, the potential BESS location is usually at substations and the number of buses is relatively small comparing to transmission networks. Therefore, in order to fully utilize the advantage of reference [50] approach, the BESS location, type and size is founded through heuristic search method for radial distribution networks instead of using integer decision variables. Each iteration of heuristic search will not take a very long time since the ACOPF is a convex problem in radial distribution networks. The total number of iterations would not be a large number as the total buses in a small radial distribution network is limited.

4.4 Model variations for different microgrids operation mode

Microgrids generally have two types of operation modes: one is the island mode and another one is the grid-connect mode. The island mode is that the microgrid satisfies its demand by its own resources. Not every microgrid can supply enough power by itself to its customers, thus, load shedding is generally considered in the microgird island mode. For implementing the investment planning model on microgrids under island mode operation, the proposed investment planning mode needs to add load shedding cost to its objective function and more constraints related to load shedding. The grid-connect mode is that the microgrid satisfies its demand through the combination of buying power from the main grid and producing power by its own resources. The main grid is typically treated as a power resource like a generator and the main grid is often modeled as a generator in terms of energy buying. Without considering selling power from the microgrid to the main grid, the proposed investment planning model can be used for mircogrids under grid-connect mode operations after some modifications, which are adding buying cost in the objective function and associated buying constraints.

CHAPTER 5

SIMULATIONS AND RESULTS

5.1 Test case

This research uses one area, the area A, of the IEEE Reliability Test System 1996 (RTS96) as the test case. This test case contains 33 generators, 24 buses and 37 branches. More details of this test case power system can be found in [25][26]. The test case system diagram is illustrated in Fig. 4. Photovoltaic stations have been added to bus 7, bus 13 and bus 22 with the amount of solar capacity 300 MW, 200 MW and 300 MW respectively. These solar resources are resulted in about 20% penetration of renewable energy. For calculation convenience and without loss of essential elements of solar energy, the same patterns and scenarios have been implemented to all three photovoltaic stations with the exception that these stations have different peak outputs. An illustration of solar scenarios is shown in Fig. 5. The five solar scenarios in Fig. 5 are deriving from National Renewable Energy Laboratory (NREL) TMY3 data set [43]. Introducing solar scenarios for an investment planning model is to improve the model accuracy by considering solar variability. But the model computational complexity has also increased. Generally, results with more scenarios are considered better. Five scenarios are a small number of solar scenarios; however, the simulation will face out-of-memory issue when more scenarios are taken into consideration due to computer capability in this simulation. Compared to day-ahead UC problem, the investment planning model contains more time periods and thus the number of scenarios for the investment planning model will be smaller for the same computational resources. Depending on the size of test base, more than five solar scenarios are possible for a smaller system. Here, in this simulation, five scenarios capturing the major solar characteristics are selected due to balancing model accuracy and computational burden.

