Stochastic Modeling and Optimization for Community Energy Storage Systems

by

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Abstract

Due to the integration of renewable energy sources such as wind turbines, significant technical challenge exists for the energy management in the future power distribution systems and/or microgrids. In particular, the efficiency and reliability of the energy management may be jeopardized by the randomness of the power production from renewable energy sources. In order to address this challenge and to harness renewable power, community energy storage (CES) systems with dispatchable capacities can be installed to buffer the intermittent supply from renewable energy sources. Yet, how to manage the CES systems still requires extensive research, as the dispatchable capacity of each CES system depends on its state-of-charge (SoC), which is also random in nature.

This thesis consists of two parts. In Part I, we focus on the stochastic model of CES system with wind power generation. The power generation of each wind turbine is modeled using a Markov modulated rate process (MMRP), while the CES system is modeled as a queuing system. Based on a diffusion approximation of the queue length, a closed-form representation of the cumulative distribution function (CDF) of the SoC of the CES system can be derived. The analytical model is validated by a case study based on the wind power generation data obtained from Changling Wind Farm in Jilin Province of Northeast China.

In Part II, we focus on the optimal energy management of the CES systems in a microgrid. During the normal operation of the microgrid, the dispatchable outputs of the CES systems are controlled to minimize the overall operation cost of the microgrid. When a fault occurs in the main grid, the microgrid operates in an islanded mode, and energy stored in the CES systems can be utilized to supply the loads in the microgrid for reliability improvement. In order to control the amount of energy stored in the CES systems, two kinds of SoC thresholds are introduced, which correspond to hard reservation and soft reservation of energy, respectively. Accordingly, the stochastic model of the

CES system developed in Part I is extended to embed the impact of the two kinds of thresholds. In order to take account of the potential bias in the forecast of wind power generation, the energy management problem is solved based on a general robust optimization technique. The performance of the stochastic model and optimization technique is evaluated based on the IEEE 123 bus test feeder as well as the wind power generation data of Changling Wind Farm.

Preface

Chapter 2 of this thesis has been published as W. Wang, H. Liang, and J. Chen, "Stochastic modeling of community energy storage system based on diffusion approximation," in *Proc. IEEE PES GM'16*, July 2016. I was responsible for the algorithm development and manuscript composition. Dr. Hao Liang and Dr. Jie Chen were the supervisory authors and were involved with manuscript composition.

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Chapter 1

Introduction

1.1 Background

1.1.1 Renewable Energy Sources

Along with the load growth and aging of power infrastructure, more and more economical and environmental issues associated with the conventional power generation arise. In order to address these issues, an evolution in the energy industry is underway. In particular, the economic pressures and environmental policy constraints make renewable energy sources more competitive and attractive for the future energy industry [1]. Typical renewable energy sources include solar, wind, hydro and biofuels, which are clean, cost effective, and environmentally friendly sources of energy supply. Also, in many developing countries or remote areas such as islands, deserts and forests, the cost of gird extension is extremely high [2]. Traditionally, diesel generators are deployed to supply the costumer demands few hours daily, at a high capital expense of diesel delivery [3]. For these scenarios, renewable energy could be a more viable and economical solution.

Background

As a widely used renewable energy source, wind power generation is non-depletable and non-polluting, and has been developed from a fringe of science to a mature technology. In recent years, wind turbine has experienced a dramatic change in the design of the power electronics and mechanical transmission system. The adoption of wind power in the electrical grid has increased significantly in the past two decades. A report by the Global Wind Energy Council (GWEC) indicates that, there are more than 80 countries in the world which have large wind power generation facilities, 24 of which have more than 1,000 MW of installation. Globally, the wind power generation has increased to 51,473 MW in 2014. As estimated, there will be a 12% increase of global wind power generation by 2020.

Although wind power generation has great potential in the future energy system, the adoption of wind turbines in electrical grid is facing significant technical challenges. Specifically, most of the world's existing electrical grids have been in existence for decades. Their monitoring and control facilities are becoming obsolete and may lead to low energy efficiency and reliability because of the increasing uncertainty introduced by wind power generation. Specifically, in the traditional electrical grids, power flows from the centralized fossil fuel power plants to the point of consumption. Coal, natural gas and diesel power plants can provide dispatchable outputs, so they can be considered as load following generators [4]. On the other hand, since the outputs of wind turbines are relatively unstable with high dependency on the environment and other random factors [5], only wind turbines working along cannot offer the same level of demand matching capabilities as traditional generators. In addition, it is difficult for wind turbines to provide power system voltage or frequency support due to the uncertainties. In extreme cases, wind farms are required to disconnect from the main grid [6], which can cause significant waste of renewable energy. Although wind energy forecast can partially address these challenges, forecast error may exist and need to be considered during power system operations. Therefore, how to maximize the utilization of wind energy while ensuring the reliability of electrical grid still requires extensive research.

1.1.2 Community Energy Storage System

The increasing amount renewable energy sources such as wind turbines requires new strategies for the operation and management of the electrical grid in order to improve the efficiency and reliability or power supply. In order to smooth out the outputs of renewable energy sources at the community level, the concept of community energy storage (CES) is introduced. In particular, each distribution system can be considered as a community, while the CES system serves a group of loads supplied by a single transformer and provides a dispatchable capacity to the community by buffering uncertain power supplies from renewable energy sources.

The main advantage of using CES systems is that the renewable energy sources in a community can be better utilized to direct supply local loads. This could enable the development of more viable, non-subsidy-dependent business models around secure and sustainable local energy supply, securing better income for the energy generated through direct sales, and drawing income for grid balancing services. Also, the utilization of CES systems can reduce the transmission and distribution losses based on the physical proximity of renewable energy sources and loads. In addition, the CES systems can improve the reliability of distribution system by providing uninterrupted power supply capabilities, especially when a fault occurs in the main grid [7].

Recently, there are several companies working on CES related projects. A few examples are given below:

- ABB CES system: The main components of the CES system are the ABB ESI-S inverter and five batteries. The inverter communicates with the utility grid and controls the performance of overall system. The batteries charge and discharge based on the commands from inverter;

- eCAMION CES system: The CES system includes patent pending module design and cooling, grid support for up to 150 homes, and smart battery management system (BMS). The intelligent control with utility grid integration and coordination can automate the CES operations based on local utility grid conditions;

- S&C PureWave system: The CES system CAN offer 25 kW for one or two hours, with enough capacity to supply power to a group of customers for the duration of most typical outages. Deployment of these units in a large scale can significantly improve the customer minutes served, while greatly reducing the emergency dispatch costs.

The energy management of CES systems can be achieved in two levels: the substation level and the CES unit level [8]. At the substation level, the group CES controller makes the optimal decisions and sends the commands to the CES systems in the distribution network. At the CES level, each CES controller schedules its battery charging/discharging process locally and reports its operating conditions and capabilities to the group CES controller in the substation. The CES scheduling method is modular and can be extended to any number of CES systems under the substation.

Although there exist tremendous benefits of utilizing CES systems, how to achieve optimal energy management of CES systems given the randomness of renewable energy sources is still an open issue. In particular, the dispatchable capacity of each CES system depends on its state-of-charge (SoC), which is also random in nature given the randomness in renewable power supply. The development of effective and efficient modeling and optimization techniques for CES systems is critical to address this issue.

1.1.3 Energy Management in Smart Grid

In a smart grid, energy is delivered from the suppliers to the customers by using modern digital technology to improve the efficiency and reliability [9]. Smart grid is equipped with intelligent controllable electrical devices and advanced communication network, which makes use of the distributed control and distributed energy management to increases the reliability, and transparency in the entire electricity delivery system [10]. An important feature of the smart grid is the demand response mechanism that provides customers with flexibility to meet their energy needs. Therefore, efficient energy management has turned out to be one of the great demands of any society in the face of increasing energy costs and decreasing availability.

Intermittent and volatile production of renewable energy lead to an unavoidable incorporation between customers and energy sources, which is making ancillary services and effective management of energy critical to large scale deployment of renewable energy sources. Regarding efficient electricity management by employing a smart grid, the management of electric power demand as well as coordinated response are crucial. In smart grid, energy management is used to monitor, control and optimize the performance of power grid by using information technology [11]. It is critical in scheduling and optimization of both renewable energy resource and customers demand. With renewable energy management algorithms, the power system will be more flexible and stable, with less operation information being required.

From a computational perspective, the production, consumption and storage management can be formulated as a multi-variable optimization problem. In order to deal with problems such as controlling emission, profiling demand, improving energy efficiency, maximizing utility, reducing cost and optimizing reactive power dispatch, researchers have investigated various mathematical tools to model and solve these optimization problems with uncertainty of renewable energy production and high computational complexity. Monte Carlo simulation, game theory, genetic algorithm (GA) and other methods can be used to achieve the management goals [12].

1.2 Literature Review

The overarching goal of this chapter is to first determine the significance of the general field of CES research and then to identify a place where new contributions can be made. The main content of this chapter is to critically evaluate the different approaches used in the CES optimization field in order to determine the appropriate method for investigating research issues.

1.2.1 Wind Power Generation Modeling

Nowadays, wind power has become one of the most popular forms of renewable energy production. In [13], the electromagnetic transient model of the wind power generator is modeled based on the principle of the actual wind farm prototype. The accuracy of calculation and the safety margin of system operation are improved by applying the high-precision wind power generation model. A hybrid operation strategy integrated with a battery energy storage system and a wind energy conversion system is presented in [14], the wind energy conversion system (WECS) was designed to have a permanent magnet synchronous generators (PMSG) model and integrated converter controller. The aggregated battery energy storage system (BESS) is connected to the WECS. Active power control focuses on achieving maximum power point tracking and using reloaded operation to obtain a power margin. In [15], the authors use least square support vector machine model to predict the short-term wind power generation. In order to verify the accuracy of prediction, experienced power curve method is used for comparison, which proved that layered statistics method can eliminate the invalid data effectively and improve the accuracy of the prediction. A study of a wind prediction model is presented in [16] to reduce adverse effects of wind power. The authors use the wavelet transform analysis method to decompose the data into five layers, reduce the input, determine the principal components of the wind power process and simplify the structure of Elman neural network for the wind farm which is not stability and has the characteristics of many uncertain factors. The Daubechies 8 (DB8) wavelet transform is used to decompose the sampled data and then the Elman neural network is applied to predict wind plants output. The method has been proven to improve the prediction accuracy and help to improve the utilization rate of wind power through the comparison.

In [17], models are presented to characterize the a power system with participation of battery and wind power generators. The combination results in a higher social benefit as well as the maximized individual profit. In research [18], a stochastic wind power model is constructed based on an autoregressive integrated moving average (ARIMA) process. The model takes non-stationarity and physical limits of stochastic wind power generation into account. The proposed limited-ARIMA (LARIMA) model introduces a limiter and characterizes the stochastic wind power generation by mean level, temporal correlation and driving noise and outperforms a first-order transition matrix based discrete Markov model in terms of temporal correlation, probability distribution and model parameter number. The model is validated against the measurement in terms of temporal correlation and probability distribution. A simplified method for power systems evaluation with wind power is introduced in [19]. The method is further simplified by determining the minimum multi-state representation for a wind farm generation model in reliability evaluation. Also, a six-step common wind speed model is presented and is applicable to multiple geographic locations and adequate for reliability evaluation of power systems containing significant wind penetration. Research [20] proposes a hybrid model for wind speed and wind power short-term forecasting application. With the combination of ARIMA and radial basis function neural network, the model is capable of increasing the forecasting accuracy as well as solution convergence. The work by Hao Gong and Hongtao Wang [21] uses the model from [22], where probabilistic approach is used to model the uncertain wind power. They model the uncertainty of wind power as multiple scenarios which are obtained from forecast results. The generation scheduling scenarios are generated by auto-regressive and moving average (ARMA) time series model and Latin hypercube sampling (LHS) method. In [23], a method to improve the accuracy of meteorological prediction is presented. This method provides a new solution for reactive power and voltage control, wind power absorption capacity enhancement, energy saving, consumption reduction and other coordinated dispatching.

