2019-01-25

Minimizing Demand Transmission Service Charges in Optimal Sizing and Scheduling Of Campus Microgrids

Karami, Mahboobeh

UNIVERSITY OF CALGARY

Minimizing Demand Transmission Service Charges in Optimal Sizing and Scheduling of Campus Microgrids

by

Mahboobeh Karami

A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE

DEGREE OF MASTER OF SCIENCE

GRADUATE PROGRAM IN ELECTRICAL ENGINEERING

CALGARY, ALBERTA

JANUARY, 2019

Abstract

Microgrids have paved the way through the exploitation of distributed generation resources and eliminating the requisite of high-duty transmission infrastructure. The study presented in this thesis develops a two-stage optimization problem for the optimal sizing and operation of campus/institutional microgrids considering delivery charges. At the first stage, a mixed integer linear programming(MILP) is implemented to determine the optimal configuration of microgrid which consists of solar Photo-Voltaics(PVs), batteries and microturbines(MTs). The incorporation of delivery charges leads to a significant reduction in transmission charges without sacrificing the power exchange limit. Resulted savings on electricity bill grants the capital investment in microgrid components. In the second stage, a mixed integer nonlinear programming(MINLP) on a rolling horizon basis is formulated for the optimal operation of the microgrid under sizing results obtained in the first stage. Moreover, an efficient Peak Load(PL) hour forecast framework is established to minimize the coincident PL charges. Both volatile and flat electricity price scenarios are studied to investigate the impact of electricity prices on microgrid optimal sizing and operation. In order to test the proposed methodology, University of Calgary main campus is selected as the case study and historical hourly load data are used.

Acknowledgements

Foremost, I would like to express my sincere gratitude to my supervisor Prof. Milana Trifkovic for the continuous support of my masters study and research, for her patience, motivation and immense knowledge.

I would also like to thank my co-supervisor Prof. Andy Knight for his brilliant ideas, guidance, enthusiasm and immense support throughout this study.

My sincere thanks also goes to the exam committee for their valuable time and comments.

I would also like to acknowledge all the members of Trifkovic research group for their valuable comments. Specifically, I would like to thank Edna, Dominic and Sagar for their priceless comments and discussions. Additionally, I am very thankful to my labmates in Power and Energy Systems research group for their support and all the memories we shared during past two years. In particular, I want to thank Mohammad for his companionship through all the sleepless nights before deadlines and exams. I am also very thankful to Soheila for being a great friend to me and sharing all her precious experiences.

I wish to thank my friend Amin for his valuable support and companionship during these two years. A special thank to my roommate Dorsa for sharing all the fun and hard moments of life with me. Also, my endless thanks goes to my friend Behnam for his continuous support from far far away.

Nobody has been more important to me in the pursuit of this degree than the members of my family. I would like to thank my parents, for their unfailing support and for giving me the opportunity to live my biggest dream. You are the source of my strength.

Dedicated to my beloved parents...

Fatemeh *and* ***Nemat-Allah***

Table of Contents

List of Figures and Illustrations

List of Tables

List of Symbols, Abbreviations and Nomenclature

Symbol	Definition
α	Annual Growth Rate
β	Discount Rate
B	Billing
BCC	Billing Capacity Charge
BSC	Bulk System Charge
c	Charge
d	Discharge
D	Day
η	Efficiency
H	Solar Irradiation
n	Number of Photo-Voltaic modules
ORC	Operating Reserve Charge
P	Power
PC	Coincident Metered Demand Charge
RSC	Regional System Charge
Sub	Substation
t	Time
$TCRCE$	Transmission Constraint Rebalancing Charge Estimate
y	Year

Subscripts and superscripts	Definition
$Batt$	Battery
$Buy, Grid$	Energy Bought from the Grid
Cap	Capacity
$Charge$	Charge to the Battery
$Discharge$	Discharge from the Battery
$Frac$	Fraction
h	Optimization Horizon
max	Maximum
min	Minimum
MT	Microturbine
$O\&M$	Operation and Maintenance

PV	Photo-Voltaic
$Sell, Grid$	Energy Sold to the Grid

Abbreviation	**Definition**
$AESO$	Alberta Electric System Operator
AUC	Alberta Utilities Commission
Btu	British Thermal Unit
CHP	Combined Heating and Cooling Plant
DER	Distributed Energy Resource
DFO	Distribution Facility Owner
DoD	Depth of Discharge
DP	Dynamic Programming
$DPLH$	Daily Peak Load Hour
$DRTO$	Dynamic Real Time Optimization
DTS	Demand Transmission Service
ESS	Energy Storage System
GHG	Greenhouse Gases
LC	Local Controller
LP	Linear Programming
MCC	Microgrid Central Controller
$MILP$	Mixed Integer Linear Programming
$MINLP$	Mixed Integer Nonlinear Programming
MIP	Mixed Integer Programming
$MPPT$	Maximum Power Point Tracking
NLP	Nonlinear Programming
NPV	Net Present Value
PCC	Point of Common Coupling
PL	Peak Load
SOC	State of Charge
TFO	Transmission Facility Owner
$UofC$	University of Calgary

Epigraph

People are capable, at any time in their lives, of doing what they dream of.

- Paulo Coelho, *The Alchemist*

Chapter 1

Introduction

1.1 Background

1.1.1 Energy Outlook

Energy plays an essential role in modern life. The breakdown of total electricity consumption by the *International Energy Agency (IEA)* declares industry as the highest energy consuming sector with 42% share of the world energy consumption in 2016. Among other energy sectors, residential users with 27% share and commercial and public services with 22% share, are reported as the primary electricity demanding sectors. The remaining 9% was consumed by transportation and other sectors such as agriculture [1].

The authors of *International Energy Outlook 2017 (IEO2017)* provide different longterm energy trend projections for major energy consumers worldwide. The Reference Case presented in IEO2017 relies on the continuous improvements in known technologies and economic and demographic forecasts for 16 world regions, under the current policies in effect. In the case mentioned above, total world energy consumption is expected to rise from 575 quadrillion British thermal units (Btu) in 2015 to 736 quadrillion Btu in 2040, denoting a 28% increase over 25 years. The IEO2017 also provides projections under uncertainty associated with economic growth rates and world oil prices. All the energy trend projections presented in IEO2017 affirm the increasing energy demand by 2040, while the high oil prices are assumed to increase economic activity and reinforce a higher increase in energy consumption specially in nonmember countries of *Organization for Economic Cooperation and Development (OECD)* [2].

The *IEA* provides three different *World Energy Outlook (WEO)* scenarios to project future energy trends. In the New Policy Scenario (NPS), authors affirm that by executing the announced policies and continuous motivations from the government, the final electricity consumption will likely increase to 34,470 TWh by 2040. Alternatively, current policies scenario provides a cautious assessment projection of 37,000 TWh demand by 2040 in the case of considering the effective policies by mid 2017 without further motivation for new actions. Sustainable Development Scenario (SDS), is an integrated *WEO* scenario which mainly aims for climate stabilization, improved air quality and universal energy access along with energy security risk reduction. A high peak in CO_2 emissions is expected in SDS scenario with a rapid decrease afterwards. All the above-mentioned scenarios confirm the growing energy demand under certain assumptions [3].

Due to the electrification of energy uses, the increase in electricity consumption is more rapid compared to other energy resources. The principal recognized governing factors for increased demand include income and population growth, technological and industrial advancement and more accessible electricity service to end users [2].

Figure 1.1 illustrates the historical data and also future projections of world total electricity generation by resource for the IEO2017 Reference Case. Thus far, coal has the largest share of net electricity generation worldwide with approximately 40% of total generation. However, coal-fired power generation produces profoundly harmful environmental impacts and pollutants which yields to global warming and public health issues. Many governments are taking actions to phase out traditional coal-fired power plants and replacing them with renewable energy resources and high-efficiency coal units.

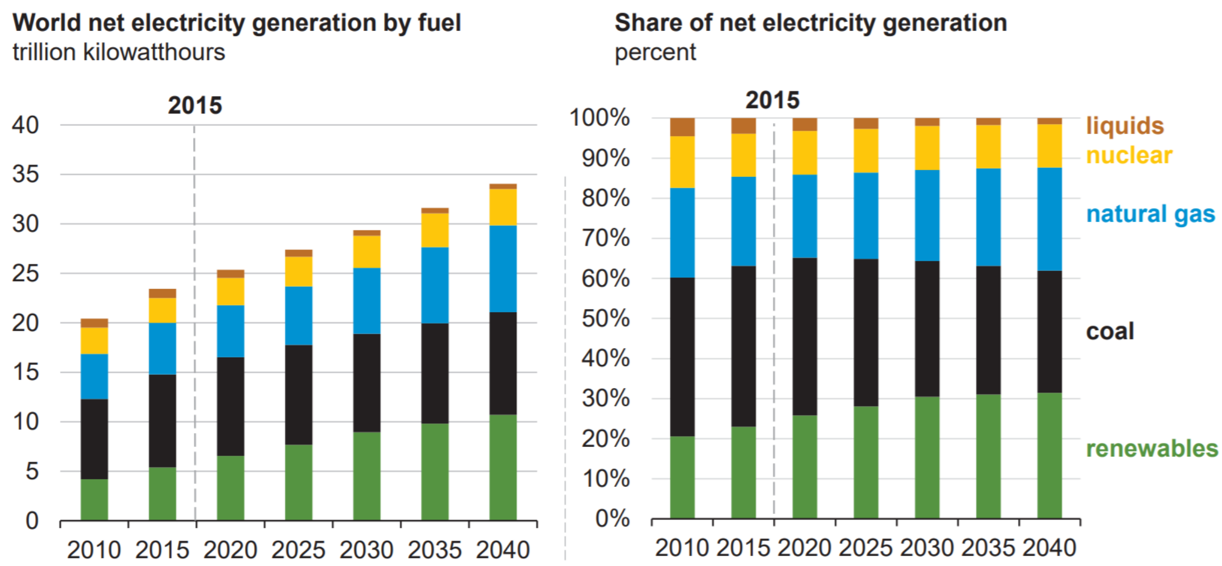

Figure 1.1: World Net Electricity Generation by Energy Resource [2].