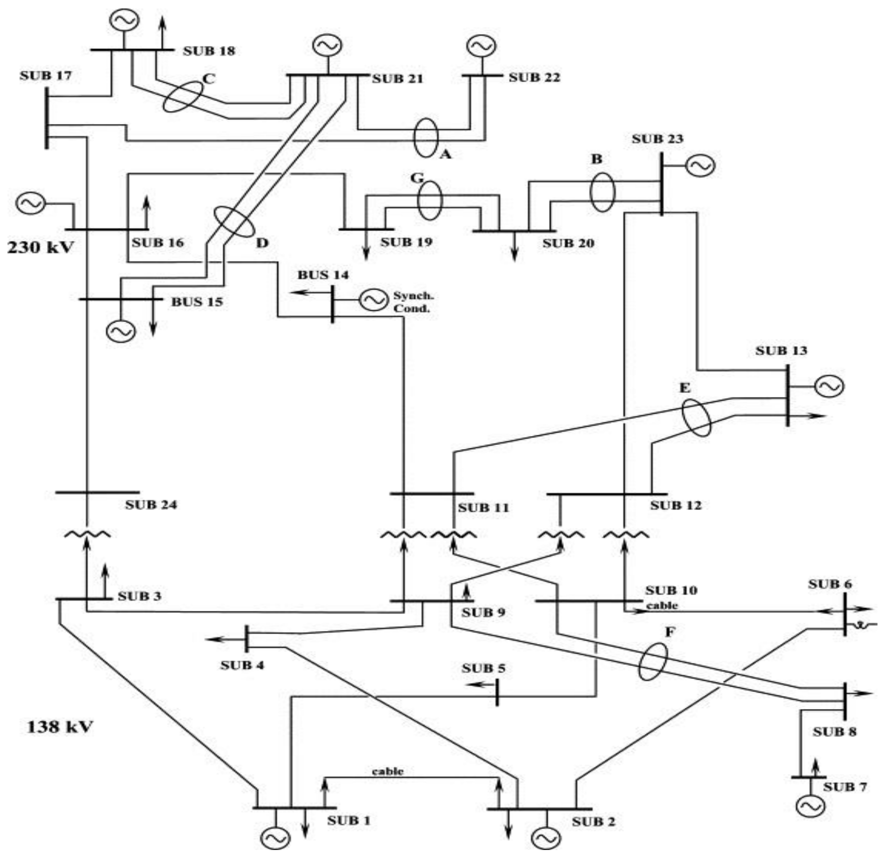

Fig. 4 IEEE RTS-96 area A

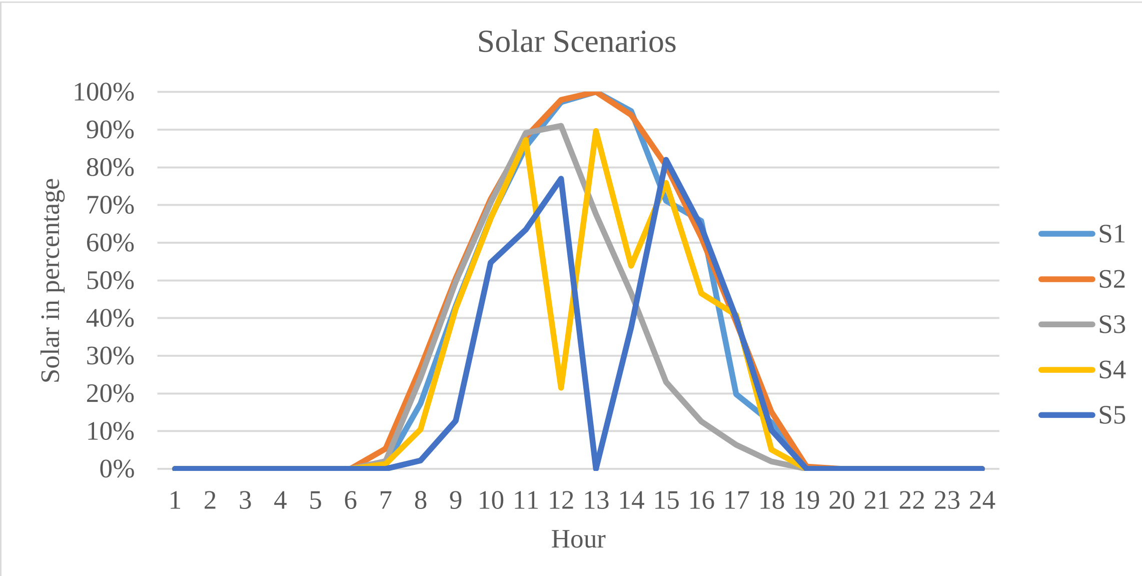

Fig. 5 Solar Scenarios

As described in section 3.2, several day types have been chosen in this simulation. For balancing computational difficulty and accuracy of results, three day types are selected in this simulation as illustrated in Fig. 6. The three day types are named “winter”, “summer” and “spring/fall”. Spring season and fall season are grouped into one day type for simplicity. The load demand for each day type is the average demand value across the corresponding season. For example, the load demand of summer day type in hour 1 (0:00-1:00) is calculated by taking the average value of each load demand of all days in summer season (day 126-210) in hour 1. Although demand values have effects on estimation results, the number of day types is more crucial. For just one day type, any kind of demand generation method is not sufficient. Here, this thesis uses average value (also equals to the expectation value in this case) because it makes more sense than peak value or off-peak value. In situation only has one day type, the peak value of demand will overestimate BESS benefits and the off-peak value will underestimate BESS benefits while the average value is expected to get a more accurate result.

More number of day types and more detailed day types will generally give higher estimation accuracy. However, more number of day types also increase the computational burden and may even make the MILP model become unsolvable. The number of day types should be used is also depending on simulation test base. In this simulation, with 5 solar scenarios and 3 day types, about 90000 variables and more than 300000 constraints are included in the decision planning model, which takes more than two days to solve it. If more day types are used for the simulation, the problem will become unsolvable within reasonable time. When six day types (winter weekday, winter weekend, summer weekday, summer weekend, spring/fall weekday and spring/fall weekend) are used for the simulation, the solver will return a run-out-of-memory result. Besides this computational difficulty, another reason to use just three day types is that these three day types can also capture the major part of the problem. Comparing the result of one winter day type and the result of winter weekday and winter weekend day type, the BESS size, type and location are the same and the result mismatch is less than 6%. The similar situation is applied for summer season and spring/fall season. That is saying, the result of three day types is within a reasonable range when more day types are tested. However, the solution time of 6 day types is more than double of the solution time for three day types. Therefore, using these three day types is the most practical way for the simulation in this thesis. The number of day types could be larger when the model is used for a smaller network than in this thesis. The annual load data of this test system can be found in [25][26]. For this test system, the annual peak load is occurred in the winter as well as the winter load profile has the highest peak demand in all three load profiles.