1.2.2 Energy Storage System Modeling

In recent years, smart grid applications with renewable energy sources and storage systems have been extensively studied and used, they are playing more important roles in energy consumption and resources exploitation. The energy storage system operation can be modeled in many different ways, where an important category is represented by an electrochemical model using an equation governing the physiochemical phenomena occurring in the battery cell [24]. The model of galvanometric charge and discharge of a lithium anode/solid polymer separator/insertion cathode battery is built using concentrated solution theory with variable physical properties. In [25], the galvanometric charge and discharge of a dual lithium ion insertion battery are modeled. Transport in the electrolyte is described with concentrated solution theory with simplified numerical calculations. Both models are described by several coupled partial differential equations with specified boundary conditions. Later in Song Li's research [26], the model is extended to include an energy balance part to predict the temperature from the isothermal. A mathematical model has been developed to study heat transfer and thermal management of lithium polymer batteries. Temperature-dependent parameters, including diffusion coefficients of lithium ions, ionic conductivity of lithium ions, number of lithium ions, etc., have been added to the previously developed electrochemical models to fully characterize the thermal behavior of lithium polymer systems. The implementation of these models involves electrochemical expertise, so their development in the field of electronic engineering is limit.

In [27], an advanced control model based on energy storage system is proposed. The mathematical formula of the controller is outlined, and then the process of applying the controller to the general energy storage model is recorded. The dynamic performance of the proposed control strategy is compared with the dynamic performance of PI-based control technology and proves a better performance of PI controller. More complex circuits are introduced to obtain a better modeling accuracy both in dynamic conditions and for battery operation in the long term [28] [29] [30] [31]. In [32], a novel real-time estimation method is proposed to achieve a good trade-off between model accuracy and algorithm complexity. In the proposed approach, the SoC and state-of-health (SoH) values are calculated using an appropriate algorithm that continuously performs a comparison between the energy storage system (ESS) voltage value calculated by the adaptive run-time circuit model and its actual value measured at the ESS terminal. Paper [33] presents a dynamic model of hybrid energy storage system based on compressed air and super-capacitors (CAES-SC). This kind of storage converts excess energy from the generators to stored pneumatic energy by applying a compressor. A super-capacitors bank (SC) is used in order to smooth the output of the storage system. Research of Martinez, Maximilian and Molina [34] proposes a model for storage system consists of fuel cells, supplying main power, and a supercritical, as backup power source. A data driven model is presented in [35]. It is capable to accurately predict the terminal voltage of a lead-acid battery at different working temperatures. The model applied is a typical feed forward structure with a variation recurrent networks and self-feedback links to the neurons. In [35], four energy storage system models are presented: Electrochemical Capacitor Energy Storage Model, Superconducting Magnetic Energy Storage Model, Compressed Air Energy Storage Model and Battery Energy Storage Model. The proposed models allow characterizing most common energy storage technologies through a given set of linear differential algebraic equations (DAEs). The proposed models prove to be able to accurately predict the dynamic behavior of batteries under disturbances, faults and loss of loads. The nonlinearity of ESS controllers and hard limits are also taken into account.

Despite all the aforementioned research works on wind power generation and energy storage system modeling, how to embed the uncertainty of wind power generation in the modeling of CES system still needs further research. Specifically, the relationship between the probability distribution of the SoC of the CES system and the statistics of wind power generation should be established. Such stochastic model can facilitate the energy management of CES system in distribution system.

1.2.3 Energy Management in Distribution Systems and Microgrids with Energy Storage Systems

Microgrids and distribution systems have emerged as a promising paradigm to the integration of renewable generators, energy storage systems and dispersed loads. In [36], a new random energy scheduling scheme for microgrid is proposed. In this method, energy scheduling is expressed as a stochastic model predictive control problem, which includes the uncertainty of both supply and demand sides. Using machine learning techniques, the corresponding stochastic optimization problems are converted to standard convex quadratic programming with a key feature that handles the coexistence of Gaussian and non-Gaussian uncertainties. An interactive operation strategy for microgrid cooperated with wind turbines, photo-voltaic (PV) system, energy storage system and predictable loads is presented in paper [37]. A day-ahead operation optimization model is proposed by taking account of electricity purchasing cost, electricity selling benefits and generation cost of distributed generators. An interactive model is proposed in which the micro-network responds to the interaction demand by adjusting the scheduling plan with the goal of processing the excessive peak load of the distributed system. A power system model is built in [38] with diesel and wind generators, loads and BESS. Simulation results show that the BESS can help in system frequency regulation and peak shaving applications. In [39], a cost-based formulation is reported. By using the grey wolf optimization algorithm, it derives the optimal size of battery energy storage while minimizing the operation cost of the micro-grid under various constraints, including BESS energy capacity, charge and discharge efficiency, distributed generator capacity, operating reserve and load demand. A smart energy management system (SEMS) to optimize the operation and minimize the operational costs of microgrid is presented in [40], where the management method considers all the relevant technical constraints, power prediction, ESS intelligent management, economic load scheduling and operating costs.

Forecasting models can predict hourly electricity production based on weather forecast inputs. Based on the power production forecast, the optimal power scheduling can be achieved by maintaining economically optimized power scheduling to meet certain load requirements. In [41], the storage system scheduling is mainly determined by the price charged, i.e., the difference between the maximum daily price and the minimum daily price. Wherein the storage charge / discharge rate is a constraint in the optimization problem and the storage scheduling depends on the comparison of the charge price with the local power generation cost. Similarly, in [42], C. Colson developed the optimal management for a cost-effective storage system, along with a model that can be determined from manufacturer data sheets and used in a real-time simulation environment to evaluate if the health of the battery is more important than the micro-grid's revenue stream. In [43], a micro-grid energy management is formulated as a optimal power flow problem, and a distributed energy management system (EMS) is proposed in which the microgrid controller and the local controller jointly calculate the optimal schedule. This paper also provides an implementation of distributed EMS based on IEC 61850 standard. An EMS is designed in [44] to control the power and energy balance of the network. The proposed EMS is based on master / slave communication methods that rely on a robust information and communication technology (ICT) infrastructure. The principles of EMS operation are logically established by defining the functionality and mode of operation of the network elements, including all possible combinations of power, storage and load under all conditions. However, significant improvements are still needed in order to improve the efficiency and intelligence of the control. In [45], a control theory framework is introduced for studying voltage stability and its robustness as well as an optimal power management in distribution system composed of networked microgrids. The framework involves a description of the load and the generator through a non-linear state space model, as well as network connections through a set of topology-based algebraic equations. Combined system leads to micro-grid system of general nonlinear state space model. Four stability margins are introduced to capture different aspects of microgrid power management capabilities and load disturbances. The linear matrix inequality (LMI) method can be used to calculate the stability margin. In [46], the authors present a hierarchical power management scheme for a typical DC microgrid. Unlike other microgrids, the DC microgrid can be connected to a distribution system through a solid-state transformer (SST) and can operate in island mode, including distributed renewable energy (DRER) and distributed energy storage (DESD) control. In addition, consideration of the SoC of the battery also involves triple control. In [47], a green energy system model was proposed to achieve implementation of a real-time green energy management system in the smart grid environment. The model includes distributed energy resources (DERs), central energy management eystem (CEMS) and seasonal thermal energy storage (STES) system. The STES system uses waste heat and solar thermal energy to provide a clean solution for the heating and cooling needs of the community. The CEMS based on fuzzy rough set theory monitors and regulates the flow of electrical and thermal energy in the proposed system.

The energy management in distribution system is often represented as a nonlinear optimization problem. Centralized solutions not only require high computational power of the central controller, but may also encroach on customer privacy. On the other hand, the existing distributed approaches assume that all generators and loads are connected to one bus and ignore the underlying distribution network and the associated power flow and system operating constraints. Thus, the scheduling generated by those algorithms may violate those constraints and, therefore, is not feasible in practice.

1.2.4 Optimal Energy Management of CES Systems

Recently, the research related to CES systems is emerging, mainly because of the economical and environmental benefits of CES systems. The survey in this field [48] provides a comprehensive overview of the current research on ESSs. It also proposes a framework for future ESS integration in distribution systems. In [49], the impact of real, non-ideal energy user decisions on the demand side management of energy trading systems in residential communities is studied. First, the non-cooperative Stackelberg game is used to study the interaction of energy trading between users and CES operators, in which the CES operator is the leader and the user is the follower. Participating users determine their optimal energy transaction start time in order to minimize their personal daily energy costs while subjectively observing the actions of their opponents. Then it studies the non-cooperative games to explore how users make decisions in the two user behavior models involved in the above-mentioned energy trading system, based on the outlook theory and the expected utility theory, respectively.

In [50], the authors present an energy management system for CES devices. The proposed EMS is an effective scheme for CES management that promotes grid efficiency by reducing peak energy consumption and provides peak load reduction and load transfer functions. The proposed control scheme can promote high penetration of PV in the distribution system by handling system problems such as reverse power flow. In the research of Mercurio [51], an optimal management for community energy system consisting of distributed generator (DG), storage and renewable energy sources (RES) is proposed. It has the ability to deploy demand-side management strategies to meet proactive demand and the potential for efficient integration of DG. The micro-grid energy management models and implementation of Lithium-ion batteries are presented in [52]. Detailed models of Lithium-Ion batteries can be considered with the operation, ramp rate controllable and uncontrollable, operating characteristics and other restrictions provided by the manufacturer costs associated degradation. In [53], a charge/discharge control strategy is proposed, which can continuously balance and dynamically adjust the power exchange with the grid in real time, and mitigate the neutral current and neutral voltage rise problems. Also a dynamic model is developed to investigate the applicability of the proposed approach. In [54], the authors present a test environment without the support of main grid, which confirms the applicability of community energy storage system in Canada. Also, the research work [55] focuses on the battery energy storage system design issues for a wind diesel off-grid power generation system in Whapmagoostui Community in Quebec. A distribution system reconfiguration with constant loads for optimal distributed generation allocation and sizing problems is studied to find an optimal solution for distribution systems in [56]. The research works [57] [58] [59] contribute to better management of a power system by providing flexibility at the system level. In [60], the use of PV power systems as the primary energy source for local community energy systems is studied. In order to facilitate the operation of these systems, this work studies the use of local storage, and proposes an EMS for the local storage. The proposed EMS can solve major operational problems such as reducing energy consumption during peak load periods and limiting excessive reverse power flow back to the utility grid. It also helps to correct power fluctuations and address the wind energy dispatch and control challenges.

From the literature reviewed above, we can see that the existing methods for CES system modeling and optimization do not fully consider the stochastic nature of the CES systems, especially the probability distribution of the SoC of the CES systems. Also, how to address the errors in wind power generation forecast in the stochastic modeling and optimization of CES systems still require further research.

1.3 Research Contributions

In this thesis, we have studied the CES system which consists of distributed power generators in terms of wind turbines and a battery energy storage. Firstly, we have investigated a stochastic model of the CES system based on diffusion approximation, where a Markov modulated rate process (MMRP) is used to characterize the power generation of each wind turbine. Based on the parallelism between the SoC of CES system and the number of customers in a queue, a queuing system model is established to characterize the CES system. Since the dispatchable capacity of the CES system is affected by the randomness of its SoC, a cumulative distribution function (CDF) of the SoC of CES system is derived in closed-form via a diffusion approximation of the queue length. Extensive analytical and simulation results based on real data collected from Changling Wind Farm in Jilin Province of Northeast China are presented to validate the proposed stochastic model.