According to Figure 1.1, natural gas accounts for approximately 22% of net electricity generation in 2015. Natural gas, the cleanest fossil fuel energy resource is absorbing the attention to displace coal-fired power plants due to the low capital costs, relatively low fuel costs, lower emissions, co-generation ability and higher efficiency. The above-mentioned advantages have made natural gas the fastest growing fossil fuel generation resource with an average yearly growth of 2.1% from 2015 to 2040 [2, 4].

Renewable energy resources are the fastest growing energy resources with an increase rate of 2.8% from 2015 to 2040 based on IEO2017 Reference Case. In 2040, green energy and coal are expected to supply the same share of world electricity generation at 31%. Hydro-power provided roughly 72% of net renewable generation in 2015, along with 14% wind and 4% solar contribution. Geothermal, biomass and waves account for the remaining 10% share of green energy. Due to technological advancement, higher conversion efficiencies, climate actions and incentive policies, wind and solar capacity are expected to rise significantly by 2040. The Reference Case projects 25% wind and 10% solar capacity for 2040 [2].

Nuclear power is one of the most efficient forms of alternative energy which provides approximately 11% share of net electricity generation in 2015. The nuclear contribution is not expected to vary much in the Reference Case projections [2].

1.1.2 Canada Electricity Production in compliance with Paris Agreement

Energy Fact Book 2018-2019 published by *Natural Resources Canada* states that Canada supplied 3% of the world net electricity generation in 2016. Statistics also report that Canada exports approximately 11% of its overall generation to the United States through 34 active interties. Hydroelectricity and nuclear power are the main generation resources in Canada with Hydro accounting for 59% of the net generation and 15% nuclear power supply. The Greenhouse Gas (GHG) emitting resources such as coal and petroleum liquids include 19% of electricity generation in Canada while the remaining 7% of generation is supplied by non-hydro renewables [5].

The adverse impacts of GHG emissions on climate change, health issues and economy urge the need for global efforts to address the issues mentioned above. *Paris Agreement* is an accord within the *United Nations Framework Convention on Climate Change (UNFCCC)*, to confederate the world's countries against the GHG emissions and climate change. *Paris Agreement*, negotiated by 196 parties, aims to maintain the increase in average temperature well below 2°C and pursue endeavors to limit the increase by 1.5°C. Under the accord, each country is required to have an individual plan or nationally determined contributions to combat GHG emissions [6].

Canada submitted its *Intended Nationally Determined Contribution (INDC)* to *UNFCCC* on November 17, 2016. Consistent with *Paris Agreement* goals, Canada's Mid-Century Strategy targets an 80% net GHG reduction by 2050, from 2005 levels. The government of Canada developed the *Pan-Canadian framework (PCF)* for clean growth and climate change which aims for a 30% emissions abatement compared to 2005 levels by 2030 and also a carbon taxation strategy on the pathway to Mid-Century Strategy. The PCF was the outcome of Canada's First Ministers and Indigenous Leaders meeting in Vancouver on March 3, 2016, who reached a consensus to boost the climate actions already taken by provinces and territories to meet Canada decarbonizing targets [7, 8].

Among the current climate actions, *Climate Leadership Plan* announced by the government of

Alberta is worth mentioning, which aims to end coal pollution by 2030. Moreover, introducing carbon taxation and reducing methane emissions by 45% by 2025 are amongst the most substantial goals of *Climate Leadership Plan* [9]. The government of Canada reported that Alberta was responsible for 53% of the overall Canada GHG emissions in 2015 [10]. Also, the government of Ontario decommissioned all the coal generators by 2014 as the leading province in taking climate and environmental actions [11].

The innovative and creative policies outlines by PFC includes carbon pricing, clean energy promotion and energy efficiency improvements. However, the effective transition to clean energy requires infrastructure considerations and investments such as creating jobs and devise competitiveness impacts on businesses [7].

1.1.3 Alberta Electricity Market

In Canada, provincial and territorial jurisdictions are responsible for the regulatory oversight of the electricity sector. While most of the provinces operate their jurisdiction through Crown corporations and regulatory agencies, Alberta and Ontario went through unique deregulation processes over the last decade [12, 13]. This thesis aims to investigate the Alberta restructured electricity market in particular.

In general, the Alberta electricity bill comprises three main components: energy charge, transmission charge and distribution charge. Energy charge accounts for the cost of producing energy whereas, transmission and distribution charges are referred to the costs associated with moving energy through the high voltage transmission lines to the substations and distributing the energy to consumers through low voltage lines, respectively. All electricity users share the transmission and distribution charges regulated by the *Alberta Utilities Commission (AUC)* for receiving the safe and reliable electricity service [14].

Electricity charges are calculated based on hourly electricity pool prices. Alberta wholesale power pool operated by *Alberta Electric System Operator (AESO)* is a competitive energy-only market in transition to a new market structure including energy market and capacity market [15].

In the current energy-only market structure, generators receive payments only for the capacity dispatched not for the available capacity. In the power pool framework, hourly electricity pool prices for buying and selling energy is the same and is set by merit order curve [16].

Canadian transmission network consists of 160,000 Kilometers (km) of high voltage lines which follows a north-south orientation and large interties between Canada and the United States. The north-south orientation is due to the large hydro and nuclear projects located in the north, while most population lies in southern regions in the border with United States [13]. Alberta provincial transmission system maintained by *Transmission Facility Owners (TFOs)* is designated a monopoly service with the AESO responsible for the planning of the transmission network and rate regulations. Alberta electricity market is unconstrained, and all the entities have open access to the grid. Approximately 89% of net electricity generation in Alberta was supplied by coal and natural gas in 2017 [14]. The current transmission network requires expansions to satisfy the increased demand, phase out the coal-fired units and accommodate higher penetration of renewables consistent with *Paris Agreement* and *Climate Leadership Plan*. The costs associated with the expansion of the infrastructure is recognized as the rationality behind the increased transmission charges in Alberta [17].

Distribution sector in Alberta is operated by *Distribution Facility Owners (DFOs)*. Distribution utilities are responsible for bringing electricity from transmission lines to end users through substations and low-voltage lines. The AUC monitors and regulates the distribution tariffs to ensure consumers receive a safe and reliable electricity service at a reasonable rate [14, 18].

In general, market participants can be connected to the distribution facility at a distribution voltage(distribution connected) or at a transmission voltage(transmission connected) based on their maximum electricity consumption. Distribution tariffs for distribution connected and transmission connected consumers is set by DFOs, whereas transmission tariffs are set by the AESO.

1.1.4 Transmission Charges

The electricity bill comprises three main components: energy charge, transmission charge and distribution charge. Energy charge will account for the cost of producing energy whereas, transmission and distribution charges are referred to the costs associated with moving energy through the high voltage transmission lines to the substations and distributing the energy to consumers through low voltage lines, respectively. All electricity users share the transmission and distribution charges approved by AUC for receiving the reliable electricity service (cite aeso) .

The breakdown of the transmission charges referred as *Demand Transmission Service (DTS)* charges is given in the following subsections.

Connection Charge

Connection charge incorporates three main elements: bulk system charge, local system charge and point of delivery charge. Charges associated with the connection to the transmission line may be fixed or variable. While variable charges are declared as charges applied to metered energy on an hourly basis, fixed costs are referred to used substation fraction. A detailed explanation of connection charge components is given in the following.

Bulk System Charge

Bulk system charge consists of coincident metered demand charges and metered energy charges. However, coincident metered demand is the most significant charge rate among all DTS rates and usually accounts for up to 50% of the overall transmission charges. Coincident metered demand charge is applied to the metered demand at the point of delivery averaged over the 15-minute period in which the bulk system demand has reached its maximum level during each month. Although the coincident metered demand charge is averaged on a 15 minutes period, the available data are usually provided hourly. For the sake of data availability, a general assumption is made in this study that the load is averaged over a one hour period to determine the monthly peak load hour.

Hence, coincident metered demand charge will be applied to metered energy at the monthly peak load hour. Monthly peak load hour is a posteriori obtained information and forecast of the exact day of its occurrence is impossible due to the significant long-term forecast errors. In the following sections, a statistical analysis is done on the historical data to develop a forecast term for monthly peak load hour.

Local System Charge

This section includes billing capacity and metered energy charges. Billing capacity is a monthly charge and can be defined as the highest metered demand in settlement period, highest metered demand in past 24 months or 90% of the contract capacity. In a microgrid system, energy storage acts as a dispatchable generator when being discharged while it acts as a load when being charged. The aggregation of demand and battery size as billing capacity in a microgrid will result in huge DTS charges, therefore, this term must be optimized in the sizing algorithm as well as the size of microgrid components. The billing capacity is a decision variable which constrains the power exchange with the grid. To ensure the reliability of the system, the minimum billing capacity must be the highest metered demand in case the internal generation by microgrid become interrupted.

Point of Delivery Charge

Point of delivery charge is associated with substation charge and volumes of billing capacity. Both of these charges are applied monthly and since calculations of the substation fraction are very complex, we assume that the substation fraction is 1. Moreover, there are fixed charges associated with fractions of billing capacity in the point of delivery section. Details of these charges are provided in Table 4.2.

Operating Reserve Charge Estimate

Reliability is the most important goal in power grids. In order to handle the unexpected imbalances between the supply and demand resulted by contingencies, faults in dispatchable generation units, uncertainty in renewable energy generation and lag periods between supply and demand, a reserved energy capacity is required. Regulating, spinning and supplemental reserves have different response times and ensure the reliability of the system in case of any imbalances. The cost of operating reserve will be calculated as a percentage of the hourly pool price and is applied to the hourly metered energy.

Voltage Control Charge

In a power system, the voltage must be within certain limits to ensure the proper operation of the electrical equipment, reduce power loss and increase power system resilience. In Alberta, AESO controls the voltage through various methods including generator terminal voltage adjustment, switching capacitor banks and reactors, transformer tap changes, static VAR compensator, transmission must run(TMR) level adjustments and line switchings. AESO calculates the hourly voltage control charge as a product of hourly metered energy and rate voltage control charge.

Other System Support Services Charge

This section comprises charges associated with highest metered demand and apparent power difference. Highest metered demand is a posteriori charge and cannot be optimized, hence it is not considered in this study. Due to the complexity of apparent power calculations, this term is also neglected in this study.