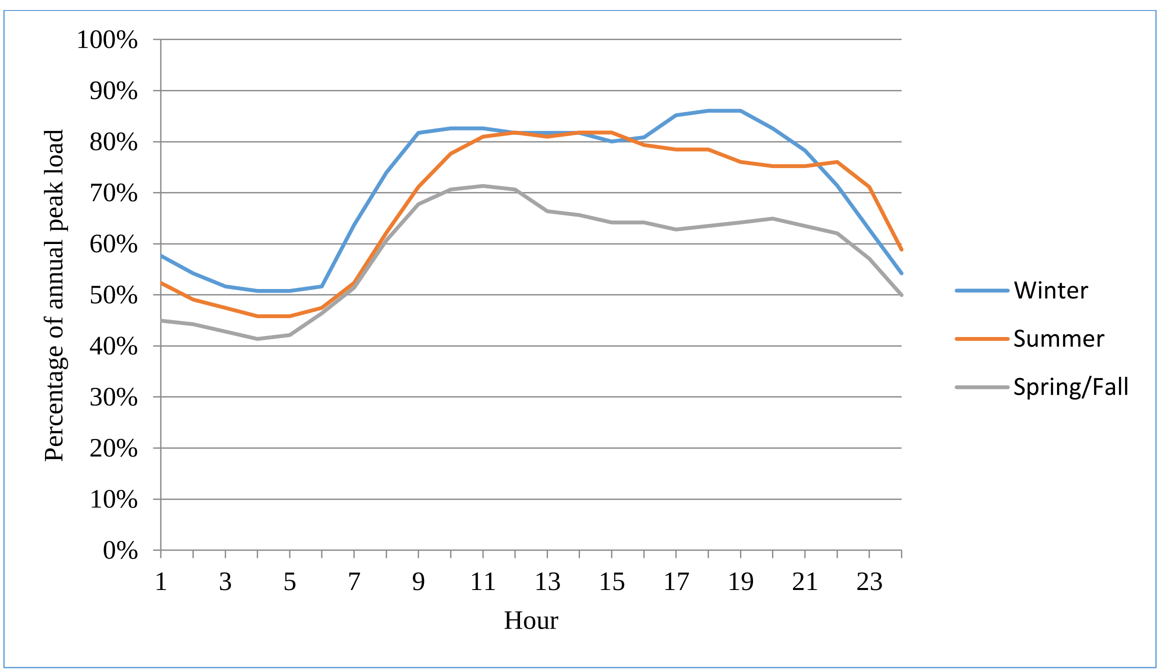

Fig. 6 Day type load profiles

The battery data used in this simulation is listed in TABLE III and the data can be found in reference [28]. The load demand growth rate for this simulation is set as 1% according to reference [49]. The interest rate is crucial to the simulation since the degradation cost is sensitive with the interest rate; the higher interest rate will give a lower degradation cost and vice versa. This thesis chooses a moderate interest rate, 6%, for the simulation.

TABLE III
BATTERY PARAMETERS IN SIMULATION

	Capital cost	Power electronics cost	Efficiency	Number of cycles (20%DOD)
Lead-acid	$330/kWh	$350/kWh	75%	2000
Li-ion	$600/kWh	$400/kWh	95%	15800

5.2 Decision planning model results

In this research, the decision planning model assumes discrete values for the battery capacity instead of treating the capacity as a continuous variable, which will add additional computational complexity to the problem. In this result, the battery capacity options have been set as 50 MWh, 100 MWh, and 150 MWh. The battery power output options have been set as 50 MW, 100 MW and 150 MW. These numbers are chosen in order to demonstrate the validity of the investment planning model. It is preferable to consider more discrete options for the battery capacity and the battery power output; however, the computational time will dramatically increase when the number of discrete options increases. In this simulation, the battery potential locations are chosen as bus 7, bus 13 and bus 22. A more exhaustive decision planning model would search for the optimal location to place the battery; however, this is left to future work. The simulation is running on a computer with two Xeon E5-2687W CPUs and 128 GB RAM. The optimal solution derived from the decision planning model is listed in TABLE IV below.

TABLE IV
OPTIMAL SOLUTION OF THE DECISION PLANNING MODEL

BESS type	BESS capacity	BESS rate	BESS location	Solution time
Li-ion	150 MWh	50 MW	Bus 7	12 hours

Li-ion battery type has been chosen in this thesis. This result indicates that even though the capital cost of Li-ion battery is substantially higher than the capital cost of lead-acid battery, the higher efficiency and higher number of cycles dominate the investment decisions. A low efficiency will directly reduce the profit of BESS. For example, a 75% efficiency will change a 100 MWh charging energy into 56.25 MWh (100MWh*75%*75%) discharging energy. In this case, in order to make a profit, the selling price will need to be about twice the buying energy price while a BESS with 95% efficiency could make profits at a much smaller price difference, about 11%, when buying and selling energy. One concern is that the current maximum capacity for Li-ion systems is smaller than the maximum capacity of lead-acid systems since large scale systems for Li-ion are still being developed. However, this result demonstrates that a Li-ion type of BESS is a better option than a lead-acid BESS when these two options have the same capacity size. Maybe Li-ion technology is infeasible for a large power system load leveling or load shifting purpose, but the result still has an important meaning for small scale power systems like a microgrid. In a small system, the capacity of Li-ion battery is comparable to the capacity of lead-acid battery even under current technologies. So the Li-ion BESS is a more attractive option for a small scale power system and the future of Li-ion system is very inspiring if the large scale Li-ion system becomes available. Besides this, these results suggest that Li-ion batteries have a bigger price cut space than mature lead-acid batteries in the future, which means that the price difference of these two types of battery will decrease in the future. At that time, Li-ion type of BESS will be a very competitive solution for a microgrid.

The model result selects 150 MWh capacity and 50 MW power output, which are the largest capacity and the smallest power output among options. This result indicates that large capacity BESS with moderate power output rate are more appropriate for load leveling or load shifting purposes. This conclusion is correspond to what is described in reference [1], which says that applications like load peaking or load shifting and arbitraging economic activities tend to prefer an energy storage with higher energy level but with less demand on its instantaneous power level. The utilization patterns of the battery in different scenarios for the three characteristic days are illustrated in Fig. 7, Fig. 8, and Fig. 9 below. The average battery energy storage utilization, which is calculated by the expectation of discharged energy of all scenarios in 24 hours, in different day types is listed in TABLE V.