In order to facilitate the energy management of the CES systems, we further extend the stochastic model of the CES system by using a G/G/1/N queuing model. In particular, we assume the energy is transferred as energy blocks into a finite buffer, with a stochastic inter-arrival time. The battery still keeps a dispatchable output, which can be assumed constant in a period of time. In addition, two different ways are proposed for energy reservation (i.e., hard reservation and soft reservation), such that the reserved energy can be used to supply the community during outages of the main grid. Based on the analytical results, an optimal energy management problem is formulated to find the optimal combination of power output from CES systems, such that the total cost of the distribution system operation is minimized. In order to address the random bias in the forecast of wind power generation, a general robust optimization technique is used to solve the problem. Specifically, the robust optimization technique is able to address optimization problems in which the some data are uncertain and are only known to belong to some uncertainty sets. However, since traditional robust optimization technique can only address linear constraints, we leverage a recently developed general robust optimization technique to handle the nonlinear constraints in the energy management problem. Simulation results based on the IEEE 123 bus test feeder and real wind power generation data are presented to demonstrate the performance of the stochastic models and optimization technique.

1.4 Outline of the Thesis

This thesis consists of two parts. In Part I, Chapter 2, we study a CES system, consisting of distributed generators in terms of wind turbines and battery energy storage. A stochastic model of the CES system based on diffusion approximation is proposed, and the CDF of the SoC is derived in a closed form. The proposed stochastic model is validated by extensive analysis and simulation based on real data collected from Changling Wind Farm in Jilin Province, Northeast China. In Part II, Chapter 3, we extend the CES system model and expand the research to optimal energy management of CES systems in distribution system. Stochastic models are developed based on queuing theory to characterize the randomness of the SoC of CES system. Based on the results of queuing analysis, an energy management problem is formulated for the CES systems. Taking into account the potential bias in the forecast of wind power generation, the energy management problem is solved based on the general robust optimization technique. The performance of the proposed stochastic models and optimization technique are evaluated based on the IEEE 123 bus test feeder and real wind power generation data. Finally, Chapter 4 concludes this research and outlines some future research topics.

Chapter 2

Stochastic Modeling of Community Energy Storage System based on Diffusion Approximation

With the high demand for renewable energy resources such as wind turbines, the future distribution systems and/or micro-grids will face more challenges in energy management, due to the intermittent nature of renewable power generation. By buffering such uncertain power supplies, CES systems can provide dispatchable capacities and are effective tools to harness renewable power in a community. However, the dispatch of a CES system is complicated due to the randomness in its SoC and thus, the randomness in dispatchable capacities. In order to address this problem, a stochastic model of CES system with wind power generation is reported in this chapter. The power generation of each wind turbine is modeled using an MMRP, while the CES system is modeled as a queuing system with heterogeneous sources and constant output. Based on a diffusion approximation of the queue length, a closed-form representation of the CDF of the SoC of CES system is

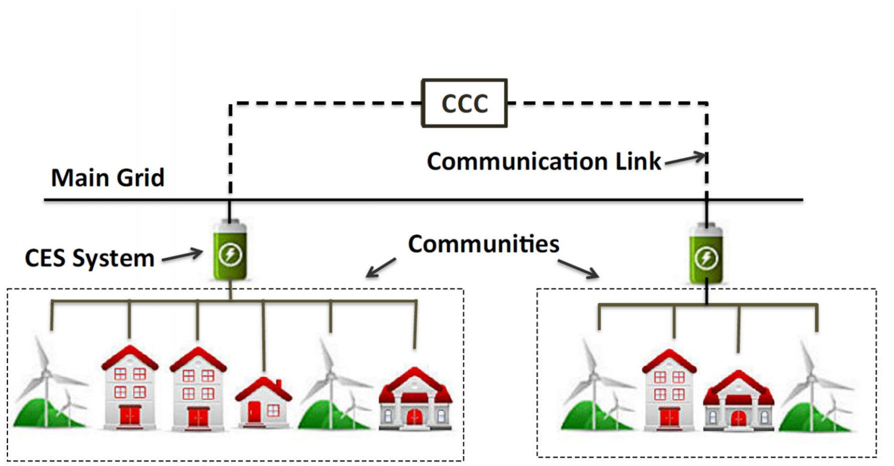

Figure 2.1: An Illustration of the CES System.

derived. The analytical model is validated by a case study based on the wind power generation data of Changling Wind Farm in Jilin Province of Northeast China.

2.1 System Model

An illustration of the community energy storage system is shown in Fig. 2.1. The main grid is typically managed by a centralized control center (CCC) and can serve multiple communities [61]. Each community consists of a group of residential customers, some of which are equipped with wind turbines. Battery-based CES system is considered in this chapter, and is interfaced with the main grid through power converter. Communication links are established between the CES systems and the CCC for energy management purposes. By buffering the uncertain power generation from wind turbines, constant output can be achieved by the CES system. In the following, the models for wind turbines and CES system are described in details.

Let K be the total number of wind turbines in the community under consideration. Finite-state Markov chain model is used to characterize wind power generation [62], where the power generation of each wind turbine is modeled as an M-state Markov chain. Here, in order to facilitate the stochastic modeling of CES system, we modified the finite-state Markov chain model to an MMRP model by introducing holding time to each state. In our model, wind turbine k has a generation rate matrix $\mathbf{G}_k = [G_{k,1}, G_{k,2}, \cdots, G_{k,M}]$, which means when the wind turbine is in state m, it generates energy at rate $G_{k,m}$ (kWh/min). Without loss of generality, we consider $G_{k,1} = 0$. For wind turbine k, denote the average holding times of states $1, 2, \cdots, M$ as $\tau_{k,1}, \tau_{k,2}, \cdots, \tau_{k,M}$, respectively. The value of $\tau_{k,m}$ can be calculated as

$$\tau_{k,m} = \frac{F(\Gamma_{k,m+1}) - F(\Gamma_{k,m})}{L(\Gamma_{k,m+1}) + L(\Gamma_{k,m})} \tag{2.1}$$

where $\Gamma_{k,m}$ and $\Gamma_{k,m+1}$ represent the lower and upper bounds of actual wind power generation in state m, respectively, while $F(\cdot)$ and $L(\cdot)$ denote CDF and level crossing rate, respectively. All parameters in (2.1) can be calculated from measurement data. Since the MMRP model is a generalization of the finite-state Markov chain model, the holding time follows a geometric (or exponential) distribution, while the average holding time is constant among all states, i.e., $\tau_{k,m} = \tau_k$, $\forall m \in \{1, 2, ..., M\}$. Based on this assumption, the values of $\Gamma_{k,m}$ ($m \in \{1, 2, ..., M\}$) can be determined. Further, for each wind turbine k ($k \in \{1, 2, ..., K\}$), the state transition probability matrix is denoted by $\mathbf{P}_k = [p_{k,i,j}]$ ($i, j = 1, 2, \cdots, M$), where $p_{k,i,j} = n_{k,i,j}/\sum_j n_{k,i,j}$, and $n_{k,i,j}$ represents the number of transitions from state i to state j of wind turbine k, calculated from measurement data over a certain period of time.

Battery is used as the storage unit of the CES system. It takes the power generation from wind turbines as inputs, and delivers power to the residential customers and/or the main grid through power converter at a constant rate D (kWh/min). The round-trip efficiency of energy conversion during battery charging/discharging is η. A battery with sufficiently large capacity is considered, which is full with low probability. In this way, the utilization of wind energy can be maximized. To facilitate the stochastic analysis, we model the SoC of the battery in kWh unit.

2.2 Stochastic Modeling of Community Energy Storage System

The objective of the stochastic modeling is to find the probability distribution of the SoC of the CES system. In literature, a stochastic model is developed in [63] for a data buffer in asynchronous transfer mode (ATM) network with multiple homogeneous sources. The CDF of the data buffer content can be derived in closed-form. However, different from the ATM network, the statistics of the power generation from different wind turbines in a community are very different even when the wind turbines are in close proximity with each other [62]. Such difference comes from various factors, such as wake effect of wind speed, diverse terrain conditions, and other environmental effects including diversified barriers such as buildings and plants. In this chapter, the stochastic model is extended by considering the heterogeneity of sources.

For each wind turbine k, define an M-dimensional processes $\mathbf{N}_k(t)$ as follows:

$$\mathbf{N}_k(t) = \left[N_{k,1}(t), N_{k,2}(t), \cdots N_{k,M}(t)\right]. \tag{2.2}$$

Here, $\mathbf{N}_k(t)$ is used to denote the state of the wind turbine at time t. For example, when the generator is operating in state 3 at time t, we have $\mathbf{N}_k(t) = [0, 0, 1, 0, ..., 0]$. Taking into account the generation rate matrix $\mathbf{G}_k$, the power generation by wind turbine k at time t can be calculated as

$$G_k(t) = \sum_{m=1}^{M} G_{k,m} N_{k,m}(t). \tag{2.3}$$

The power generation from all wind turbines in the community at time t is given by

$$G(t) = \sum_{k=1}^{K} G_k(t). \tag{2.4}$$

Let $\tilde{G}(t)$ be the diffusion approximation of process $G(t)$, given by

$$\tilde{G}(t) = \sum_{k=1}^{K} \sum_{m=1}^{M} G_{k,m} X_{k,m}(t) \tag{2.5}$$

where $\mathbf{X}_k(t) = [X_{k,1}(t), X_{k,2}(t), \cdots X_{k,M}(t)]$ is the continuous-state Markov process approximation of $\mathbf{N}_k(t)$, which follows an M-dimensional Ornstein-Uhlenbeck (O-U) process. Then, the mean and variance of $\tilde{G}(t)$ can be calculated as

$$\mu_{\tilde{G}} = \sum_{k=1}^{K} \mu_{\tilde{G},k} = \sum_{k=1}^{K} \lim_{t\to\infty} E[\tilde{G}_k(t)] \tag{2.6}$$

$$\sigma^2_{\tilde{G}} = \sum_{k=1}^{K} \sigma^2_{\tilde{G},k} = \sum_{k=1}^{K} \lim_{t\to\infty} \mathrm{Var}[\tilde{G}_k(t)]. \tag{2.7}$$

The values of $\mu_{\tilde{G},k}$ and $\sigma^2_{\tilde{G},k}$ can be calculated in closed-form based on the procedures presented in [63]. Detailed derivations are omitted here due to space limitation. It is worth mentioning that, since the original procedure in [63] was developed for homogeneous sources linked with a buffer in ATM network, extension has been made for both (2.6) and (2.7) to account for the heterogeneity of wind turbines in a community. The mathematical foundation of this extension can be found in [64]. Specifically, when a buffer is linked with multiple types of sources, each source can be modeled separately, and the aggregated process can be simplified as a sum of all the individual processes. To derive (2.7), we consider the power generation from wind turbines to be independent with each other in accordance with [62], since the measurement of power generation is performed by each wind turbine, rather than at specific meteorological towers.