1.1.5 Distribution Charges

After transmission systems, distribution systems ensure a safe and reliable delivery of the energy to the end users through low voltage lines, substations, and transformers. Distribution companies have monopoly positions in their areas, hence a strict regulation is necessary to ensure a fair distribution rate to consumers. Distribution rates are regulated by Alberta Utilities Commission (AUC) in Alberta. Consumers may be connected to the distribution company facilities at a distribution voltage or transmission voltage.

Transmission Connected

For consumers connected to distribution facilities at a transmission voltage, the distribution access service fee is applied. Service charge is a fixed daily charge and is included in the electricity bill calculations.

Distribution Connected

Large distributed generation sites with on-site generation with a minimum export capacity of 1,000 kVA which are connected in parallel with the electric distribution system are defined as distribution connected. In addition to the daily service charge, a charge is also applied to energy consumption for distribution connected sites during on peak hours which is from 8.00 AM to 9:00 PM from Monday to Friday.

In this study a transmission connected microgrid is studied.

1.1.6 Microgrid Motivation

The social and environmental concerns arising from the current electrical energy generation resources, growing demand and technological advancement urge the need for increased deployment of renewable energy resources. *Distributed Energy Resources (DERs)* play a crucial role to accomplish this goal [19].

DERs consists of relatively small-scale generation units and energy storage systems which are capable of serving the grid individually or aggregated. Whereas higher energy efficiency, increased reliability, energy independence, lower transmission losses and lower electricity costs are accredited as the privileges of DERs, making the renewable energy resources exploitation conceivable is DERs' most significant environmental advantage [20, 21].

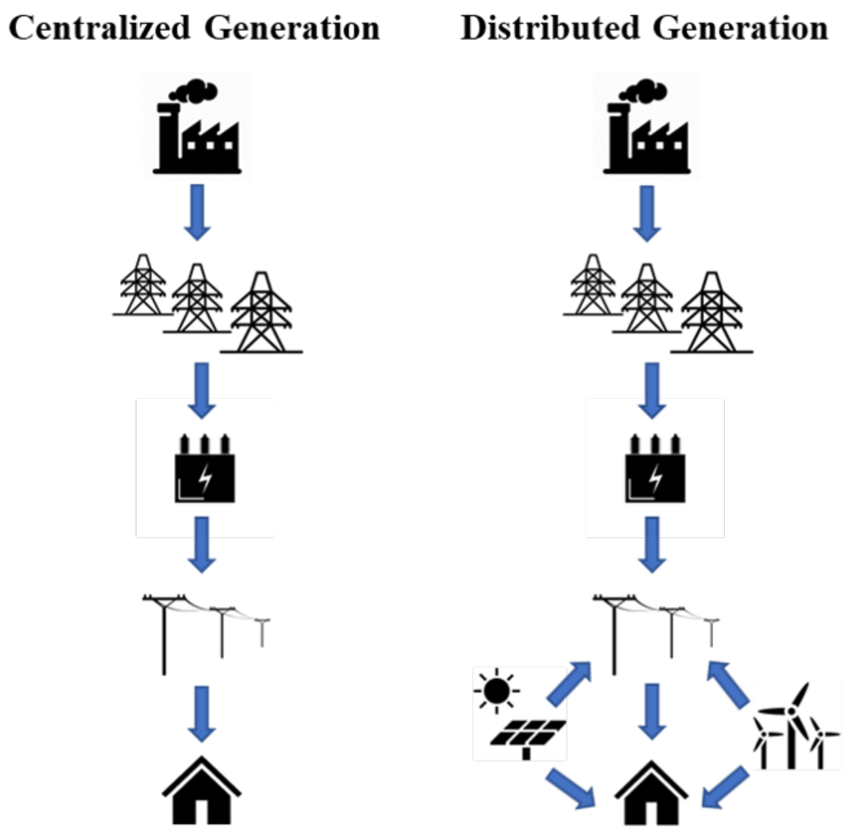

Figure 1.2: Centralized Generation vs. Distributed Generation

Though, the penetration of the renewable energy will also raise concerns associated with their the inherent intermittency. The full deployment of renewable energy is feasible through installation and coordination of multiple DERs to absorb the intermittency of renewable generation and ensure the reliability of the system. Figure 1.2 illustrates the centralized generation and distributed generation structure.

According to Figure 1.2, the resource management is relatively simple in the centralized generation while coordination of DERs requires smart multi-directional communications between load and resources in distributed generation.

Microgrids have appeared as the solution to overcome the challenges and issues associated with the implementation of DERs to the current power system infrastructure [22, 23]. Microgrids structure considers an aggregation of dispatchable and non-dispatchable micro-generation resources along with energy storage systems as a fully or partially self-sustained subsystem of the power system [24, 25]. Depending on their connection to the grid, microgrids fall into two categories: grid-connected or islanded. Microgrids are connected to the grid at the *Point of Common Coupling (PCC)*.

1.2 Motivation and Problem Statement

Issues regarding the deployment of DERs in microgrid structure are twofold. First, the reliable and economic operation of the microgrid entails the optimal and proper sizes of geographically feasible DERs. Moreover, effective energy management techniques are needed to ensure the uninterrupted satisfaction of the load and reliable and economic operation of the microgrid considering the interactions with the main grid.

The focus of this study is on optimal sizing and scheduling of tight geographical campuses or communities. In this category of microgrids, the technical feasibility of DERs is predefined, whereas the proposed methodology will investigate the economic and environmental aspects. The previous work done in the optimal sizing and scheduling only considers the energy charges of the microgrids. Due to the excess generation in the province, 2017 pool prices have experienced a $11\frac{\$}{MWh}$ decline in average compared to 2015 resulting in flat price dynamics. On the basis thereof, arbitrage opportunities and selling energy to the grid are no longer efficient revenue streams which will highly jeopardize the interest in microgrids investments.

Implementation of DERs and on-site generation profoundly impacts the delivery charges of the microgrid. Depending on the microgrid connection to the grid (transmission-connected or distribution connected), delivery charges may be fixed or variable. Incorporating the delivery charge items in the design and operation of microgrids can effectively reduce the electricity bill.

The campus microgrid in the present work comprises solar PV systems, MT, battery energy storage and connection to the main grid at a transmission voltage. It is important to mention that wind turbine technology is not technically and environmentally feasible in municipal areas where campuses are located.

This study aims to incorporate the sizing and scheduling problem in a two-stage optimization algorithm. In the first stage, a MILP formulation tackles the optimal design problem under consideration of environmental and economic requirements. This formulation approaches electricity and fuel prices, demand and weather parameters in a deterministic way, although they are stochastic in nature. This is due to the unpredictable characteristic of the aforementioned parameters in an hourly basis for the 15 years lifetime of the project. The final output of this algorithm is a compendium of optimal size and number of the DERs, economic results including capital and operational costs and revenues, in addition to the transmission service parameters.

In the following stage of the optimization problem, the acquired sizes and parameters from the previous stage is the primary input to a *Dynamic Real Time Optimization (DRTO)* algorithm in a MINLP framework for the optimal operation of the system. This section also includes a statistical analysis of the monthly peak load hour in the bulk system. The dynamic programming takes into account the uncertainty of the stochastic parameters to efficiently manage the resources and battery operation. The forecast of stochastic parameters including load, weather data, electricity pool price and fuel prices is beyond the scope of this study. Incorporating the perfect knowledge of stochastic parameters shows the efficacy of the PL hour forecast.

1.3 Contribution

Microgrid technologies are subject to very high capital costs. The primary advantage of this approach is inessential external investments as on-site generation creates many opportunities for cost reduction and profit maximization. The work presented in this thesis enables the full exploitation of the microgrid resources and also market opportunities in both design and operation stages.

The contributions of this work are listed as below:

- Delivery charges can account for up to 50% of the final electricity bill. This novel approach not only takes into account these charges realistically, but also takes advantage of the available opportunities of microgrid to minimize the delivery costs and even approach it as a revenue stream. The reduced delivery charges along with energy exchange revenues in the project life span are invested in the purchasing microgrid components. In addition to the optimal size and number of DERs, this algorithm will consider the aggregation of loads and on-site generation and genuinely determines the billing capacity.

- While coincident metered demand charge is reflected as an after the fact delivery charge item, the daily peak load hour forecast in this thesis not only avoids this charge effectively, but also accredits coincident metered demand as substantial revenue stream.

- Lastly, the implementation of the optimal sizes of microgrid components and billing capacity along with the precise peak load hour forecast in a proactive scheduling framework will notably reduce the electricity bill.

Although this methodology does not investigate the optimal placement of the components owing to tight geographical locations of campus microgrids, it is applicable to other centralized sets of loads such as communities.

1.4 Thesis Structure

The rest of this thesis is organized as follows. Chapter 2 reviews the literature regarding the optimization techniques and optimal sizing and scheduling of microgrids. Chapter 3 presents a two-stage optimization problem including the MILP problem for the optimal sizing problem followed by a DRTO algorithm in a MINLP framework for the optimal operation. Chapter 4 provides the general assumptions along with the analysis and comparison of sizing and scheduling simulation results. Finally, chapter 5 covers a summary of the present work's conclusions and recommendations for future work.

Chapter 2

Literature Review

2.1 Optimization Overview

Mathematical optimization is concerned with systematical selection of the best element from a set of alternative solutions $x = \{x_1, x_2, ..., x_n\}$ under given circumstances $h_i(x)$ and $g_j(x)$ in order to either minimize or maximize a function $f(x)$. [26, 27].

The general formulation of an optimization problem is represented as:

$$\min_x f(x), \quad s.t. \begin{cases} h_i(x) = 0, & i = 1, ..., m_h \\ g_j(x) \leq 0, & j = 1, ..., m_g \end{cases} \tag{2.1}$$

Where $f(x)$ is the objective function, x is the vector of decision variables, m_h and m_g are positive integers and $h_i(x)$ and $g_j(x)$ are the equality and inequality constraints, respectively.

Optimization problems have been categorized with regards to the form of equations and type of decision variables or constraints as follows:

- Linear and Nonlinear
- Continues, Discrete and Mixed-integer
- Deterministic and Stochastic

- Constrained and unconstrained
- Static and Dynamic
- Convex and Non-convex

Briefly, if linear relationships represent the requirements of a problem it falls in linear programming category. Otherwise, the problem belongs to nonlinear programming. The nature of decision variables determines if the optimization is continuous or discrete. If both integer and continuous variables are present in the optimization, it is called mixed-integer programming. The data for the given problem may be perfectly known or be subject to uncertainties, resulting in deterministic and stochastic optimization problems, respectively. The limitations of decision variables may be incorporated in the formulations as constraints or penalty terms, whereas the former is called constrained optimization and the latter is unconstrained optimization. Dynamic optimization takes into account the impact of current decisions on future possibilities. Convexness of the constraints determine if the optimization is convex or non-convex [28].