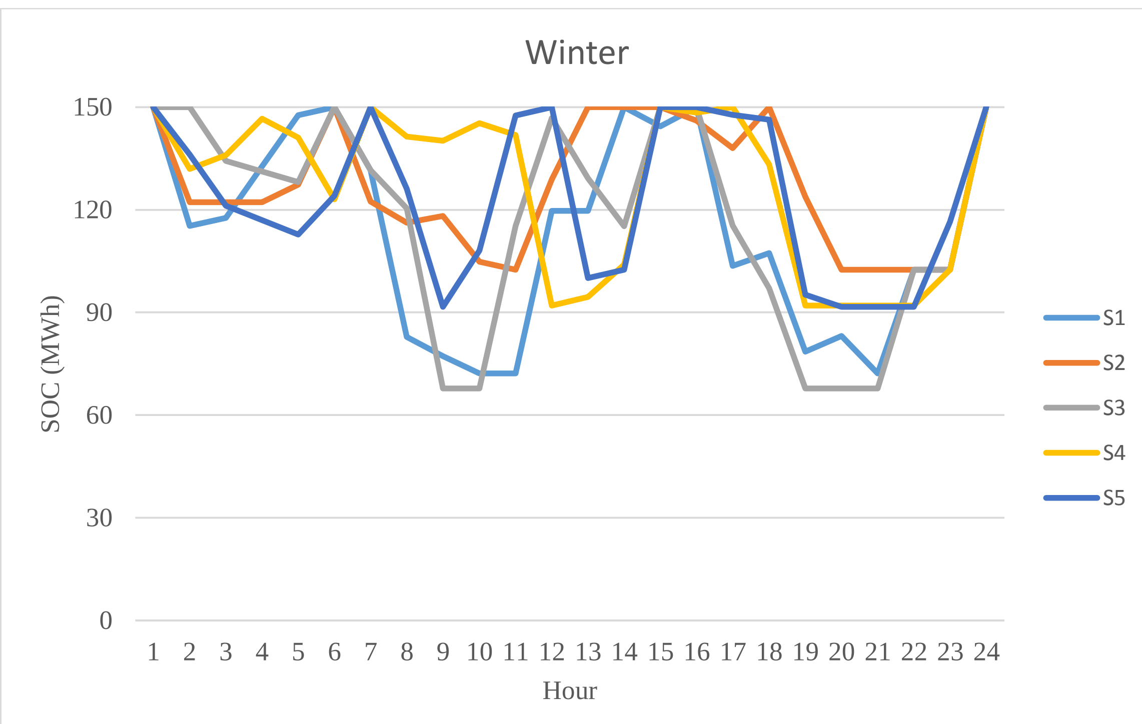

Fig. 7 The pattern of utilizing battery in winter days

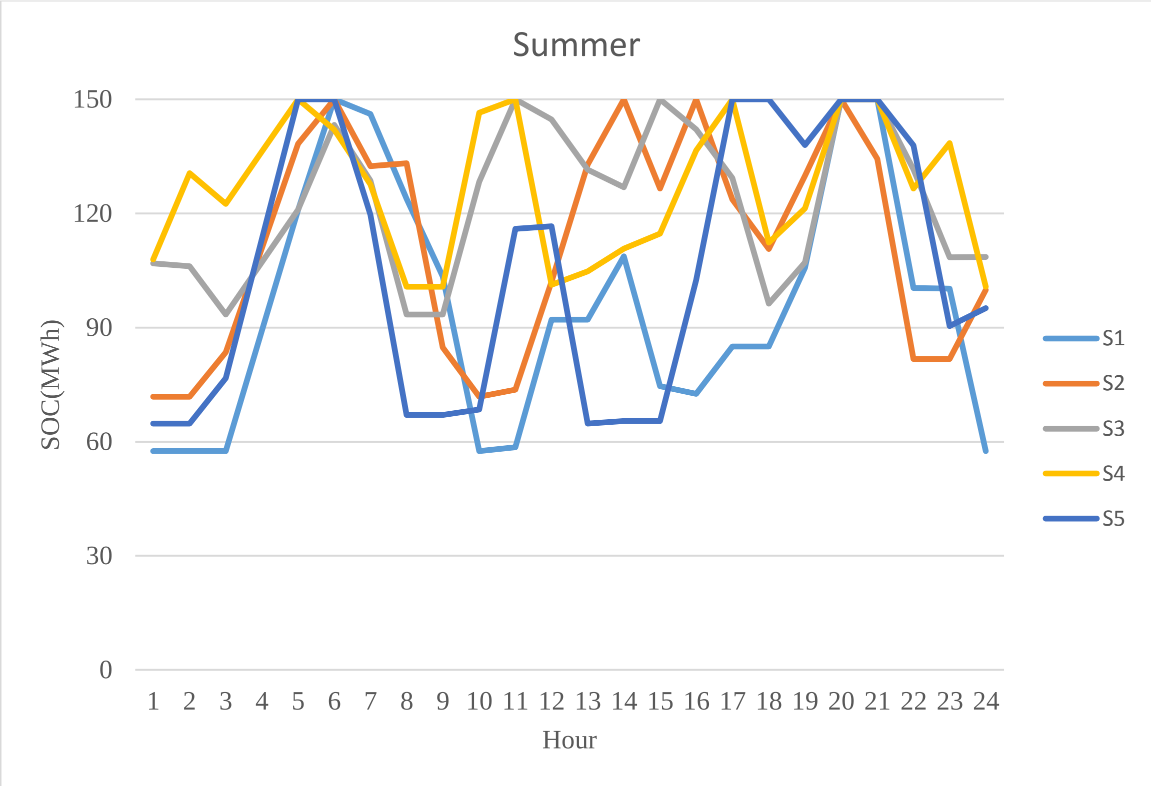

Fig. 8 The pattern of utilizing battery in summer days

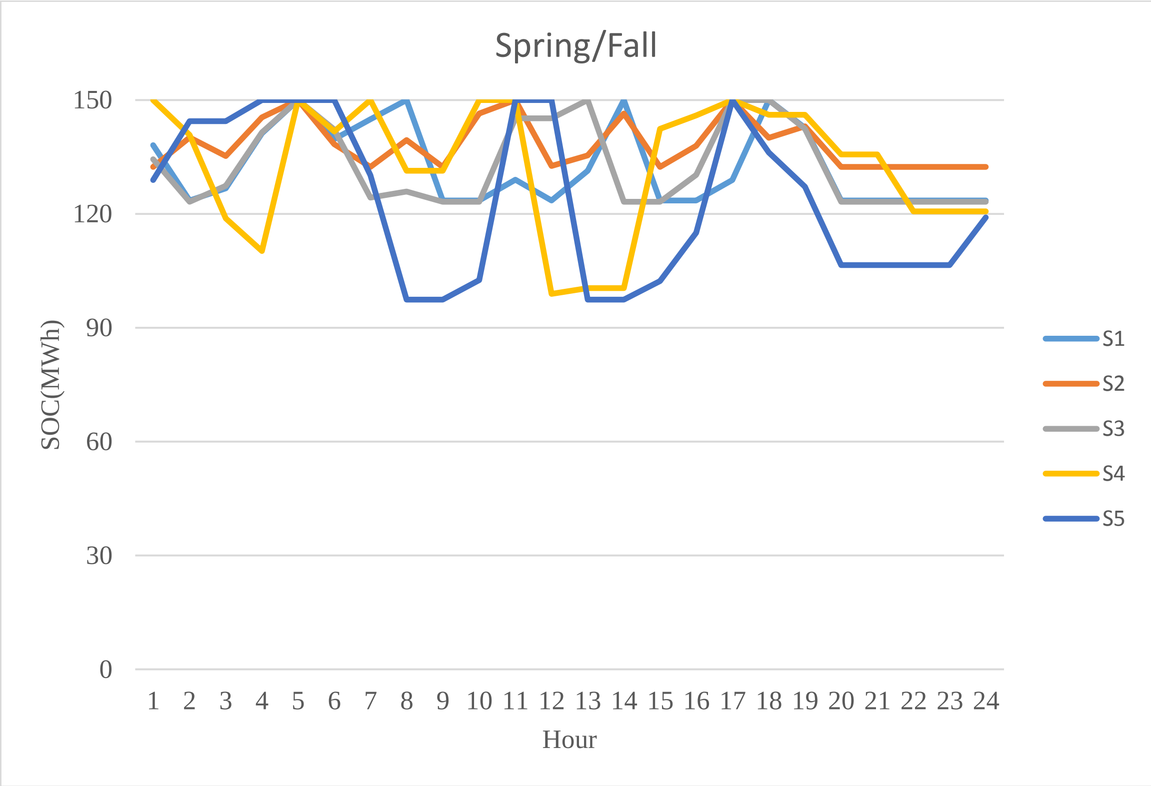

Fig. 9 The pattern of utilizing battery in spring or fall days

TABLE V
BATTERY UTILIZATION IN DIFFERENT DAY TYPES

	Winter	Summer	Spring/Fall
Expectation of utilization in 24 hours	185 MWh	220 MWh	119 MWh
Maximum utilization of a single hour	82 MWh	92 MWh	52 MWh

TABLE V results show that the utilization of the BESS is correlated to the system demand. That is, the higher load is very likely to require more energy from the BESS as the load demand in winter days and summer days is higher than in spring or fall days as shown in Fig. 6. This phenomenon can also be observed from Fig. 7, Fig. 8 and Fig. 9. In the summer, the BESS has the largest SOC variation, both in the total amount and the deepest SOC point. For winter days, the deepest SOC is about 70 MW, which occurred in scenario 3; for summer days, the deepest SOC is about 60 MW, which occurred in scenario 1; for spring and fall days, the deepest SOC is about 100 MW, which occurred in scenario 5. Basically, a BESS is cycled at on-peak hours and off-peak hours while noticing that several cycles occurred in 24 hours of one day and this implied that a BESS operating strategy is not necessary to only cycle the battery once a day. Many researchers make this assumption that a BESS charges at off-peak hours and discharge at on-peak hours to calculate the value of the BESS. From Fig. 7, Fig. 8 and Fig. 9 above, it is easy to find that a charge-discharge cycle could also occur in off-peak hours or on-peak hours. For example, in scenario 2 of summer days, the BESS is discharging at off-peak hours when the load is increasing. This example and similar examples imply that charging at off-peak hours and then discharging at on-peak hours may not be the only way to collect revenue for a BESS. By accounting for the cost associated to the utilization of BESS, more profitable cycles have been found in a daily load profile.