To model the queuing behavior, let $Q(t)$ be the SoC of the CES system at time t. Since the CES system maintains a constant output D (kWh/min) based on system dis-

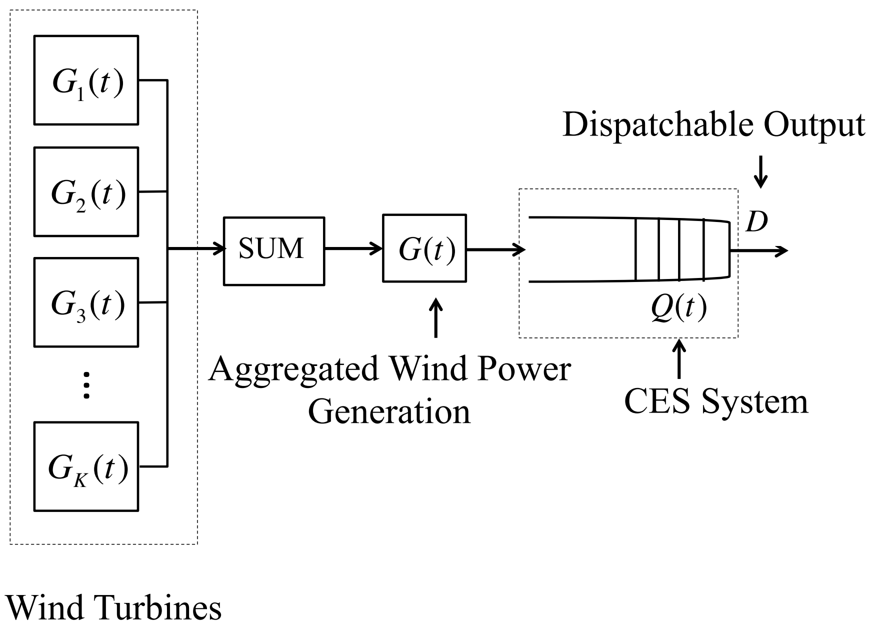

Figure 2.2: An Illustration of the Stochastic CES Model.

patch decisions, the change of SoC can be described by a stochastic differential equation, given by

$$\frac{dQ(t)}{dt} = \begin{cases} G(t) - \frac{D}{\eta}, & \text{if } G(t) > \frac{D}{\eta} \text{ or } Q(t) > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{2.8}$$

Here, the round-trip efficiency (η) is used to characterize the energy losses in both charging and discharging processes. In other words, the ratio of retrieved energy to the input energy is the round-trip efficiency, expressed as a percentage (%). Then, the stochastic CES model proposed in this chapter can be described by Fig. 2.2.

Let $\tilde{Q}(t)$ be the diffusion approximation of $Q(t)$. Then, the CDF of $\tilde{Q}(t)$ can be approximated as [63]:

$$P(\tilde{Q}(t) < x) \approx 1 - \frac{\exp(-\theta^2/2)}{\theta\sqrt{2\pi}} \cdot \exp(-\frac{2\sigma_{\tilde{G}}\theta}{\epsilon}x) \tag{2.9}$$

where $\mu_{\tilde{G}}$ and $\sigma_{\tilde{G}}$ are given by (2.6) and (2.7), respectively. The parameter θ can be derived from $\mu_{\tilde{G}}$ and $\sigma_{\tilde{G}}$, given by

$$\theta = \sum_{k=1}^{K} \frac{\frac{D}{\eta} - \mu_{\tilde{G},k}}{\sigma_{\tilde{G},k}}. \tag{2.10}$$

Further, the value of ϵ can be calculated as

$$\epsilon \approx \sum_{k=1}^{K} 2 \int_0^\infty \mathbf{G}_k \psi_k e^{\tau \mathbf{B}_k} \mathbf{G}_k{}' d\tau. \tag{2.11}$$

And for calculating ψ_k, the following equation is used:

$$\psi_k = \int_0^\infty \exp(\mathbf{B}_k t) \mathbf{A}_k \exp(\mathbf{B}'_k t) dt \tag{2.12}$$

where the matrix $\mathbf{B}_k$ is given by

$$\mathbf{B}_k = \tau_k^{-1} \begin{bmatrix} -1 & p_{k,2,1} & \cdots & p_{k,M,1} \\ p_{k,1,2} & -1 & \ddots & p_{k,M,2} \\ \vdots & \vdots & \ddots & \vdots \\ p_{k,1,M} & p_{k,2,M} & \cdots & -1 \end{bmatrix}. \tag{2.13}$$

Let $\mathbf{x}_k^* = (x_{k,1}^*, x_{k,2}^*, \cdots, x_{k,M}^*)$ be the equilibrium state of $\mathbf{X}_k(t)$, which satisfies $\mathbf{B}_k \mathbf{x}_k^* = 0$. The matrix $\mathbf{A}_k$ can be calculated as

$$\mathbf{A}_k = \sum_{l=1}^{M} \frac{\mathbf{v}_{k,l} \cdot \mathbf{v}'_{k,l}}{\tau_k} \cdot x_{k,l} + \mathcal{H}_k(x) \tag{2.14}$$

where $\mathbf{v}_{k,l}$ is an M-dimensional column vector with its l-th element being unity and the m-th element ($m \neq l$) being $-p_{k,l,m}$, while $\mathcal{H}_k(x)$ is an $M \times M$ matrix with elements:

$$h_{k,m,n}(x) = \sum_{l=1}^{M} \frac{p_{k,l,m}(\delta_{mn} - p_{k,l,n})}{\tau_k} \cdot x_{k,l}, \ 1 \leq m, n \leq M \tag{2.15}$$

where δ_{mn} equals 1 if m equals n and 0 otherwise.

Note that the diffusion approximation $\tilde{G}(t)$ can be applied only when $G_{k,1} = 0$, which means the source is in off condition (without output) in state 1. In reality, a

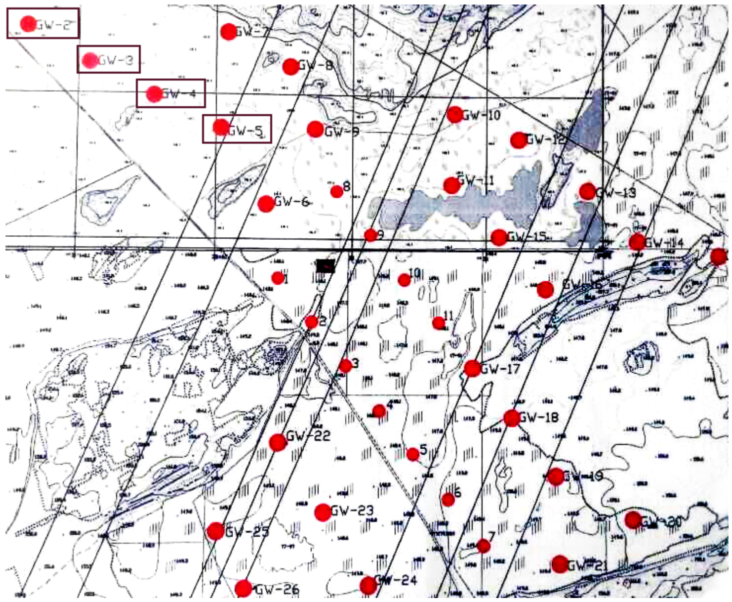

Figure 2.3: The Map for Changling Wind Farm in Jilin, China.

normal operating wind turbine may not have an off state due to limited measurement data. Therefore, we need to consider a new generation rate matrix, constructed based on the original generation rate matrix $\mathbf{G}_k$ (with $G_{k,1} \neq 0$) by subtracting $G_{k,1}$ from each of its elements. Accordingly, $G_{k,1}$ should be subtracted from $\frac{D}{\eta}$ when calculating the CDF $P(\tilde{Q}(t) < x)$. Note that we always have $G_{k,1} < \frac{D}{\eta}$, which ensures the stability of CES system.

2.3 Case Study

In this section, we present a case study to verify our proposed stochastic model. The case study is carried out based on data collected from Changling Wind Farm in Jilin Province in Northeast China, which covers an area of approximately 15 km^2. The map of the wind farm is shown in Fig. 2.3. Four wind turbines (GW-2, GW-3, GW-4, and GW-5, all rated at 850 kW) are chosen as an example, which is sufficient to supply a relatively large community. Accordingly, we have $K = 4$. The measurements of wind power generation are taken every minute during September 28, 2015 and October 28, 2015. The number of states for wind power generation (M) can be determined based on a trade off between modeling accuracy and complexity. According to research [62], choosing $M = 4$ can strike a good balance between accuracy and complexity. Based on our system model, the average holding times (τ_k) of different states are equal for each wind turbine, given by 6.00, 5.10, 4.60, and 6.84 minutes for GW-2, GW-3, GW-4, and GW-5, respectively. The state transition matrices of the four wind turbines can be calculated and are, respectively, given by

$$\mathbf{P}_1 = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0.2656 & 0 & 0.7344 & 0 \\ 0 & 0.5000 & 0 & 0.5000 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{2.16}$$

$$\mathbf{P}_2 = \begin{bmatrix} 0 & 0.9714 & 0.0286 & 0 \\ 0.3778 & 0 & 0.6222 & 0 \\ 0.0102 & 0.5714 & 0 & 0.4184 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{2.17}$$

$$\mathbf{P}_3 = \begin{bmatrix} 0 & 0.9815 & 0.0185 & 0 \\ 0.5243 & 0 & 0.4757 & 0 \\ 0 & 0.5208 & 0 & 0.4792 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{2.18}$$

$$\mathbf{P}_4 = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0.3673 & 0 & 0.6327 & 0 \\ 0 & 74708 & 0 & 0.2530 \\ 0 & 0 & 1 & 0 \end{bmatrix}. \tag{2.19}$$

Accordingly, the generation rate matrices (in kWh/min) of the four wind turbines are given by

$$\mathbf{G}_1 = \begin{bmatrix} 2.0762 & 3.4029 & 5.4826 & 7.8039 \end{bmatrix} \tag{2.20}$$

$$\mathbf{G}_2 = \begin{bmatrix} 2.6804 & 3.8936 & 5.6898 & 7.9430 \end{bmatrix} \tag{2.21}$$

$$\mathbf{G}_3 = \begin{bmatrix} 2.7722 & 3.9302 & 5.6733 & 7.5814 \end{bmatrix} \tag{2.22}$$

$$\mathbf{G}_4 = \begin{bmatrix} 2.5729 & 3.7995 & 5.7396 & 7.8477 \end{bmatrix}. \tag{2.23}$$

The data we got from Changling wind farm is the best dataset we can get so far. And the model we built based on it has the similar parameters from the model in [62], which help us to guarantee the availability of the dataset. We will double-check our model once we find another suitable data available in the future.

The simulation is completed by using the wind turbine data as the input of the CES system while the estimation is performed by using equation (2.9). The results of the CDF of the SoC of the CES system obtained from both simulation and estimation are compared as following. Fig. 2.4 illustrates the CDF of the SoC of CES system ($P(\tilde{Q}(t) < x)$) when we let the aggregated power generation of all four wind turbines be the input of the CES system. Meanwhile, a constant (or dispatchable) output of the CES system is considered with $D = 12.0$ (kWh/min). The round trip efficiency is set to $\eta = 0.8$ and $\eta = 0.9$, respectively. The estimation results are obtained based on our proposed stochastic model of CES system based on diffusion approximation, while extensive Monte Carlo simulations are performed for comparison. As we can see, the analytical and simulation results agree with each other very well. This is mainly due to the accuracy of the diffusion approximation of aggregated wind power generation ($\tilde{G}(t)$). Specifically, the mean and variance of $\tilde{G}(t)$ (denoted by $\mu_{\tilde{G}}$ and $\sigma_{\tilde{G}}$ and calculated based on (2.6) and (2.7)) are given by 9.5060 and 10.1018, respectively, which match well with the simulation results of 9.4881 and 10.4478. Moreover, with a lower round-trip efficiency

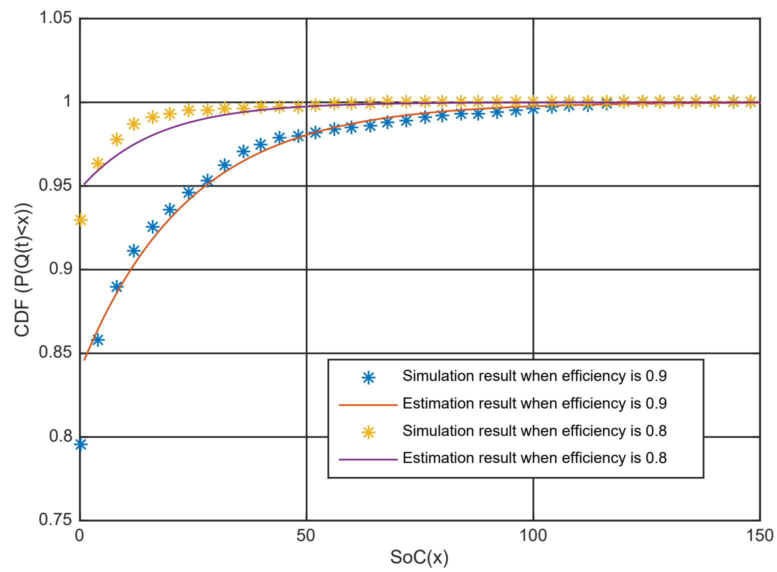

Figure 2.4: CDF of the SoC of CES System when $D = 12$.

of energy conversion during battery charging/discharging (η), the CES system is empty with a higher probability. The main reason is that, to obtain a constant output D, more energy should be discharged from the CES system when the efficiency is lower.