In the following, common optimization problems in power systems and specifically this thesis will be discussed in a more detailed manner.

2.1.1 Linear Programming (LP)

In general, a Linear Programming (LP) problem aims to minimize a linear objective function of continuous real variables exposed to linear constraints. Equation 2.2 describes the general form of LP as:

$$\min_{x} c^T x, \quad s.t. \begin{cases} Ax = b \\ Cx \leq d \\ x \in X \end{cases} \tag{2.2}$$

where $c^T x$ allude to the linear objective function, with c representing the cost vector. $Ax = b$

and $Cx \leq d$ are the set of equality and inequality constraints which define a convex polytope as the feasibility region required to acquire the optimal solution of the objective function. Lastly, the unknown decision variables x belong to X which represents the feasible solution space [29].

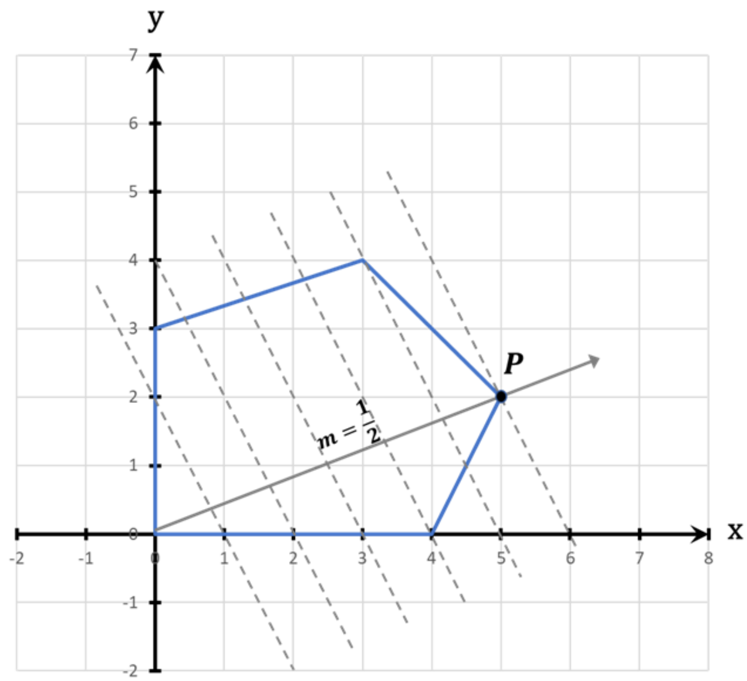

Figure 2.1: Geometrical representation of a linear program [30]

Figure 2.1 illustrates the geometrical representation of a linear problem. The equalities and inequalities have formed a convex polyhedral feasible region. The level curves(dashed lines) of the linear objective function $f(x,y) = 2x + y$ are hyperplanes orthogonal to the gray solid line with the slope of $m = \frac{1}{2}$. The maximum is determined to be 12 occurring at point $P = (5,2)$ [31].

Simplex algorithm and interior point method are well-known solving algorithms for LP. The simplex method, developed by George Dantzig in 1941, introduces a systematic approach to test the feasible set's adjacent vertices in sequence, ensuring that at every new vertex, the objective function is non-decreasing [32, 33]. On the other hand, in 1984 Narendra Karmarkar introduced the first efficient algorithm for solving LP problems in polynomial time. Karmarkar's algorithm falls within the interior-point methods category, which traverses the interior of the feasible region to reach the optimal solution [34,35]. While both algorithms are efficient in practice, interior-point methods are proved to handle highly constrained LPs better. Moreover, interior-point methods have been used in solving constrained and convex nonlinear problems [36].

2.1.2 Non-Linear Programming(NLP)

Nonlinear programming(NLP) is referred to the solving optimization problems where nonlinearities are present in either the objective function or some of the constraints. The mathematical representation of NLP is given by equation 2.3:

$$\min_{x} f(x), \quad s.t. \begin{cases} h_i(x) = 0, \quad i = 1, ..., m_h \\ g_j(x) \leq 0, \quad j = 1, ..., m_g \\ x \in X \end{cases} \tag{2.3}$$

Where $f(x)$ is the objective function, $h_i(x)$ and $g_j(x)$ are the equality and inequality constraints which define the feasible region X and at least one of the $f(x)$, $h_i(x)$ and $g_j(x)$ are nonlinear.

Unlike LP problems, the feasible region of NLPs may not be convex necessarily. In fact, the convexity of feasible region in NLP is specified by equalities and inequalities. That is, if function $f(x,y)$ is convex and if the points x and y satisfy the equation 2.4:

$$f(\alpha x + \beta y) \leq \alpha f(x) + \beta f(y) \tag{2.4}$$

For all α , $\beta \in R$, and $\alpha + \beta = 1$ with $\alpha \geq 0, \beta \geq 0$.

The solving methods for NLPs highly depend on the convexity of the problem. Contrary to the convex problems in which local optima is the global optima, multiple locally optimum solutions may exist in non-convex problems and finding the global optimum is often difficult. Convex optimization problems can be solved by various methods including interior-point methods, bundle methods and cutting-plane methods efficiently [31].

Several approaches also exist for solving non-convex problems. NLPs can be immediately reformulated utilizing linear approximation methods which leads to a more computationally tractable problem with a guaranteed global optimum. Another approach is to employ branch and bound techniques consisting of systematic enumerations of feasible solutions set by state space search in the form of a rooted tree. In this algorithm design paradigm, a solution of the optimization problem must be found heuristically and be set as an upper bound U on the candidate solutions. Afterwards, the feasible region is splitting into two or more subsets recursively, called ”branching”. In the minimization problem, the lower bound of all the candidate solutions in the branched subsets is computed which is regarded as ”bounding”. If the computed lower bound is less than the upper bound, it will replace U. Otherwise, this branch will not lead to an optimal solution and must be pruned or eliminated. The pruning does not affect the algorithm but reduces the storage requirements. The algorithm terminates if the difference of lower bound and upper bound is less than a predefined value ε [37, 38].

Necessary and sufficient optimality conditions in NLPs are provided by Karush–Kuhn–Tucker conditions [39].

2.1.3 Mixed Integer Linear and Nonlinear Programming (MILP and MINLP)

In the previous optimization techniques, all the design variables were assumed to be continuous which could take any real value. Some design variables such as on/off status of machines may take binary values only or the number of physical components and devices can take positive integers only. If one or some of the design variables are restricted to take on integer values only, then the problem is called *Mixed-Integer Programming (MIP)*. Equation 2.5 represents the mathematical formulation of MIP:

$$\min_{x} \; Z = f(x,y) \quad s.t. \begin{cases} h(x,y) = 0 \\ g(x,y) \leq 0 \\ x \in X, y \in Y \end{cases} \tag{2.5}$$

where $f(x,y)$, $h(x,y)$, and $g(x,y)$ can be either linear or nonlinear which will determine if the problem is *Mixed-Integer Linear Programming (MILP)* or *Mixed-Integer Nonlinear Programming (MINLP)*, respectively. Decision variable x can take any real value, whilst y is restricted to take integer values [26].

Among the several techniques available for solving MIP problems, the aforementioned branch and bound and the cutting-plane of Ralph E. Gomory have proved to be efficient and relatively fast [40]. Cutting plane method for solving integer convex programming problems assumes that a bounded minimum exists and embeds a portion of the feasible region set in a compact polyhedral convex set. This algorithm will then cut off parts of the feasible region of linear relaxation such that the optimal integer solution becomes an extreme point which can be easily found by the simplex method. The cutting process takes place by finding an inequality based on separation problem. Eventually, the algorithm either converges after finite iterations due to the finite number of integers in the compact polyhedral set or obtains information regarding the infeasibility of the problem [41]. The efficient combination of two ”branch and bound” and ”cutting plane” methods, called ”branch and cut” has overcome the numerical instabilities associated to cutting plane methods, making the branch and cut algorithm very successful and widespread [42]. For MINLP problems, the improved branch-and-bound algorithm [43] and the extended cutting plane algorithm [44, 45] are proved to efficiently solve convex and non-convex problems. In addition, outer approximation algorithm [46] and generalized benders decomposition [47] method are widely used in the nonlinear convex class of MINLP problems.

2.1.4 Dynamic Programming(DP)

Dynamic programming(DP) is concerned with solving inter-temporal optimization problems, specifically in economic theory and practice which requires a sequential decision making process over time. In fact, in dynamic optimization, present time decisions affect the future possibilities and taking this impact into account is demanded. Hence, the optimization problem is extended in the future horizon to equip the algorithm with the future parameters [48, 49]. The general state-space form of dynamic problems is:

$$\min_{u(\tau)} \int_{t^0}^{t^0+t^h} \Phi(z(\tau),u(\tau),\chi(\tau))d\tau \quad s.t. \begin{cases} \frac{dz}{d\tau} = f(z(\tau),u(\tau),\chi(\tau)) \\ 0 = g(z(\tau),u(\tau),\chi(\tau)) \\ 0 \geq h(z(\tau),u(\tau),\chi(\tau)) \\ z(t^0) = z^0, \quad \forall \tau \in [t^0, t^0+t^h] \end{cases} \tag{2.6}$$

where t^0 is the current time and t^h indicates the receding horizon, $z(\tau)$ is the set of state variables, $u(\tau)$ is the set of decision variable, and $\chi(\tau)$ are the system disturbances. The first two equations describe the dynamic model constrained by the third inequality. System's initial state is given by z^0 [50].

DP was developed by Richard Bellman in the 1950s and is increasingly employed in several areas of decision making. This category of problems is usually complex which can be handled by breaking down into simpler sub-problems in a recursive manner [51]. Among the advantages of DP is its capability to effectively cope with discrete variables and non-convex, non-differentiable and discontinuous functions. Moreover, the stochastic variability can be incorporated in DP with simple modifications to the deterministic procedure [26].