From the BESS utilization patterns above, this thesis also finds several relationships between solar scenarios and utilizing of the BESS. One relationship is that a BESS seems to be cycled more frequently in a cloudy scenario. Scenario 2 is a sunny day solar radiation profile and the result BESS SOC pattern of scenario 2 has 4 cycles of charge/discharge, while the BESS has 6 charge/discharge cycles on a cloudy day like scenario 4. Another relationship is that a BESS is likely to discharge at a deeper SOC level on a cloudy day than on a sunny day. For example, the discharging SOC level for cloudy days in the spring/fall like scenario 4 and 5 is deeper than it for the summer sunny day like scenario 2.

From those three utilization patterns above, a conclusion can be inferred that partial cycles are preferred to full charge/discharge cycles for load shifting purpose since full charge/discharge cycles have much higher degradation costs. This type of result may not be very intuitive because people generally expect to fully utilize a generator's capacity and impose this idea to BESS. However, a key difference between a generator and BESS is that a generator's lifetime will not (or maybe slightly) affected by its operating level while BESS lifetime is associated with DOD level. This means that to pursue BESS short term profits by shifting load may result in a long term loss due to the reduction of BESS lifetime. Since the degradation cost is not linear, the cost for utilizing half of a BESS capacity is much higher (more than 2 times) than just utilizing 1/4 part of it. So even if the first situation has double discharging energy than the later one but the first situation is actually losing money when arbitrage prices of two situations are the same. In other words, the profitable arbitrage price will be pushed higher when BESS tries to collect more money through discharging more energy.

Although the SOC level seems to be never below a certain value in those three figures, but the BESS can cycle at a deeper level. Note that the three load profiles are average values of some load profiles and there is few load demand varieties shown in them. More demand varieties and maybe subsequently more energy price volatilities will be observed when a smaller time scale, like 15-minute, is used in simulations. In this situation, arbitrage activities of BESS are expected to increase and the lowest SOC level may go deeper that what are illustrated in Fig. 7, Fig. 8 and Fig. 9.

5.3 Production cost model results

In the second part of the investment planning model, the production cost model finds the operating cost of the system with the BESS and without the BESS. The annual benefits of the BESS are calculated from the savings between the two operating costs above. In the simulation, the annual benefits of BESS at year 1, 3, 5 and 10 are calculated by the production cost model and the annual benefits of BESS in the rest years are estimated by interpolating. Each annual benefits result is gained from the production cost model with 365 days load profiles. The system load profile used is from [25][26] and 1% load increment is assumed in this case. Results are shown in TABLE VI. From results in TABLE VI, the extrapolations of savings for the rest of the years are given in Fig. 10.

TABLE VI
ESTMATION OF THE BESS ANNUAL SAVINGS

Year	Annual cost without BESS	Annual cost with BESS	Annual Savings
1	396915000	395353000	1562000
3	401598000	399994000	1604000
5	406721000	405087000	1634000
10	421905000	420123000	1782000