Fig. 2.5 and Fig. 2.6 show the cases when $D = 11.0$ and 10.0 (kWh/min), respectively. Again, we can observe a good match between the analytical and simulation results. However, a special case can be observed when $D = 10.0$ with $\eta = 0.9$, for which a relatively large estimation error exists. This is due to the fact that the charging power and discharging power of the CES system are very close to each other. As a result, the CES system becomes less stable, as the utilization of the queue approaches one. How to improve the accuracy of the stochastic model of CES system under this scenario still needs further study.

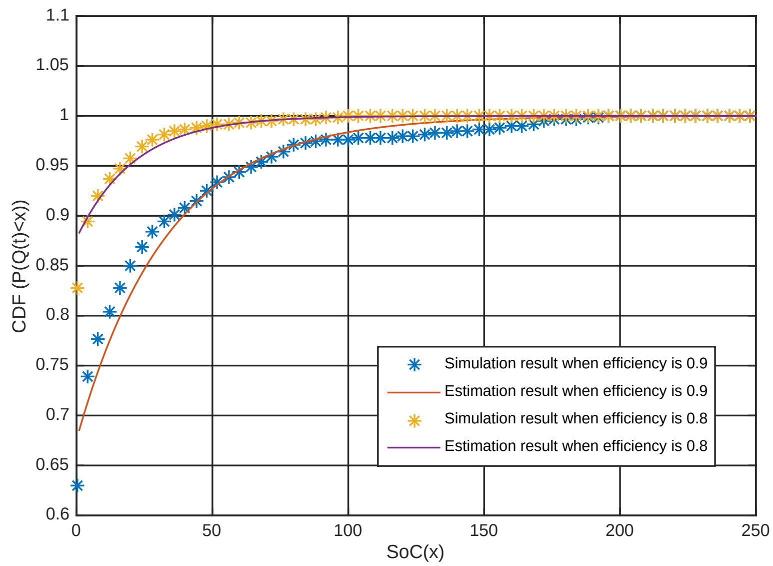

Figure 2.5: CDF of the SoC of CES System when $D = 11$.

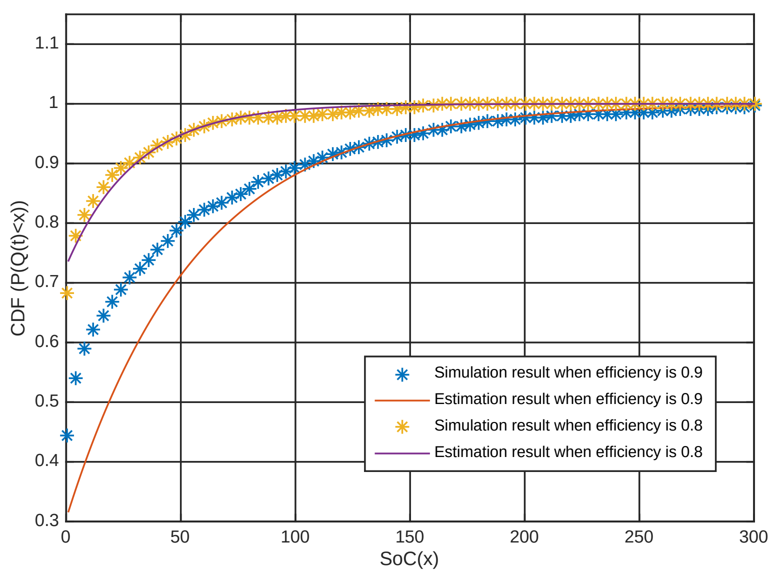

Figure 2.6: CDF of the SoC of CES System when $D = 10$.

2.4 Summary

In this chapter, we have studied a CES system which consists of distributed power generators in terms of wind turbines and a battery energy storage. A stochastic model of

the CES system based on diffusion approximation is proposed, and the CDF of the SoC is derived in closed-form. Extensive analytical and simulation results based on real data collected from Changling Wind Farm in Jilin Province of Northeast China are presented to validate the proposed stochastic model.

Chapter 3

Stochastic Modeling and Optimization for Community Energy Storage Systems in Distribution System

In this chapter, stochastic models are established for the CES systems based on the queuing theory. Two kinds of energy reservation modes are considered, i.e., hard reservation and soft reservation, such the reserved energy can be used to supply the community during outages of the main grid. Based on the analytical results, an optimal energy management problem is formulated. In order to address the random bias in the forecast of wind power generation, the general robust optimization technique is used to solve the problem. Simulation results based on the IEEE 123 bus test feeder and real wind power generation data are presented to demonstrate the performance of the stochastic models and optimization technique.

3.1 System Model

Consider the same CES system as shown in Fig. 2.1. The whole distribution system is controlled by a CCC system and can serve multiple communities. CCC makes optimized decision base on the information such as energy consumption estimation of each house, energy price for 24 hours ahead and distributed generator generation forecast. The real time data are sent to the CCC through communication links. Each community is equipped with a CES system as well as several wind turbines. The CES system can store the unstable output from the wind turbines, and keep a adjustable output controlled by the CCC system. During each control period of the CCC system, the output of CES system can be regarded constant. Therefore, the unstable output of the wind turbines can be smoothed and considered as the dispatchable output of CES system. The energy stored in the CES system is planned to be used during peak hours, while when the energy price is low, the main energy supply can be switched to the main grid. In this way, residents can reduce energy expense and power utilities can cut down transmission line maintenance expense due to the peak shaving and local self-supporting effect. Also, community battery will provide backup energy in case of faults in the main grid. In the community system, we still use 4-state Markov Chains to modulate the wind turbines by the method from last chapter. Then the mean and variance of wind turbine generation can be derived.

In this chapter, we model the battery as a stochastic buffer with arbitrary input and constant output respect to [65]. As shown in Fig. 3.1, the battery is modeled as a G/G/1/N queue. We consider the energy transfer into the CES system as energy blocks arriving in a finite buffer, with a stochastic inter-arrival time with mean $1/\lambda$ and variance v_a. Both parameters can be derived from the wind turbine model we developed in the last chapter. The CES system keeps a controllable output, which can be assumed constant

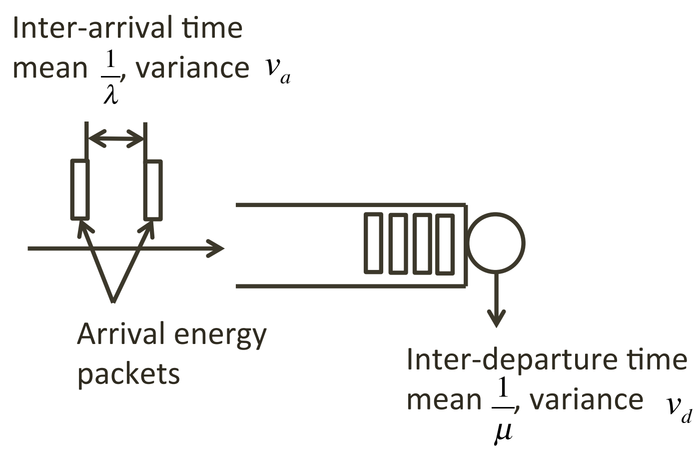

Figure 3.1: An Illustration of the Stochastic Buffer Model.

in a period of time. One main function of CES system is to avoid unexpected faults of the main grid. There are two different way to reserve energy, i.e., hard reservation and soft reservation, respectively, to be introduced as follows.

3.1.1 Hard Reservation

Hard reservation means the CES system alway reserves a certain amount of energy b' so when a fault happens in the main grid, there will be at least this amount of energy to supply the community. The hard reservation mode is shown in Fig. 3.2, where b' is hard reservation limit for the fault in main grid. This part of energy will always be reserved until a fault occurs. Also, B ($B > b$) is CES system capacity. When the battery is full, the arrived energy packets will be dropped, which cause the waste of wind energy.

Here we denote Pr^H_{loss} as the energy loss probability for hard reservation mode, which can be calculated as

$$Pr^H_{loss} = \lim_{t\to\infty} Pr(X(t)) = B \tag{3.1}$$

where $X(t)$ is the SoC of the CES system at time t. The continuity of discharging in

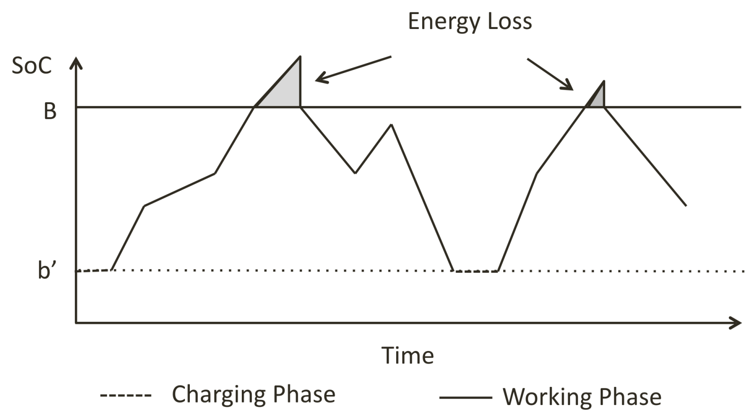

Figure 3.2: An Illustration of CES System Hard Reservation Mode.

hard reservation mode is evaluated by the charging probability, denoted by Pr_{chg}^{H}, which is defined as the probability that the discharging is paused and the battery is in charging phase at any time instant. From [65], Pr_{chg}^{H} and Pr_{loss}^{H} can be calculated as

$$Pr_{chg}^{H} = \left(\frac{\lambda^2 r e^{r(B-b'-1)}}{\beta\mu} - \frac{\mu}{\beta} \right)^{-1} \tag{3.2}$$

$$Pr_{loss}^{H} = \left(\frac{-(1-e^{-r})\mu^2}{\beta\lambda r e^{r(B-b'-1)}} + \frac{\lambda}{\beta} \right)^{-1} \tag{3.3}$$

where $r = 2\beta/\alpha$, while α and β are diffusion and drift coefficients, given by

$$\alpha = Var(\lim_{\triangle t \to 0} \frac{X(t)}{\triangle t}) = \lambda^3 v_a + \mu^3 v_s \tag{3.4}$$

$$\beta = E(\lim_{\triangle t \to 0} \frac{X(t)}{\triangle t}) = \lambda - \mu. \tag{3.5}$$

In the equations above, μ is the inverse of the mean of discarding inter-departure time, and v_s is the inverse of the variance of inter-departure time.

Also, we can derive the conditional probability density function (PDF) of the queue length $p^H(x, t|0)$, which is the SoC of the battery in hard reservation mode, defined by

$p^H(x,t|0) = Pr\{x \leqslant X(t) < x+dx|X(0)=0\}$, where $\delta(x)$ is the Dirac delta function. When $\lim_{t\to\infty}(\partial p(x,t|0)/\partial t) = 0$, we have

$$p^H(x,\infty|b) = \begin{cases} \frac{\lambda Pr^H_{loss} e^{rx}\cdot r}{\beta}, & 0 < x \leqslant B-1 \\ \frac{\mu Pr^H_{chg}(1-e^{r(x-B-b')})}{\beta}, & B-1 < x \leqslant B. \end{cases}$$

3.1.2 Soft Reservation

In hard reservation mode, we can make sure there is always backup energy for outages in the main grid. However, the reserved part of the CES system cannot be used during normal system operation, which may be seen as a waste. So we also consider another method called soft reservation to prevent this kind of waste.