2.1.5 Other Optimization Problems

In reality, uncertain parameters are present in the optimization problems which may arise from either random objective functions or random constraints. This randomness leads to the category of stochastic optimization [52–54]. Other optimization techniques including probabilistic programming, robust programming and fuzzy programming have also approached the problems with stochastic nature [55]. Similar to stochastic programming, robust programming aims to deal with the uncertainty present in the problem. Robust programming is concerned with finding solutions that are valid, even under the worst case scenario [56–59]. Fuzzy programming is equipped to tackle the uncertainties in the form of imprecision and ambiguity of system data and linguistic vagueness [60–62]. In the case there is not enough data to support previous stochastic models, scenario and policy aggregation techniques can be incorporated [63].

The previously discussed optimization techniques were all exact methods. Applying these methods to complicated problems may not be feasible in polynomial time. Conversely, heuristic algorithms have been proved to converge in a reasonable time frame. The major drawback of heuristic algorithms is that they do not guarantee the global optimum, although while used in conjunction with exact methods their efficiency can improve. Simulated Annealing(SA) [64], Cuckoo search algorithm [65], Ant Colony Optimization [66, 67], Genetic Algorithm(GA) [68], Particle Swarm Optimization(PSO) [69] are among the widely used heuristic optimization techniques.

2.2 Microgrids

2.2.1 Microgrids Optimal Sizing

The early stage planning of microgrids is concerned with the optimal combination of type and capacity of DERs and energy storage along with their optimal placement, considering social, environmental, technological and economic concerns. Based on microgrid ownership, developers may prioritize one concern over another in the microgrid project deployment. The following items are recognized as the main objectives of microgrids projects:

- Maximizing green energy production
- Minimizing or capping GHG emissions

- Maximizing economic profit
- Minimizing operational costs
- Minimizing the fuel consumption to diminish dependency on fuel imports
- Minimizing voltage deviations
- Operating at the highest reliability level
- Minimizing transmission losses

Concerns regarding the optimal sitting of the DERs in microgrids depends on the type of microgrids. For tight geographical multiple loads or single load projects, optimal selection, sizing and sitting of DER components tends to take into account the techno-economic parameters regardless of the spatial considerations. In this approach, DERs are connected next to the load as studied in [70–74]. Alternatively, for microgrids in utility-scale or distributed multiple loads, DER planning requires the consideration of available spatial resources to ensure the fulfillment of the social, environmental and technological policies. One of the successful techniques applied to the optimal sitting problem is the *Geographic Information System (GIS)* which aims to find the suitable locations for DER installation [75–78]. In [79], MILP and MINLP optimization models are designed and tested for the optimal sizing and placement of DERs. The methodology proposed has two main parts, whereas the first part implements a Geographic Information System/Multicriteria decision analysis (GIS/MCDA) to find the suitable location for DERs placement. In the second part, the optimal size and final installation location of the DERs are determined. Moreover, the literature review indicates that power flow analysis techniques are required in the planning and operation stages of microgrid projects to ensure that installed size and location of DERs are compatible with the characteristics of common distribution system in steady state operation [80–82]. Traditional power flow analysis methods using different types of buses such as PV, PQ and $V\theta$ buses cannot be applied to microgrid projects directly arising from the following reasons: Relatively small sizes of DERs cannot be treated as a slack bus capable of maintaining the system frequency and its local bus voltage constant; modeling the DERs as PV/PQ buses requires a pre-specified amount of power supplied by each unit which is not applicable realistically; due to the intermittency of DER power generation, microgrid frequency is not fixed and varies within a range. The authors of [83–85] proposed novel power flow techniques to overcome the aforementioned limitations.

Disregarding the optimal sitting perspective, rich literature is dedicated to the optimal selection and sizing of microgrid components. Generally, studies on the optimal sizing problem may be classified into two main categories. The first category adopts a pre-specified operation strategy for some or all of the operation parameters. Hence the obtained sizing results are optimal only under specific conditions. In [86], Soroudi and Ehsan proposed a dynamic multi-objective model which includes placement, sizing and timing of DERs owned by distribution utility. The two-stage optimization problem considers capital costs while running costs are disregarded and a fuzzy satisfying method for technical constraints is introduced to choose the best solution of the non-dominated results set of the heuristic search method. The study lacks an optimal management strategy in addition to the included capital investment consideration. Arabali et al. presented a stochastic framework for optimal sizing and reliability analysis of a hybrid power system. The study aims to minimize the capital costs and satisfy the reliability requirements by incorporating a pattern search optimization method and sequential Monte Carlo Simulation. A compromise-solution technique is exerted to find a trade-off between costs and reliability level while the operation rules are preset [87]. Also, Wishart et al. do not consider optimized management of DERs, although enhanced control strategies based on frequency droop for DERs in islanded microgrid operation is adopted [88]. The study proposed in [89] considers the lifetime characteristics of battery energy storage in a multi-objective optimization problem aiming to minimize power generation costs and maximize the useful life of the battery in simultaneous sizing and operation of an islanded microgrid. The incorporation of battery lifetime characteristics and their associated costs established a set of optimal parameters for economic operation of the microgrid, however the basic flow of operation for the rest of microgrid components in priori known . In addition, traditional optimal design studies usually are carried out through minimum capital and operation costs. However, the deregulated energy markets have created many opportunities to exploit the potentials of the market where the optimal design is not necessarily obtained by cost minimization. Hence, the optimal design postulates the contemplation of optimal management strategies.

In the second category, the optimal sizing and operation strategy are optimized simultaneously and the design scenarios consider the evaluation of both operational and capital costs. Within this category, two main approaches exist. The first approach incorporates two-stage optimization techniques considering the investment as the master problem and operation as the sub-problem. Moradi et al. developed a hybrid optimization method to solve the master-slave objective function addressing economic efficiency, environmental restrictions, and reliability improvement. The hybrid optimization utilized PSO and fuzzy algorithm to minimize operational and outage costs and obtain the optimal capacity of DERs [90]. An optimized multi-objective management is explicitly considered in the optimal design of DERs in microgrids by means of a generalized double-shell framework presented by the authors of [91]. In the proposed study, the internal shell provides the outer shell with an evaluation of the multi-objective operation of each design solution via the nested formulation. The high-quality design scenarios are captured by incorporation of a multimodal optimizer with an indicator based evolutionary algorithm. Another two-stage optimization is utilized in the optimal planning and design of combined cooling, heat and power (CCHP) microgrid system. Non-dominated sorting genetic algorithm-II (NSGA-II) and mixed integer linear problem (MILP) are employed in the optimal design and optimal operation stages, respectively [92]. In such problems with several stages of optimization to find the optimal design results and test their efficiency in operation stage, heuristic algorithms such as PSO and GA are incorporated in most of the work reported in the literature when optimal results are not easy to obtain.

The second approach integrates the planning and operation problems into a single optimization problem. Atia and Yamada [70], employed a MILP to solve the operation and sizing of a residential microgrid including solar and wind energy, thermal load and battery energy storage considering demand response programs. The unified objective function for design and operation problems returns the optimal capacities of DERs and inverters along with the hourly optimal power dispatch in the optimization horizon. Chen et al. proposed a technique for sizing of grid-connected microgrids with the assistance of demand-side management considering joint-optimization of design and operation. The original double-objective function aims to minimize the total annual costs and maximize customer satisfaction which is converted to a single-objective function using a fuzzy satisfaction-maximizing method. The final problem is solved using MILP [93].

2.2.2 Microgrids Energy Management

After the sizing and placement phase of the microgrid project, an efficient energy management strategy is required due to the high deployment of intermittent renewable energy and increased controllable loads. The energy management system for microgrid encompasses both supply and demand side management to ensure the satisfaction of technical constraints along with the economical, reliable and sustainable operation of microgrid. The decision making process for optimal operation entails monitoring, analyzing and forecasting of power generation resources, electrical and thermal demand, meteorological data, energy market prices and ancillary service market prices. The aforementioned information when incorporated in the energy management system provides the optimal schedule of power generation resources, battery energy storage, controllable loads and power exchange with the main grid. The effective management and coordination of DERs and loads improve the system performance, sustainable development and handling the disturbances. However, the implementation of optimal schedules requires a control scheme to enforce the determined set-points. Figure 2.2 depicts the flow of information to the Microgrid Central Controller(MCC) and decisions sent to the Local Controllers(LC) in a centralized energy management system [94].

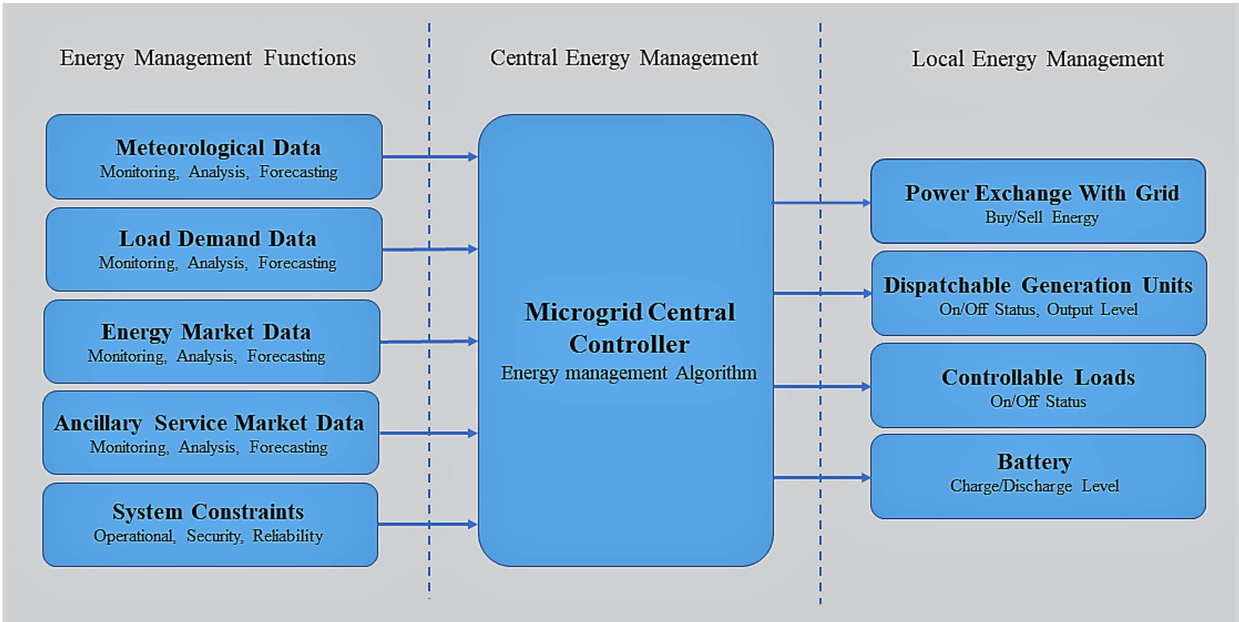

Figure 2.2: Microgrid Energy Management System

MCC is responsible for the proper coordination of all local LCs for their corresponding task through the accumulation of all the information and cost function. The returned decisions and set-points by optimization algorithm which are sent to each LC to enforce the optimal operation of microgrid components.