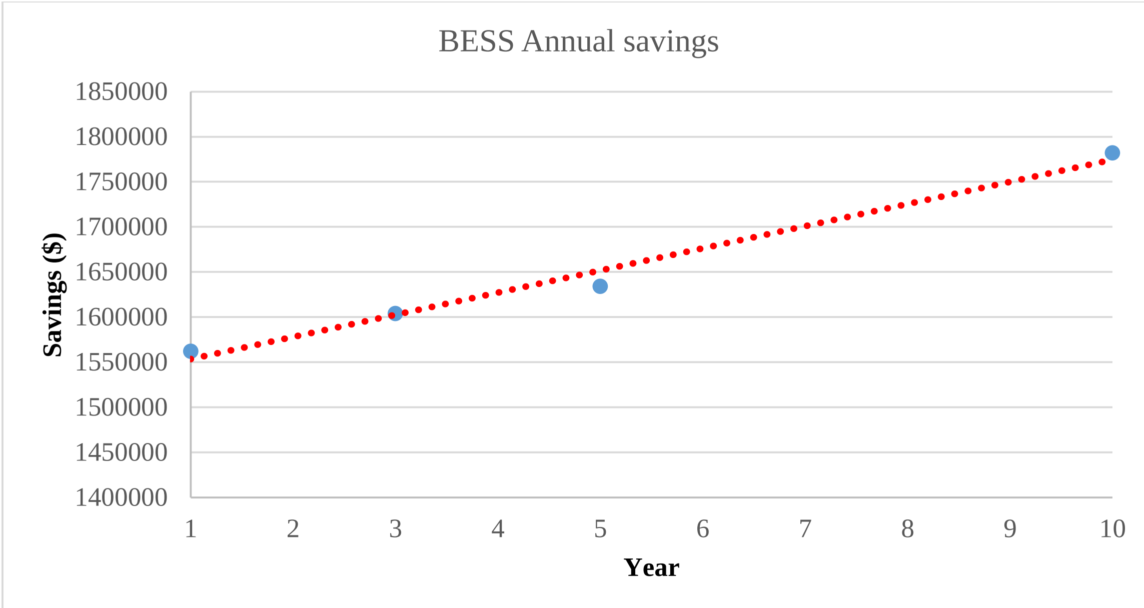

Fig. 10 Extrapolations of the BESS annual savings

TABLE VII
ANNUAL CAPACITY DEGRADATION OF FIG.10

Year	1	3	5	10
Capacity degradation	1.63%	1.65%	1.61%	1.62%

The results shown in Fig. 10 are BESS annual savings without considering capacity degradations. TABLE VII gives the annual capacity degradation rate in percentage of the BESS capacity in previous year. As described in chapter 3, BESS generally will lose its capacity as it keeps cycling. This effect is important and, therefore, this thesis considers this effect and reruns the simulation by assuming a constant capacity degradation rate 1.6% based on information in TABLE VII. Capacity degradations are correlated to utilizations of BESS but the problem will become a nonlinear programming problem if the BESS capacity is modeled as a function of BESS utilizations. Therefore, modeling the capacity degradation effect as a constant degrading rate is more practical. The rerun simulation result is illustrated in Fig. 11.

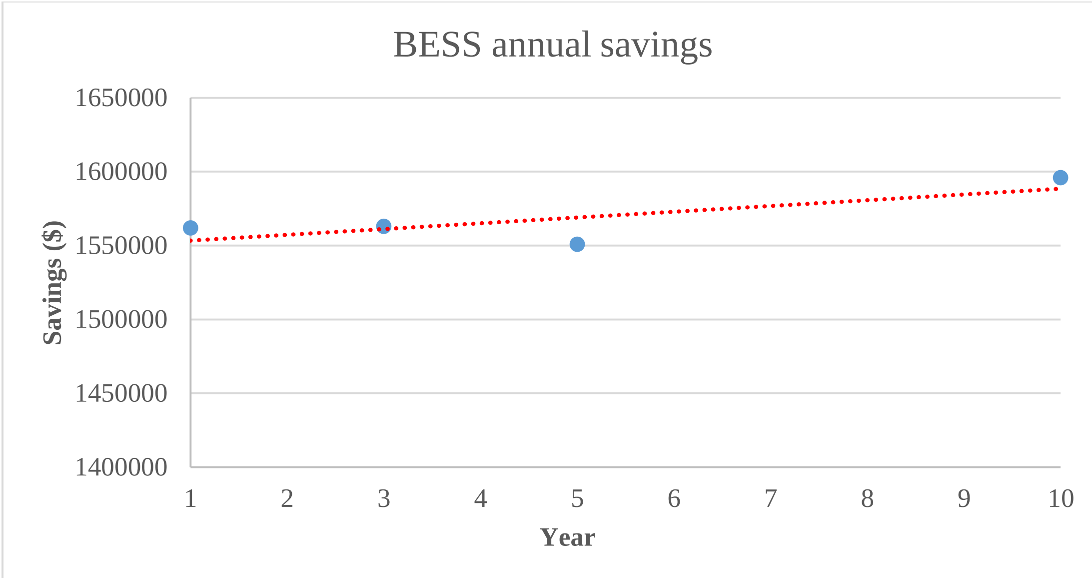

Fig. 11 BESS annual savings considering capacity degradation

TABLE VIII
ANNUAL CAPACITY DEGRADATION OF FIG.11

Year	1	3	5	10
Capacity degradation	1.63%	1.61%	1.60%	1.61%

The annual capacity degradation of Fig. 11 results are presented in TABLE VIII. Comparing TABLE VII and TABLE VIII, the result of capacity degradation rate seems not to be biased a lot by taking the phenomenon of degrading capacity into consideration. The BESS annual savings are affected by this phenomenon; not just the overall savings are decreased but also almost every single year's savings become smaller. The reason behind this is quite straightforward: a smaller BESS is expected to have a lower profit capability. Since the capacity degradation rates are not deviating much in those two simulations, the result with considering BESS capacity degradation is a more accurate estimation.

The total estimated savings are about 17 million dollars. Although the estimated savings are less than the capital cost of the BESS, the actual savings would be larger than this number because several types of cost are neglected in the production cost model, for instance, generators' no load cost and start-up/shut-down cost. An expensive generator may not need to start up due to the BESS and the startup cost and no load cost of the expensive generators are also the savings of the BESS. BESS can save money from emission regulations. Power systems containing high pollution generators, such as old type coal plants, may want BESS to reduce their emissions by operating the high emission generator less frequently. A BESS is also a good power system ancillary service provider due to the fast response speed. A BESS may provide regulation and spinning reserve with properly designed power electronic devices. There would be substantial amount of revenue for a BESS participating in those reserve markets. Taking the BESS established by Golden Valley Electric Association (GVEA) [11] as an example, the BESS is in operation for 10 years and it has covered more than 60 percent of power supply type of outages. GVEA has published annual total number of outages covered by this BESS online [44]. From this point of view, the overall system stability has been greatly improved and the BESS could gain significant savings from preventing a large amount of outages. Although GVEA did not report the specific amount of money, which is also hard to quantify as this thesis stated before, this amount of money must be played a very important role in recovering the capital cost of the BESS. As the capital cost decreases, BESS will become even more attractive. Furthermore, considering that this research only calculates the benefit of the BESS for load leveling usage, the actual benefits of the BESS are larger than the number shown in TABLE VI as the BESS has other applications mentioned in chapter 2 like black start capability, voltage support etc. These benefits are not included in this study but they are left for future work.