As shown in Fig. 3.3, in soft reservation mode, the hard limit b' is replaced by a soft boundary b. The charging phase starts once the CES system is empty. In this case, the CES system is charged with continuous energy from wind turbines and the output is stopped. During the charging phase, customers can only use energy from the main grid. After soft boundary b is reached, energy starts to be discharged from the CES system. Due to dynamic energy arrivals and departures, the working phase may stall again. The charging phase will repeat until the energy status reaches b again.

Similar to the hard reservation mode, in the working phase, the queue length of the CES system is upper bounded by the buffer size B. When the battery is full, the arrived wind energy will be wasted. Then, the charging probability Pr^S_{chg} and energy loss probability Pr^S_{loss} can be calculated as:

$$Pr^S_{chg} = \left(\frac{\lambda^2(1-e^{-rb})e^{r(B-1)}}{(1-e^{-r})\beta\mu b} - \frac{\mu}{\beta}\right)^{-1} \tag{3.6}$$

$$Pr^S_{loss} = \left(\frac{-(1-e^{-r})b\mu^2}{(1-e^{-rb})\beta\lambda e^{r(B-1)}} + \frac{\lambda}{\beta}\right)^{-1}. \tag{3.7}$$

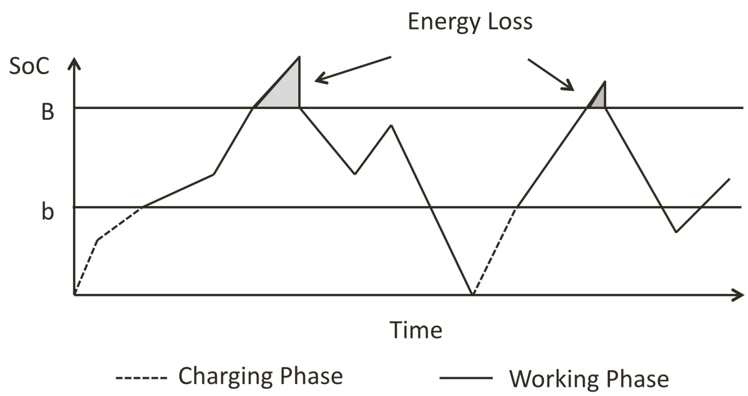

Figure 3.3: An Illustration of CES System Soft Reservation Mode.

For the PDF of the SoC, we have

$$p^S(x,\infty|b) = \begin{cases} \frac{\lambda Pr^S_{loss}(e^{rx}-1)}{b\beta}, & 0 < x \leqslant b \\ \frac{\lambda Pr^S_{loss}e^{rx}(1-e^{-rb})}{b\beta}, & b < x \leqslant B-1 \\ \frac{\mu Pr^S_{chg}(1-e^{r(x-B)})}{\beta}, & B-1 < x \leqslant B. \end{cases} \tag{3.8}$$

3.1.3 Model of Battery Cost

The cost of battery comes from the gradual wearing process, since the first second the battery is manufactured until the end of its life [66]. This irreversible phenomenon occurs even if the battery is not used. The wear of the battery can be divided into two categories. The first one is the calenderic aging mechanism, caused by the time pass. The second one is the cyclic aging mechanism, caused by the charging and discharging processes of the battery [67]. The capacity and the power of the battery keep decreasing because of these two reasons.

It is widely accepted that the lifetime of a battery comes to its end when the capacity fade reaches 20% of the initial battery capacity [68]. Since the investment cost (price) of the battery is the only monetary value related to the battery, the price of the battery is an important parameter of the cost of use and needs to be involved in the development of the model. Since the total "cost of use" cannot surpass the price of the battery, in the end of the lifetime (80% of the original battery capacity [69]) of the battery, the total "cost of use" is equal to the price of the battery, which is the only monetary value related. Additionally, the "cost of use" of the battery is affected by a large number of parameters under which the battery operates and is stored, like cell voltage, temperature, power rate and depth-of-discharge (DoD). DoD is the main parameter in the cyclic wearing mechanism, while other parameters are important for the calendric aging mechanism [66].

Here we assume cyclic wearing only depends on DoD, the relation between DoD and cyclic wearing can be determined by the proportion of faded life cycles out of the total life cycles for a certain DoD. The wear of the battery can be expressed as [70]:

$$wear = \frac{1}{2}\left[\left(\frac{1}{N(DoD_1)} - \frac{1}{N(DoD_0)}\right) + \left(\frac{1}{N(DoD_1)} - \frac{1}{N(DoD_2)}\right)\right] \tag{3.9}$$

where $N(DoD)$ is the empirical function of the relation between DoD and number of cycles. For Lithium-iron-phosphate (LFP) batteries, the relation can be evaluated as the following function [71]:

$$N(DoD) = \frac{\alpha_b}{(DoD)^{\beta_b}} \tag{3.10}$$

where α_b and β_b are the curve-fitting parameters which can be obtained from battery performance curve. This equation estimates the wear of a battery for a complete cycle, which is composed by a charging process when the battery is charged from the DoD_1 to DoD_2 and the discharging process during which the battery is discharged from DoD_1 to DoD_0. However, the wear of the battery cycles needs to be calculated at certain time interval (ti). Therefore, the equation is broken down into two parts each for every time interval (ti), leading to:

$$wear(ti) = \frac{1}{2} \cdot \left|\frac{1}{N(DoD_{t_i})} - \frac{1}{N(DoD_{t_{i-1}})}\right|. \tag{3.11}$$

Then the cost of battery use with respect to hourly energy consuming $P_{s,h}$ is given by

$$C(P_{s,h}) = \frac{1}{2} \cdot \frac{(C_b \Delta DoD_h)^{\beta_b}}{\alpha_b} \tag{3.12}$$

where the battery installation cost C_b can be derived as

$$C_b = C_a \cdot \epsilon \tag{3.13}$$

where ϵ is the unit price of battery in \$/kWh, and C_a is the battery capacity. Also, ΔDoD is the DoD change. From [71], we have

$$\Delta DoD_h = \frac{P_{s,h} \cdot T}{H \cdot V \cdot C_a} \tag{3.14}$$

where H is the standard discharging time for battery, V is battery rated voltage, and k is Peukert's exponent to reflect the impact of discharging power on the effective capacity of battery.

3.2 Problem Formulation

The output of the CES system needs to be effectively managed, so that the total electricity cost can be minimized under the dynamic real-time electricity price environment. Smart meters would collect operational and electricity market information, including real-time electricity prices as well as requirements of individual appliances. The objective of the energy management is to find the optimal combination of charging/discharging of CES systems that minimizes the total cost to customers while satisfying equality and inequality constraints of the distribution system. The problem formulation consists of two parts. The first part is the optimization of individual community energy cost in one day based on the fluctuation of electricity price and wind turbine generation. In order to improve the controllability and flexibility of CES systems, we connect all the CES systems in a distribution system based on communication links and then, dispatch the energy output centrally. Accordingly, in the second part, we minimize the energy cost of a bigger aggregated area controlled by one CCC system. In order to solve the optimization problem for daily energy cost minimization, we divide one day into NH time slots with equal duration T, and then obtain the optimal energy management for each time slot h ($h \in \{1, 2, \cdots, NH\}$). For simplicity, we choose NH as the number as hours in one day and accordingly, T corresponds to one hour.

When considering the operation of only one community, the objective function is the minimization of the sum of the costs of all the customers in a community. The controllable variables are the battery discharging threshold b and battery charging/discharging rate, which are regarded as the decision variables in our optimization problem. Denote battery discharging threshold and output in time slot h as b_h and $P_{s,h}$, respectively. Then, the decision variables are given by

$$P_s = (P_{s,1}, P_{s,2}, \cdots, P_{s,NH}) \tag{3.15}$$

$$b_s = (b_1, b_2, \cdots, b_{NH}). \tag{3.16}$$

After determining the decision variables, we can derive the cost function as follows:

$$C = \sum_{h=1}^{NH} P_{m,h} C_{m,h} + \sum_{h=1}^{NH} Pr_{chg,h} \cdot C_{s,h}(P_{s,h}) \tag{3.17}$$

where C is the overall cost in one community, $P_{m,h}$ is the power used from the main grid in hours h, and $C_{m,h}$ is the electricity price in hour h. Since it is possible that the battery is in charge status and we can only use energy from the main grid, we need to take charge probability Pr_{chg} into account. The energy demand P_d is predictable in a community. Neglecting the loss, we can say the demand is equal to the sum of main gird power consumption and storage system output. Then, we can derive the energy drawn from main grid in hour h as

$$P_{m,h} = P_{d,h} - Pr_{chg,h} \cdot P_{s,h}. \tag{3.18}$$

The optimal energy management problem can be formulated as

$$\begin{aligned} \min \quad & C \\ \text{s.t.} \quad & \begin{cases} P_s^{min} \leqslant P_{s,h} \leqslant P_s^{max} \\ Pr_{loss,h} \leqslant L_{loss} \\ IOR_h \geqslant \overline{IOR}. \end{cases} \end{aligned} \tag{3.19}$$

In the first inequality, the output of CES system is bounded between its minimum and maximum limits, given by $P_s^{\min}$ and $P_s^{\max}$, respectively. And in the second inequality, for each time period h, the probability of loss is bounded by L_{loss}, which is the upper limit of the loss probability of wind energy. In the third inequality, the Index of Reliability (IOR) is lower bounded by $\overline{IOR}$, which can be calculated based on the per unit of annual customer-hours that service is available [72], given by

$$IOR = \frac{8760\, hours\, per\, year - SAIDI}{8760\, hours\, per\, year} \tag{3.20}$$

where SAIDI corresponds to the System Average Interruption Duration Index. When we have CES systems deployed in the distribution system, SAIDI can be derived as

$$SAIDI = (CAIDI - \frac{\overline{SoC}}{\overline{P_d}}) \times SAIFI \tag{3.21}$$

where $CAIDI = \frac{\text{sum of all customer interruption durations}}{\text{total number of customer interruptions}}$ represents the Customer Average Interruption Duration Index, while $SAIFI = \frac{\text{total number of customer interruptions}}{\text{total number of customers served}}$ is the System Average Interruption Frequency Index. Here, $\overline{SoC}$ and $\overline{P_d}$ are the average SoC of the CES system and the average demand of the distribution system, respectively. In other words, the benefit of deploying CES system for distribution system reliability improvement comes from the reduction of customer average interruption duration.

When evaluating the operation of power systems with multiple communities, the consideration of voltage variations in the distribution system is indispensable, as the CES systems can affect the bus voltages by changing the loads on distribution feeders [73]. Therefore, an additional constraint related to bus voltages is considered, as follows:

$$V^{\min} \leqslant V_{h,nv} \leqslant V^{\max} \tag{3.22}$$

where $V^{\max}$ and $V^{\min}$ are the upper and lower bounds of voltage in per unit, $V_{h,nv}$ is voltage in hour h at node nv, and $nv \in \{1, 2, \cdots, NN\}$ with NN being the number of buses in whole distribution system.