Economic dispatch and unit commitment problems were traditionally used in energy management of power system and microgrids. Economic dispatch is concerned with the optimal short-term allocation of output power among various supply resources available to serve the load at net minimum cost. Unit commitment problem is similar to economic dispatch but also involves determining the start-up and shut down schedule of thermal and electrical supply resources to meet demand at minimum operational cost or environmental impact. Economic dispatch and unit commitment both require a constant estimation of generation and load parameters within a given time. Many efforts have been made to make the classic economic dispatch and unit commitment problems work for the restructured power system and microgrids [95–100]. However with the increased integration of renewable resources, battery energy storages and electric vehicles, the energy management strategies used in microgrids have been diversified from classic economic dispatch and unit commitment problems. The substantial research done in the field of microgrid energy management is categorized as follow s.

Energy Management Techniques Based on MILP and MINLP

Typically, the scheduling problem of microgrids has objective function including cost, profit or emissions optimization(continuous variables) or on/off schedule(binary variables) of dispatchable resources and controllable loads. Hence, one of the most common techniques used in optimal energy management of microgrids is the MIP as described in 2.1.3. This category of optimization problems are solved by various state of the art solvers such as Gurobi and CPLEX, available in commercial programming softwares and programming languages such as the *General Algebraic Modeling System (GAMS)* [101], the *A Mathematical Programming Language (AMPL)* [102, 103], MATLAB, Python and R.

The authors of [104] presented a MILP method to determine the generation and load policies aiming for minimizing operational costs of a grid-connected microgrid system consisting of MT, Fuel Cell(FC), battery bank, wind and photovoltaic energy resources. The technical constraint such as ramps, minimum up and downtime, and generation limits are addressed in the modeling of MTs and FCs. Moreover, the controllable load modeling includes three kinds of critical, reschedulable and curtailable loads. Although the model is developed for the energy management of microgrids, it can be incorporated in the planning and design stages of a microgrid project.

Luna et al. developed an adaptable online energy management strategy through MILP aiming for minimization of operational costs and load disconnections in grid-connected and islanded microgrids. The proposed work in tested experimentally and is able to deal with the variation in renewable energy. This study considers the generation side management only, while an evaluation framework is established to quantitatively assess the enhancements in savings and computational time with the investigation of three cases including perfect forecast, imperfect forecast and accurate information [105].

Helal et al. proposed a MINLP for the optimal scheduling of a remote hybrid AC/DC microgrid considering demand response program for home appliances and water desalination units. The algorithm intends to minimize the operational costs of microgrid by droop control of DERs. The microgrid controller also ensures the stable operation of microgrid by controlling the power exchange between the AC and DC sides [106].

Energy Management Techniques Based on Dynamic Programming

One of the characteristics of microgrid scheduling is the multi-stage sequential decision making since decisions at the current time affect the decisions to be made in future. The concept of DP in energy management systems benefits the supervisory control with the possibility of taking into account a finite number of future states for renewable generation, load demand, electricity and ancillary service market prices to optimally determine the schedule of supply and demand resources and most importantly battery energy storage charge/discharge decisions. The potential future states are provided to the algorithm through forecast or estimation of parameters. DP gives the sequence of the optimal decisions also called optimal policies for the studied future, however, only the first policy is applied and the rest of decisions will be disregarded. As the algorithm receives the predicted future states, calculations repeat for the new time step. In the case accurate forecasts are available for volatile parameters such as electricity prices, a DP can significantly enhance the profitability of microgrid.

Palma-Behnke et al. proposed a rolling horizon strategy for a microgrid comprising solar panels, wind turbines, battery energy storage and a diesel generator. This study is based on solving a MIP for each iteration, where the forecast information for renewables and load demand is provided by phenomenological models and neural network, respectively. The results of unit commitment rolling horizon strategy are compared to the standard unit commitment to prove the advantage of the proposed algorithm in handling updated data from forecasted variables [107].

Trifkovic et al. presented a dynamic real-time optimization(DRTO) and control for a standalone hybrid microgrid consisting of photovoltaic arrays, wind turbine, battery, electrolyzers, hydrogen storage tanks, and fuel cells in Lambton College, Sarnia, Canada. Two levels of hierarchy are incorporated in this study with the DRTO(supervisory level) responsible for determination of optimal policies and low-level control layer accounting for enforcing the optimal policies to the DERs and communicating the forecasted variables and system states back to the supervisory level. Through the establishment of the bidirectional communication between the two control levels, unforeseen internal and exogenous disturbances are addressed quickly [50].

In [108], an optimal energy management strategy is developed which aims for minimizing the cash flow including power exchange with the main grid and battery ageing cost in a grid-connected microgrid. The power exchange with grid considers two cases of autonomy tariff and dynamic prices and the maximum net import is desired.

Energy Management Techniques Based on Stochastic and Robust programming

The previous literature discussed was based on deterministic approaches toward the forecasted uncertain and intermittent parameters such as renewable generation, load demand and market prices. Although powerful forecast tools are developed for load demand [109–111], solar irradiation [112, 113], wind energy [114, 115], electricity prices [116–118] and fuel prices [119], but these uncertain parameters are forecasted only to an accuracy. Hence, the deterministic approaches based on forecasts do not guarantee the optimal operation. Stochastic programming [120–123], chance constrained programming [124], scenario-based optimization [125], probabilistic programming [126], robust optimization [127–129] and parametric programming [130] are among the techniques developed to deal with the uncertainties in microgrid scheduling.

In [120], a two-stage stochastic optimization problem is formulated for the optimal operation of a microgrid to accommodate the uncertainties arising from renewable energy resources. The MINLP problem is decomposed into one master problem for energy scheduling with the purpose of minimizing the operational costs and power losses, and one subproblem for power flow computation considering wind and solar intermittencies. Two subproblems are solved iteratively until the power losses fall into a specified limit.

The authors of [124] present a chance-constrained programming framework for the peak power shaving and frequency regulation of a grid-connected microgrid while systematically incorporating uncertainties of renewable energy resources and random demands. Chance constraints are developed to bound the magnitude and capacity of uncertain renewable output for protection purpose and frequency regulation, respectively. Case study results verify the superiority of the proposed method over greedy planning, scenario-based and robust programming approaches in terms of average cost saving.

Mohammadi et al. proposed a scenario-based stochastic framework for the optimal operation of a microgrid under concurrent incorporation of uncertainties raised from load demand, solar and wind energy generation and market prices. The proposed method has two phases, where in the first phase scenarios are generated using Probability Distribution Function(PDF) of each uncertain variable and then most dissimilar and probable scenarios are selected by means of scenario reduction techniques. The selected deterministic scenarios with certain probabilities are solved by Adaptive Modified Firefly Algorithm (AMFA) meeting different equality and inequality constraints in the second phase. Results demonstrate dependability enhancements of optimal solutions due to more than three times uncertainty spectrum captured compared to deterministic framework [125].

Xiang et al. developed a scenario-based robust energy management technique to optimize the worst-case realization of renewable energy generation production and load. The robust method aims for maximum total exchange cost and minimum social benefit costs simultaneously. Taguchi orthogonal array(OA) utilizes the uncertainty sets for renewable generation and load which are provided by interval prediction to generate a limited number of testing scenarios with best statistical information. A search strategy based OA is designed to optimize the worst case scenario and the results are proved to be robust against most possible realizations of the modeled uncertain set by Monte Carlo [127].

Umeozor et al. propose a parametric MILP problem for the operational energy management of a grid-connected microgrid by means of parameterization of uncertain coordinates of wind and solar power production. The original nonlinear problem is transformed into a linear bi-level problem with the upper level responsible for the parameterizing scheme and lower level accounting for the optimal operation decisions. The proposed methodology enables better handling of uncertainty, more accurate solutions and faster computations [130].

Energy Management Techniques Based on Heuristic Optimization

The multiple number of renewable energy resources, battery energy storages and demand response programs significantly increase the number of variables that must be taken into account in optimal scheduling problem. Moreover, the incorporation of the uncertain variables leads to highly non-convex MINLP computationally demanding problems. Heuristic algorithms are based on local optimization and will always lead to a reasonable solution to complex problems at a fast computational speed, however mostly with the sacrifice of guarantee of optimality. Hence, heuristic methods are largely employed in microgrid energy management problems. The popular approaches are GA [131, 132], memory-based GA [133], PSO [134, 135], Artificial bee colony(ABC) [136, 137] and SA [138].

Elsied et al. present a multi-objective real-time energy management system based on GA which aims for energy cost minimization, GHG emissions minimization and maximization of the available renewable energy resources. The robust and reliable ZigBee communication infrastructure is used to exchange the information and commands between MCC and DERs in real-time [131].

In [134], an energy management strategy based on PSO is presented for a microgrid consisting of different distributed generation units and energy storage devices. The uncertainty of the renewable generation resources, load and market prices are incorporated in the proposed probabilistic approach. The goal of this PSO based scheduling is minimizing the total energy and operating cost of the microgrid. PSO is proved to be more or comparably efficient in finding the best solution compared to the techniques reported in the literature [139].