The red dot line is the trend line for annual savings, which implies that the annual savings is growing up as the BESS service time increases. In this simulation, generator expansions and transmission line planning are not included. As load demand increases annually, the overall production cost will also increase and the system congestions will become larger. With BESS implemented in the system, the congestions are decreased and then the system overall production cost is expected to decrease. The role of BESS is generally more important in more congested system; thus, the annual savings of BESS is higher in later years of its life.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

This thesis focuses on the modeling of a BESS and proposes a BESS investment planning analysis. This model tries to provide a useful tool for the BESS investment planning by putting a cost for utilizing the BESS based on the opportunity cost caused by degradation of the BESS. This proposed BESS degradation model is a generic model and it is suited for both transmission level and distribution level networks. Some formulation modifications are needed when the investment planning model is applied for distribution networks. There are several conclusions that can be drawn from the results of this thesis.

The capital cost of a BESS is very important in investment planning, but the efficiency, the number of charge/discharge cycles, and the deep charge/discharge capability are also very important for the BESS investment planning problem. A high value of efficiency can substantially improve the profit of a BESS and such that reduces the investment recovery period. A BESS with a higher tolerance for charge/discharge cycles over its life time could save money by not having to replace the BESS too frequently. The capability to charge/discharge with higher DOD levels for a BESS gives a BESS higher effective capacity and provides a higher ramping reserve to power systems.

A BESS utilization pattern is related to load demand of power systems. A proper way to utilize a BESS is charging/discharging the BESS with a deeper cycle in summer or winter and saving the BESS lifetime in spring/fall by using it at a shallow level. Through this type of strategy, a BESS would gain its major revenue in high demand period (like summer or winter in chapter 5) and recover the lost lifetime in low demand period (like spring or fall in chapter 5).

Variations in the solar production have an impact on the number of charge/discharge cycles of a BESS and the depth of those cycles. Two types of solar uncertainties take the main roles in terms of influencing the BESS investment planning decisions: the frequency of solar radiation changes and the deviation of solar radiation changes. A place with frequent short time weather changes may prefer a battery with a large number of shallow charge/discharge cycles while a location with occasional long time weather changes may select the battery type with high DOD cycling capability.

Current battery technologies may still be too expansive for load shifting or load leveling purposes in power systems. If load shifting and load leveling are the only tasks for an energy storage system in power systems, then other energy storage technologies may be more attractive. However, a BESS can provide variety of ancillary services like voltage regulation and power factor compensation in a short response time. Since the response time of a BESS is typically less than one minute, a BESS can provide services from regulation (highest response time requirement) to non-spinning reserve (lowest response time requirement) in the ancillary service market. This type of capability is very important to small scale power systems, especially for microgrids to ensure a reliable, stable operating condition. Moreover, a BESS can receive substantial amount of revenue by providing service like regulation reserves and spinning reserves. Depending on the microgrid conditions and electricity market structure, a BESS could be a crucial component to improve system stability and save large amounts of money even under current BESS technology cost. The described GVEA example in chapter 5 is a very good demonstration of BESS for improving power system stability. When BESS technology cost decreases in the future, BESS will become much popular for improving power system stability and have a higher economic benefit.

This thesis has considered BESS in power systems to save the operating costs; the future work will take plug-in hybrid electric vehicle (PHEV) into considerations. PHEVs are considered as valuable resources and potential energy storage options for power systems. Prior researches have proposed that PHEVs may provide vehicle-to-grid (V2G) services to a power system from distributed charging stations in the network. At that time, a power system would require fewer reserves from traditional generators and improve its stability and flexibility by acquiring fast response reserves from distributed PHEVs. PHEVs are usually using batteries as their energy storage devices and the degradation model in this thesis could be used to study V2G service. The battery degradation model of this thesis provides a valuable tool to analyze the benefits of PHEVs and gives power system operators a better understanding of utilizing V2G services from PHEVs in order to maximizing the overall social benefits.

Furthermore, the model proposed in this thesis will take wind into consideration as well as solar. As another important renewable energy, wind can act as an important role like solar. Typically, wind turbines have a large power level than solar panels. Unlike solar panels, wind turbines could produce electricity at night when there is no sunshine. The power outputs of wind turbines are directly related to wind speed; the wind power production is a nonlinear function of wind speed. References [41] and [42] provide approaches to model wind outputs according to wind speeds. Note that wind forecasts usually need a lot of scenarios to show uncertainties. This consequence will cause more computational difficulties and it is a main issue that should be considered in future work.

As discussed in previous chapters, the decision planning model is very hard to solve in a short time. However, several advanced algorithm can mitigate this difficulty such as decomposition techniques like Benders' decomposition [40]. Benders' decomposition method breaks one large problem into smaller parts and then solves those smaller problems instead of the original large problem. The computational burden of the original large problem is likely to decrease as this is the purpose of Benders' decomposition. Depending on different cases, Benders' decomposition or other methods could be applied to the investment planning model in this thesis to reduce the solution time in the future work.

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