When evaluating the operation of distribution system consisting of more than one CES systems, the consideration of power loss on the distribution feeders is unavoidable, as the CES systems can effectively decrease the power loss by reducing the heavy burdens of distribution lines connecting communities. Therefore, after adding power losses to our optimization problem, the cost function for the entire distribution system with more than one community is given by

$$C_{all} = \sum_{h=1}^{NH} (\sum_{i=1}^{NI} P_{d,h,i} + P_{loss,h} - Pr_{chg,h,i} \cdot P_{s,h,i}) C_{m,h} + \sum_{h=1}^{NH} \sum_{i=1}^{NI} C_{s,h}(P_{s,h,i}) \tag{3.23}$$

where i is the index of the CES systems, while NI is the number of CES systems in the distribution system. Therefore, in multiple communities scenario, by taking account of the boundaries of bus voltages, we have

$$\begin{aligned} \min \quad & C_{all} \\ \text{s.t.} \quad & \begin{cases} P_s^{min} \leqslant P_{s,h,i} \leqslant P_s^{max} \\ Pr_{loss,h,i} \leqslant L_{loss} \\ IOR_h \geqslant \overline{IOR} \\ V^{\min} \leqslant V_{h,nv} \leqslant V^{\max}. \end{cases} \end{aligned} \tag{3.24}$$

3.3 Robust Optimization

In traditional optimization problems, all parameters are assigned certain values. However, in practical applications, there are always some unavoidable deviations from standard parameter values due to either randoms noises, unrealistic assumptions, forecast errors or calculation precision limitation. Errors in estimation of some important parameters can lead to sever affect of optimization solution and actual performance. In the optimization problem considered in this research, random error (or bias) may exist in the forecast related to wind power production (λ), typically due to a limited amount of historical data [74]. In this case, more advanced optimization method should be used [75].

Robust optimization is a mature method for the optimization with parameter uncertainties, especially in the areas of linear programming, second-order cone programming and semi-definite programming. However, since traditional robust optimization technique only applies to problems with linear constraints, it does not have the ability to handle the nonlinear constraints in the energy management problem. In order to address this issue, we use the general robust optimization method recently introduced in [76]. In the following, the method is explained in details. Here, we consider the following non-linear optimization problem:

$$\begin{array}{rl} \min & \phi(P_{s,h,i}, b, \lambda) \\ s.t. & G(P_{s,h,i}, b, \lambda) \leqslant 0 \end{array} .$$

where $\lambda \in \Re^{N_\lambda}$ is the vector of the parameters, $P_{s,h,i}, b$ are the decision variable for soft reservation, b can be replaced by b' for hard reservarion mode . Assuming the number of constraints functions $G(P_{s,h,i}, b, \lambda) \in \Re^m$ is m.

For nonlinear constraints, it is easy to rewrite the inequality constraints as:

$$G(P_{s,h,i}, b, \lambda) \leqslant 0, \forall \lambda \in \Lambda \Longleftrightarrow \max_{\lambda \in \Lambda} g_i(P_{s,h,i}, b, \lambda) \leqslant 0, i = 1 : m \tag{3.25}$$

To linearize the right functions in estimated parameter $\hat{\lambda}$ and restrict the set of Λ into a less complex form, we define $\tau > 0$ and $p \geqslant 1$, then we have:

$$S_\tau := \{\hat{\lambda} + \tau D\sigma : \|\sigma\|_p \leqslant 1\} \tag{3.26}$$

where τ is magnitude of the variance and $\sigma \in \Re^{N_d}$ is the parameter variation. D is an identity matrix. After first-order of Taylor approximation at $\hat{\lambda}$, when τ is sufficiently small and for $i = 1 : m$, we have

$$g_i(P_{s,h,i}, b, \hat{\lambda} + \tau D\sigma) \approx g_i(P_{s,h,i}, b, \hat{\lambda}) + \tau\langle \nabla_\lambda g_i(P_s, \lambda), D\sigma\rangle \tag{3.27}$$

where $\nabla_\lambda g_i$ is the gradient of g_i respect to λ. Accordingly, after replacing Λ by Λ_τ, we have:

$$\begin{aligned} \max_{\lambda\in\Lambda_\tau} g_i(P_{s,h,i}, b, \lambda) &\approx g_i(P_{s,h,i}, b, \hat{\lambda}) + \tau \max_{\|\sigma\|_p - 1} \langle D^T \nabla_\lambda g_i(P_{s,h,i}, b, \lambda), \sigma\rangle \\ &= g_i(P_{s,h,i}, b, \hat{\lambda}) + \tau \|D^T \nabla_\lambda g_i(P_{s,h,i}, b, \hat{\lambda})\|_q \end{aligned} \tag{3.28}$$

where $q \geqslant 1$, which need to satisfy $1/p + 1/q = 1$. And from the Holder's inequality:

$$|\langle a, b\rangle| \leqslant \|a\|_p \|b\|_q \tag{3.29}$$

$$for \quad \frac{1}{p} + \frac{1}{q} = 1, 1 \leqslant p, q \leqslant +\infty \tag{3.30}$$

when the equality satisfies $\|a\|_p \leqslant 1$, we can get:

$$\max_{\|a\|_p=1} \langle a, b\rangle = \|b\|_q \tag{3.31}$$

Then we can obtain the linearized version of the robust optimization problem as follows:

$$\min \quad \phi(P_{s,h,i}, b, \hat{\lambda}) \tag{3.32}$$

$$s.t. \quad g_i(P_{s,h,i}, b, \lambda) = g_i(P_{s,h,i}, b, \hat{\lambda}) + \tau \|D^T \nabla_\lambda g_i(P_{s,h,i}, b, \hat{\lambda})\|_q \leqslant 0 \tag{3.33}$$

Notice that we have eliminated the uncertainty of parameter λ, so that only the estimated value $\hat{\lambda}$ is applied in the problem.

Currently, in each hour, wind generation forecast for an individual wind farm typically has an 15 % to 20% error [77]. Therefore, in our optimization problems, the uncertain parameter corresponds to the mean of CES system input. Accordingly, the constrains related to IOR and loss of wind energy can be modified to as

$$IOR(P_{s,h,i}, \hat{\lambda}) - \overline{IOR} + \tau \| D^T \nabla_{\lambda} IOR(P_{s,h,i}, \hat{\lambda}) \|_q \leqslant 0 \tag{3.34}$$

$$Pr_{loss}(P_{s,h,i}, \hat{\lambda}) - L_{loss} + \tau \| D^T \nabla_{\lambda} Pr_{loss}(P_{s,h,i}, \hat{\lambda}) \|_q \leqslant 0 \tag{3.35}$$

3.4 Case Study

In this research, we use the IEEE 123 bus test feeder [78] for case study, for which the buses can be aggregated to form a 56 bus distribution system [79]. In this system, only the three-phase overhead lines and underground cables are considered. Lines are assumed to be symmetric, while loads are assumed to be balanced PQ loads. Switches are considered to be in their normal position, and voltage regulators are modeled as ideal transformers with variable tap position. The topology of the distribution system is shown in Fig. 3.4. From a study in [80], the optimal locations of CES systems are on buses 10, 11 and 47, which can be modeled as PV buses. Here, bus 56 is the slack bus and represents the connection point to the main grid. Bus 1 to bus 10, bus 11 to bus 39 and bus 40 to bus 55 represent three communities which have different types of customers, and each of the three communities has one CES system. In this case study, we use customer energy demand data in [81]. From the data we can derive that the average of one-day energy consumption of one house is around 29.3 KWh. The demand curve derived from the data is shown in Fig. 3.5. Also, there are 3 clusters of wind turbines attached to the CES systems at buses 10, 11 and 47, respectively. The capacities of the three CES systems are 2 MWh, 4 MWh and 6 MWh, respectively.

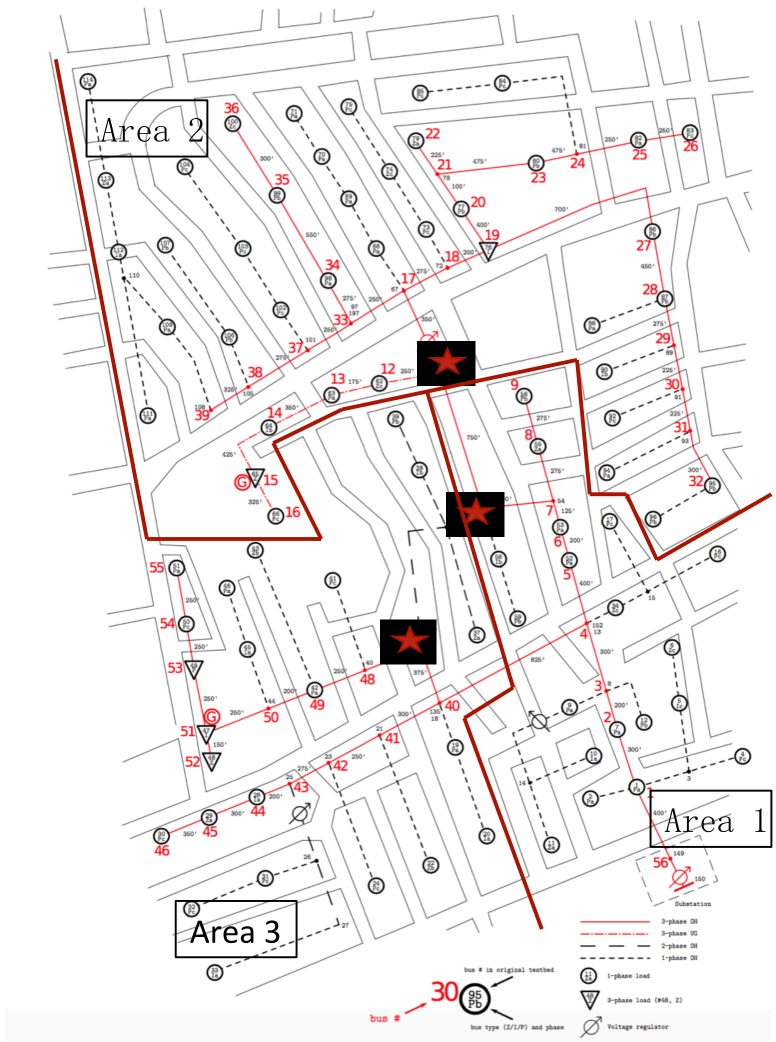

Figure 3.4: Topology of the Distribution System in Case Study.

The simulation of wind power generation for wind turbine clusters is carried out based on data collected from Changling Wind Farm in Jilin Province in Northeast China. Depending on the loads of residence and capacity of CES system in each area, we attach 1, 2 and 3 wind turbines to the three CES systems, respectively. We convert the mean and variance of wind turbine generation rate to mean and variance of energy packet interarrival time. After calculation, for area 1, λ and v_a are 0.5732 and 0.3008, respectively. For

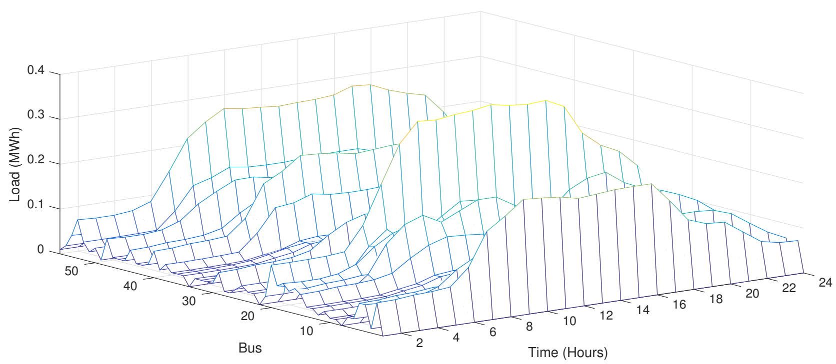

Figure 3.5: Loads of the 56 Buses in 24 Hours.

area 2, λ and v_a are 1.1463 and 0.9401, respectively.For area 3, λ and v_a are 1.5957 and 0.0334, respectively. Since we keep a constant output of battery, v_s is 0.

For the energy price from main grid, we use the real price in Ontario, Canada, which has off-peak time (8.7 cents/kWh), mid-peakt time (13.2 cents/kWh) and on-peak time (18.0 cents/kWh).