Chapter 3

Methodology

Sizing and scheduling are the main parts of microgrid projects whereas scheduling efficacy highly depends on the size of microgrid components and parameters. Many studies have approached the design and operation of microgrids considering energy costs only. In the proposed methodology, in addition to the energy costs, transmission and distribution costs are also incorporated. While distribution costs are fixed for transmission connected microgrids, transmission costs can be minimized by taking advantage of the daily PL hour forecast developed in this chapter. This methodology formulates a two-stage optimization problem for the design and operation of campus microgrids. In the first stage, a MILP formulation tackles the optimal design problem under consideration of environmental and economic policies. While maximizing green energy production seeks to prioritize environmental concerns, minimizing electricity bill under capped carbon emissions integrates environmental and economic concerns in optimal sizing problem. Savings on electricity bill resulted from minimized transmission costs and microgrid optimal operation, would be invested in purchasing microgrid technologies. Optimal number and size of microgrid technologies, along with the estimated revenues, operational costs and capital costs are the resultants of the sizing algorithm under various scenarios.

Subsequently, the obtained number and size of microgrid technologies are the primary inputs to the next stage of the optimal design and operation problem. Also, the hourly microgrid power exchange limit with the main grid is imported form the sizing algorithm. Eventually, the scheduling problem is formulated on a rolling horizon basis which enables the microgrid to determine the optimal policies of each technology, considering future states of uncertain variables. The consequential MINLP aims to minimize the microgrid electricity bill under the designed sizing scenarios and avoiding the coincident metered demand charge.

3.1 Coincident Peak Load Forecast

The coincident metered demand charge is a posteriori charge and accounts for the metered demand at the monthly PL hour in the bulk system. The information required to deal with the coincident metered demand is twofold; hour of the day and day of the month.

The monthly PL hour for the years 2011 to 2017 are provided in Table 3.1. According to historical data, the monthly PL hour has a repeating pattern at least for 6 months of the year. Whereas, the exact occurrence day of PL does not have a repeating pattern and in order to determine it, the whole month's load data is required at the beginning of the month. Since long term forecasts are usually unavailable or very inaccurate, estimating the day of the month in which the PL occurs is infeasible. Therefore, a statistical analysis of historical data is developed to only estimate the PL hour for each month.

Table 3.1: Monthly peak load hour for years 2011 to 2017

	Jan	***Feb***	***Mar***	***Apr***	***May***	***Jun***	***Jul***	***Aug***	***Sep***	***Oct***	***Nov***	***Dec***
2011	18	20	20	12	17	13	16	17	17	19	18	18
2012	18	19	20	11	17	14	14	14	15	19	18	18
2013	18	19	21	12	17	16	16	17	17	20	18	18
2014	18	19	20	12	14	17	16	16	17	19	18	18
2015	18	19	20	12	17	15	17	15	15	20	18	18
2016	18	19	20	14	17	15	16	16	16	10	18	18
2017	18	19	20	10	17	17	17	17	17	18	18	18

First, the bulk system load data are clustered into months and the frequency analysis is applied to each month's load data, separately. For example, to determine the PL hour of January, only the historical data for January are utilized in the frequency analysis. The load vector data is converted into a matrix $Load_{Hour,Day}$ with rows representing hours and columns representing days. The maximum daily load and its corresponding hour, are extracted from the data by equation 3.1:

$$(PL\_Hour, PL\_Magnitude) = \sum_{Day=1}^{D} Max(Load_{Hour,Day}) \tag{3.1}$$

PL_Hour is the set of daily PL hours over D days, where D depends on the number of days studied. The PL probability for each hour is given by equation 3.2.

$$Probability(h) = \sum_{h=1}^{24} \frac{number\ of\ h\ in\ PL\_Hour}{D} \quad \forall \quad h \in \{1, ..., 24\} \tag{3.2}$$

The hour with maximum probability is considered as the PL hour for the studied month. In other words, the probability vector implies that the PL occurs in one of the days in the month at the hour with maximum probability. Accordingly, this approach does not give any information regarding the occurrence day of PL. To resolve this issue, instead of applying the coincident metered demand charge once in a month, it is applied every day at the estimated PL hour. Hence, only an accurate PL hour forecast is required to guarantee the minimization of coincident metered demand charges.

The final output of the algorithm is a *Daily Peak Load Hour (DPLH)* vector with binary elements, where 1 indicates daily PL hour and 0 indicates non-PL hours described in equation 3.3. For example, if hour 18:00 is the most probable PL hour in January, the elements of DPLH(t) associated to hour 18:00 equals 1 for the month of January.

$$DPLH(t) = \begin{cases} 1, & \text{If } t \text{ is a daily peak load hour} \\ 0, & Else \end{cases} \quad \forall \quad (t) \tag{3.3}$$

The actual PL hour or the monthly PL hour from historical data also forms a vector with binary values, where only one element of this vector equals 1 in each month. This vector will be used in the scheduling algorithm to test the efficacy of DPLH(t) estimation.

3.2 Microgrid Sizing

In this section, the structure and formulations of campus microgrid sizing are discussed. The proposed algorithm is based on the work of [79], while some of the restrictions are relaxed due to the specific geographical location of the campus. The focus of this methodology is to determine the size and configuration of aggregated on-site power generation from PV modules and a MT, along with a battery and connection to the main grid in a tight geographical location.

3.2.1 Microgrid structure

Figure 3.1 depicts the proposed microgrid structure. This fully interconnected microgrid is connected to the main grid at the PCC.

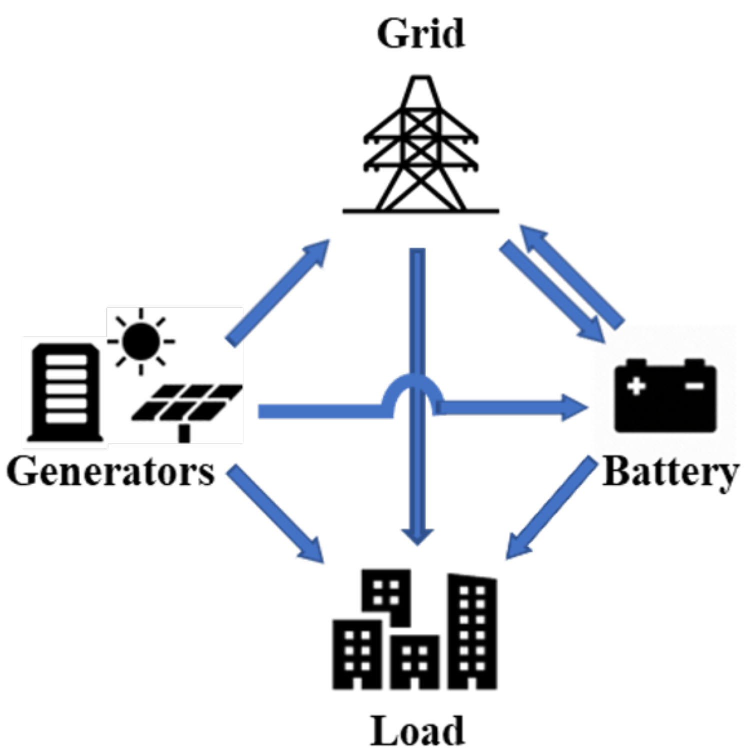

Figure 3.1: Microgrid Structure

The excess internal generation can charge the battery or be sold to the grid. Demand may be supplied by internal generation, purchasing energy from the grid or discharging the battery. The energy inputs to the battery are grid and internal generation. Also, battery may retain its energy for future hours, send it to the load or sell it to the main grid.

3.2.2 Microgrid Components

This section overviews the detailed description of microgrid technologies used in this study. Solar and wind energy are the primary renewable energy resources in microgrid projects, although, restrictions may apply to their exploitation.

In Alberta, municipalities determine the wind turbine setbacks and validate them in land use bylaws. These land use bylaws for placement of wind turbines are one of the most critical elements in microgrid design phase. Bylaws may cover municipal roadways, property lines and also dwellings on lands for participating and non-participating land owners and sites of potential residence locations. Some municipalities have bylaws designating specific setbacks while others may refer to provincial regulatory policies for noise from wind turbines or in some cases consider no specific regulatory. However, all stages of wind turbine installation projects must consider local zoning requirements provided in municipal development plans or land use bylaws. Based on municipal constraints, 500 meters and 750 meters setbacks are required from participating and non-participating residents, respectively [140]. Due to the limitations mentioned above and considering the location of campuses in urban areas, wind turbine placement is not feasible in campus microgrid projects.

Photovoltaic modules

Solar energy is the only renewable resource that can be exploited in campus microgrid projects. Depending on the weather conditions and temperature, there are various mathematical models for expressing the output of the PV modules. The new PV modules are equipped with *Maximum Power Point Tracking (MPPT)* technology which enables the PV panel to optimally absorb the solar irradiation and maximize the efficiency of the conversion system. Since the campus microgrid projects are quite large scale projects, poly-crystal silicon-based modules are preferred due to economic aspects. Detailed specifications of the PV module under standard test conditions is provided in the table 3.2. All the specifications are provided by *Allesun Industries Inc* data sheet for 310-330W modules.

Table 3.2: Specifications of the PV modules at 1000 $\frac{W}{m^2}$ and 25°C

Specifications	***Value***
Maximum Power	325 W
Module Efficiency	16.85%
Module Operating Temperature	-40° to +90° F
Module Area	1.75 m^2

The hourly output of the aggregated PV modules is given in equation 3.4.

$$P_{PV}(t) = n_{PV} * P_{rated,PV} * \frac{H(t)}{H_{Rated}} \quad \forall \quad (t) \tag{3.4}$$

Where, n_{PV} is the optimal number of PV modules, $P_{rated,PV}$ is the maximum module power, $\eta_{Module,PV}$ is the module efficiency and $H(t)$ is the hourly solar irradiation [141].

Natural Gas Microturbine (MT)

Natural gas MTs offer several advantages including lower emissions, lower electricity costs, co-generation ability and higher efficiency compared to other fossil fuel power generation technologies. Thus, MTs are selected as the dispatchable power generation resource in the proposed hybrid microgrid structure.

Due to the low efficiency in low set points, the minimum power output of MT is set to 50% of the MT size and is formulated as follows :

$$0.5 * Size_{MT} \leq P_{MT}(t) \leq Size_{MT} \quad \forall \quad (t) \tag{3.5}$$

Carbon emissions is a limiting factor in MT sizing under scenarios in which the environmental impacts of the microgrid are considered. Equation 3.6 formulates the carbon emissions for the MT technology used in this study.

$$\text{Carbon Emissions} = \sum_{t=1}^{T} P_{MT}(t) * (V_{Fuel} * E_{Fuel}) \tag{3.6}$$

Where V_{Fuel} is the volume of fuel to energy ratio for natural gas in $\frac{m^3}{MWh}$ and E_{Fuel} is the carbon emission to volume of fuel ratio for natural gas in $\frac{kg}{m^3}$.