3.4.1 Results for Soft Reservation Mode

First we analyze the loss of the distribution system when we change the load of each bus. The results are shown in Fig. 3.6. We can see from the plot that when only degradation is applied, the system loss is the most sensitive to load change. When we add robust optimization to the energy management, the system loss becomes less sensitive to load change. Since the robust optimization can help CES systems handle unpredictable battery charging rate, it leads to a relatively higher battery discharging rate within feasible region. As a result, when the load of the distribution system is light (i.e., lower than 95% of the nominal value), the higher output of the CES systems can cause reverse power flow in some branches. When comparing the purple line and the

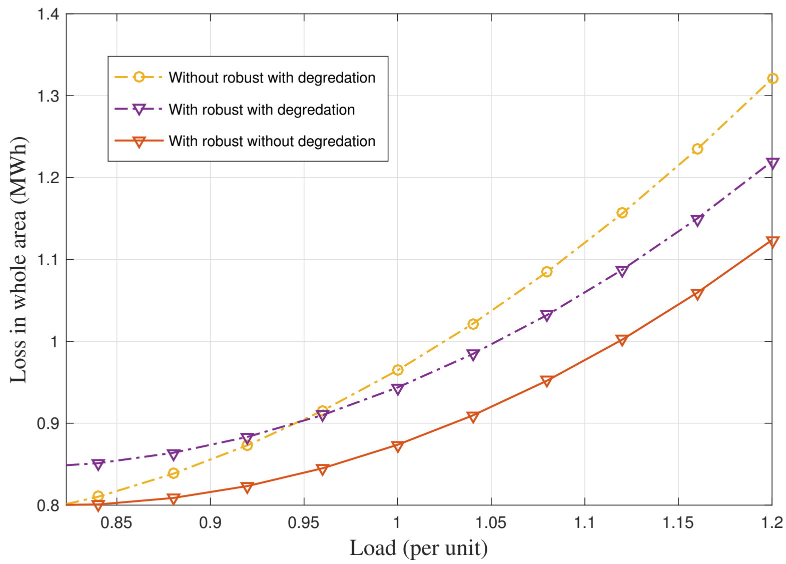

Figure 3.6: Loss of the Distribution System versus Load under Soft Reservation Mode.

red line, where the difference is the degradation of the battery, it shows when we take degradation into consideration, there is a performance penalty. The reason of the penalty is that we need to lower the discharging rate to lengthen the battery life, and this requires the main grid to provide more energy to the customers, which is the cause of higher loss in the distribution system.

Then we analyze the cost of the system when we change battery capacity in all three areas. The results are shown in Fig. 3.7. From this figure it is easy to see that the system has a relatively more stable performance with robust optimization. Besides, there is a better performance when degradation is taken into consideration. The reason is that when we lower the discharging rate, the cost per kWh drops significantly due to the nonlinear relationship between battery DoD and battery life. Also, we can see the two dashed lines have a decreasing trend when we increase the battery capacity. This is because the battery capacity cost is inversely proportional to battery size. On the other hand, when we look at the other two lines without degradation, they do not change much

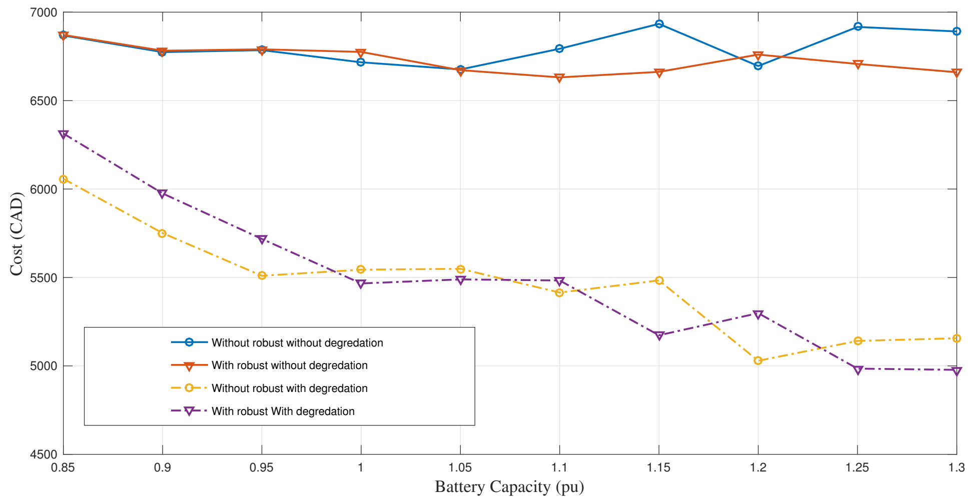

Figure 3.7: Cost of the System versus Battery Capacity under Soft Reservation Mode.

when battery capacity changes. The main reason is that in this case, battery capacity does not impact battery energy cost, so that the energy management of the CES systems cannot take into account the battery degradation. As a result, the cost remains at a high level for different battery capacities.

3.4.2 Results for Hard Reservation Mode

For hard reservation mode we do the same simulation as previous subsection. When we analyze the loss of the distribution system system when we change costumer demand, Fig. 3.8 shows a similar behavior as that of soft reservation mode. Degradation brings higher sensitivity of loss with respect to load changes. Also, robust optimization helps to deal with unpredictable battery charging rate and leads to a smoother system performance. Compared with the soft reservation, hard reservation presents a lower loss. This is because in this mode, battery will always keep working when battery level is higher than b'. In contrast, for the soft reservation mode, b needs be set to a relatively higher

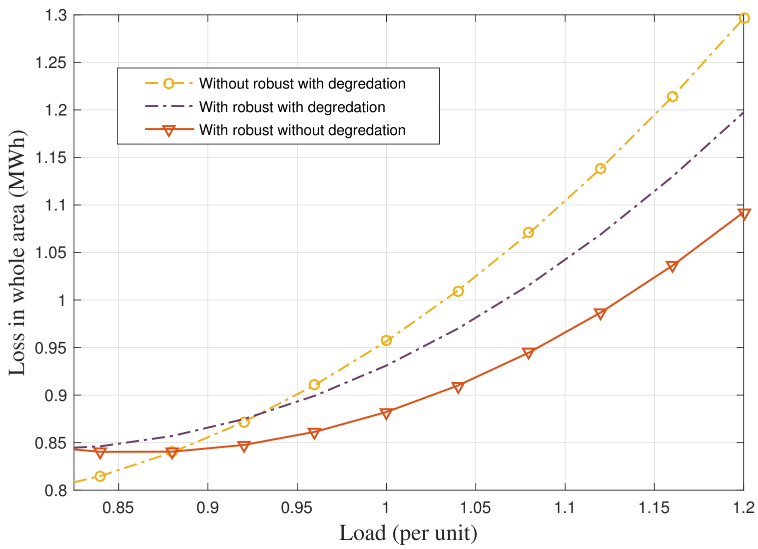

Figure 3.8: Loss of the Distribution System versus Load under Hard Reservation.

value to satisfy the IOR requirements of the distribution system. Therefore, in the hard reservation mode, the battery has a higher output than soft reservation mode, which is the reason of the lower loss under hard restriction mode.

Then, we change battery capacity to analyze the cost of the system, and the results are shown in Fig. 3.9. We can see that, the system also has a similar behavior as that of the soft reservation mode. Specifically, tt has a more stable performance with robust optimization and a better performance when considering battery degradation. Likewise, there is a slightly decreasing trend when battery size increases. When we compare the costs calculated under soft and hard reservation modes, for the two lines without considering battery degradation, there is not much difference between soft and hard reservation modes, and the costs are all around 6800 CAD. When battery degradation is considered, soft reservation mode has a lower cost. The main reason is that when we use hard reservation mode, the CES system gets over discharged more often than the soft reservation mode. Since battery energy cost increases significantly when DoD increases, the overall

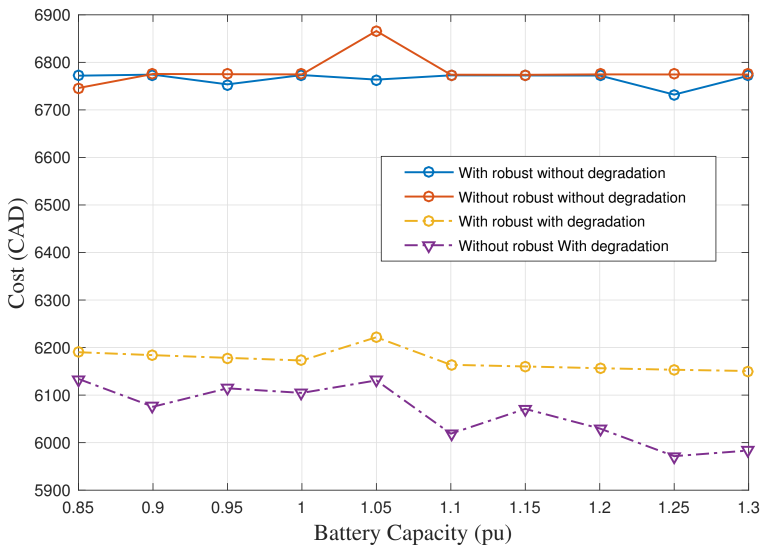

Figure 3.9: Cost of the System versus Battery Capacity under Hard Reservation Mode.

system cost is higher due to over discharging under hard reservation mode.

3.5 Summary

In this chapter, stochastic models are established for the CES systems, by considering two kinds of energy reservation modes, i.e., hard reservation and soft reservation. Based on the analytical results, an optimal energy management problem is formulated and solved based on the general robust optimization technique. Simulation results based on the IEEE 123 bus test feeder and real wind power generation data are presented to demonstrate the performance of the stochastic models and optimization technique. It can be concluded that the proposed scheme results in lower system costs, in comparison with the scheme without using robust optimization. Also, the hard reservation mode can lower the loss in the distribution system, while increasing the overall cost of the system, as compared to the soft reservation mode.

Chapter 4

Conclusions and Future Work

In this chapter, we summarize the major research contributions and discuss future research work.

4.1 Major Research Contributions

In this resarch, we focus on the development of stochastic models and optimization techniques for CES systems. The main contributions are summarized as follows.

- We develop a stochastic model of the CES system based on diffusion approximation, where the power generation of each wind turbine is characterized by an MMRP. A queuing system model is established for the CES system based on an analogy between the SoC of CES system and the number of customers in a queue. The CDF of the SoC of CES system is derived in closed-form.
- The stochastic model of the CES system is further extended by using a G/G/1/N queuing model to facilitate energy management. Specifically, we model the charing

process of each CES system as the transfer of energy blocks into a finite buffer, with a stochastic inter-arrival time. Further, two different ways are proposed for energy reservation (i.e., hard reservation and soft reservation, respectively), such that the reserved energy can be used to supply the community during outages of the main grid. Both energy reservation modes are embedded in the stochastic model of the CES system.

- Based on the analytical results, an optimal energy management problem is formulated to find the optimal combination of power output from CES systems, such that the total cost of the distribution system operation is minimized. To address the random bias in the forecast of wind power generation and the nonlinear constraints, the general robust optimization technique is applied to solve the energy management problem.

The stochastic models and optimization techniques proposed in this thesis are evaluated based on the IEEE 123 bus test feeder and real data collected from Changling Wind Farm in Jilin Province of Northeast China.

4.2 Future Work

Stochastic modeling and optimization for CES systems are broad research areas. Although several critical issues have been addressed in this thesis, there are still many open research issues to be investigated.

- This research focuses on CES systems with wind turbines as renewable energy sources. Future research includes the integration of other renewable energy sources such as PV panels and geothermal heat pumps. The stochastic models developed in this thesis needs to be extended to accommodate the new renewable energy sources.

- This research mainly addresses the operation of distribution systems and/or microgrids. How to extend the proposed scheme to facilitate the power system planning with CES systems still needs extensive research.
- The stochastic models and optimization techniques developed in this thesis can be potentially extended to other energy storage applications such as the distributed energy storage at the residential houses (e.g., based on products like Tesla Powerwall). For this kinds of applications, the number of energy storage devices is much larger than that of CES applications. Therefore, how to reduce the computational complexity of the stochastic models and optimization techniques for mass distributed energy storage is still an open issue and requires future research.

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