Energy Storage System

Energy storage systems play diverse important roles in microgrid projects. ESS systems are used for peak shaving, emergency power resource and arbitrage. In the proposed study the most important role of the ESS is to take advantage of the arbitrage opportunities in the very volatile electricity market and also supply the demand at the PL hour which is usually in the evening when there is no solar generation and the electricity prices are quite high.

Due to the higher efficiency and power density of lithium ion batteries, they are the most popular batteries in both grid scale and small scale applications [142, 143]. The detailed specification of the battery used in this algorithm is provided in table 3.3.

Table 3.3: Li-ion battery design characteristics

Characteristics	***Value***
Maximum possible storage capacity	20 MWh
Maximum possible power charged or discharged	40MW
Minimum discharge and charge duration	30 min
Lifetime	≈ 15 years
Number of cycles	≈ 3500 cycles
Charging efficiency	90%
Discharging efficiency	95%
DoD	80%

Equation 3.7 expresses the mathematical formulation of battery *State of Charge (SOC)*.

$$SOC(t) = SOC(t-1) + \eta_c * P_{Charge}(t) - \frac{P_{Discharge}(t)}{\eta_d} \quad \forall \quad (t) \tag{3.7}$$

The current hour SOC depends on the previous hour SOC and the power discharged or charged to the battery. $P_{Charge}(t)$ and $P_{Discharge}(t)$ are the decision variables in the optimization problem.

However, safe and efficient operation of battery requires important considerations. Batteries should not be discharged under 20% of their capacity, because it damages the battery and reduces its life span drastically. Overcharging the battery may also cause damaging the battery and even burn it. The restriction on SOC is given by equation 3.8.

$$(1-DoD)*Size_{Batt} < SOC(t) < size_{Batt} \quad \forall \quad (t) \tag{3.8}$$

In equation 3.9 battery size is restricted by the maximum allowed size for battery in the design.

$$0 \leq Size_{Batt} \leq Size_{Batt,Max} \tag{3.9}$$

Power charged or discharged from the battery is also restricted by the battery size and is formulated in 3.10 and 3.11.

$$0 \leq P_{Charge}(t) \leq Size_{Batt} \quad \forall \quad (t) \tag{3.10}$$

$$0 \leq P_{Discharge}(t) \leq Size_{Batt} \quad \forall \quad (t) \tag{3.11}$$

However the life span of the battery is 15 years, repeated battery charge and discharge will degrade the battery resulting in declining capacity and elevated self discharge. Thus, batteries may be discharged a limited number of cycles. In this study, a full discharge of the usable capacity of the battery, is considered as one cycle. Equation 3.12 bounds the number of cycles for the one year of project operation.

$$\sum_{t=1}^{T} P_{Discharge}(t) \leq \frac{Maximum\ Battery\ Cycles}{Project\ Life\ Span} * DoD * Size_{Batt} \tag{3.12}$$

3.2.3 Problem Formulation

Capital Costs

Capital costs for tight geography microgrid projects such as campus microgrids comprises the cost of purchasing and installing power generation technologies. In this project, capital costs include the cost of purchasing PV modules, MT and Battery which is formulated in equation 3.13.

$$\text{Capital Cost} = n_{PV} * Cost_{Buy,PV} + Size_{MT} * Cost_{Buy,MT} + Size_{Batt} * Cost_{Buy,Batt} \tag{3.13}$$

$Cost_{Buy,PV}$ includes cost of the panel, inverter, racks, cable, $DC - AC$ boxes and installation of each PV module, while n_{PV} is the optimal number of PV panels calculated by the optimization problem. $Cost_{Buy,MT}$ is the cost of MT per MW while $Size_{MT}$ is the optimized MT size. The third term in the capital costs is the cost of battery and is a product of battery size in MWh, and cost of battery per MWh.

Operational Costs

After purchasing the microgrid technologies, the operation of each technology and connection to the main grid forms operational costs in microgrid operation. Operational costs include cost of buying energy from the grid, DTS charges and *Operation and Maintenance* (*O&M*) cost of PV, MT and battery. Equation 3.14 gives the mathematical formulation of operational cost:

$$\begin{aligned}\text{Opeartional Costs} = Cost_{O\&M,PV} + Cost_{O\&M,MT} + Cost_{O\&M,Batt} + Cost_{Buy,Grid} + \\ Cost_{Transmission} + Cost_{Distribution}\end{aligned} \tag{3.14}$$

Detailed discussion of operational costs components is given in the following.

- *O&M Cost of PV*

  PV modules require cleaning since over time they accumulate dirt and their efficiency decreases. Also, due to the high cost of repair and also profit loss during shut down of solar technology, monitoring of PV modules is highly recommended as preventative actions will minimize the profit loss. Cleaning and monitoring costs account for $O\&M_{PV}$. Equation 3.15 formulates the operational cost of PV which is a product of power produced by PV and $O\&M$ cost of PV which is per MWh.

$$Cost_{O\&M,PV} = \sum_{t=1}^{T} P_{PV}(t) * O\&M_{PV} \tag{3.15}$$

- *O&M Cost of MT*

  Reliable and uninterrupted operation of MT also requires maintenance and preventative actions which are categorized as $O\&M_{MT}$. In addition to the $O\&M$ costs, carbon taxation also applies to the CO_2 produced by MT. Equation 3.16 formulates the overall $O\&M$ costs of MT.

$$Cost_{O\&M,MT} = \sum_{t=1}^{T} P_{MT}(t) * (O\&M_{MT} + V_{Fuel} * (Cost_{Fuel}(t) + E_{Fuel} * Tax_{Fuel})) \tag{3.16}$$

- *O&M Cost of Battery*

  Energy storage systems require annual monitoring to ensure reliable operation. $O\&M_{Batt}$ are in $\$/MWh$ and will be applied to the energy discharged from battery.

$$Cost_{O\&M,batt} = \sum_{t=1}^{T} P_{Discharge}(t) * O\&M_{Batt} \tag{3.17}$$

- *Cost of Purchasing Energy from the Main Grid*

  In grid connected microgrids, when the internal generation is not sufficient to meet the demand or charge the battery, the needed energy is bought from the main grid. Microgrid may also buy energy from the main grid to charge the battery. Cost of buying power from the grid is a product of amount of energy bought from the grid and price of electricity at the specified hour as formulated in equation 3.18.

$$Cost_{Buy,Grid} = \sum_{t=1}^{T} P_{Buy,Grid}(t) * Price_{Electricity}(t) \tag{3.18}$$

- *Transmission Charges*

  This item formulates $Cost_{Transmission}$ which is referred as DTS charges discussed in section 1.1.4. Billing capacity charges and substation charges are applied only once a month, hence, we introduce a billing term which is zero except for the last hour of each month. Second term in equation 3.19 is related to all the charges applied to the metered energy. The most significant charge among all DTS charges is the coincident metered demand charge which is applied to the energy bought from the grid at the monthly PL hour represented by the term PeakLoad(t).

$$\begin{aligned} Cost_{Transmission} = \sum_{t=1}^{T} (B_{Cap} * BCC + Sub_{Frac} + Sub_{Charge}) * Billing(t) + (TCRCE + \\ BSC + RSC + VCC + ORC * Price\_Electricity(t)) * P_{Buy,Grid}(t) + PeakLoad(t) * \\ PC * P_{Buy,Grid}(t) \end{aligned} \tag{3.19}$$

  Actual bulk system load data are used to determine the PeakLoad(t) which is a binary vector with 0 values at all hours except for the hour with maximum system load in the month.

- *Distribution Charges*

  Distribution charges discussed in section 1.1.5 for transmission connected sites are calculated on a daily basis as follows:

$$Cost_{Distribution} = \sum_{t=1}^{T} Service\_Charge * Distribution\_Billing(t) \tag{3.20}$$

  The term $Distribution\_Billing(t)$ is a vector of binaries which is 1 only at the ending hour of each day, representing the daily service charge hour.

Revenue

In a centralized energy market, cost of buying and selling the energy is the same and is referred as pool price. Hence, the revenue obtained from selling energy to the grid is a product of energy sold to the grid and price of electricity at the respective hour. However, at the monthly PL hour, there is another revenue term for the power sold to the main grid. The profit made by consumers must be carried back to them through distribution company. Equation 3.21 formulates the two terms of revenue in the studied microgrid.

$$Revenue = \sum_{t=1}^{T} P_{Sell,Grid}(t) * Price_{Electricity}(t) + PeakLoad(t) * P_{Sell,Grid}(t) * PC \tag{3.21}$$

Pay-Off Time

The centralized electricity market prices are very volatile and long term hourly forecasts are not feasible. Also, by averaging the data on longer periods, important parts of the information will be lost. Hence, in this study, the first year's perfect data will be given to the optimization problem. The optimization problem is solved subject to an increase rate associated to operational costs, revenues and no microgrid electricity bill for the upcoming years.

The main source of investment for purchasing microgrid components is the savings on electricity bill in the case of installing a microgrid. In order to calculate the savings, first the normal electricity bill must be calculated. In the absence of microgrid, the electricity bill will include the power purchasing costs from the grid, transmission and distribution charges and also operational costs of any existing on-site generation. The annual growth of costs and revenues is assumed to be equal and is represented by the term α.

$$Campus\_Normal\_Bill(y) = (1+\alpha) * Campus\_Normal\_Bill(y-1) \quad \forall \quad (y > 1) \tag{3.22}$$

$$Revenue(y) = (1+\alpha) * Revenue(y-1) \quad \forall \quad (y > 1) \tag{3.23}$$

$$Operational\_Costs(y) = (1+\alpha) * Operational\_Costs(y-1) \quad \forall \quad (y>1) \tag{3.24}$$

In this study, the owner perspective is investigated. The electricity bill to be paid after installing the microgrid is defined as the difference of revenue and operational costs. The Saving term is formulated in equation 3.25.

$$\begin{aligned} Savings = \sum_{y=1}^{Y} \frac{1}{(1+\beta)^{(y-1)}} * (Campus\_Normal\_Bill(y) + Revenue(y) - \\ Operational\_Costs(y)) \end{aligned} \tag{3.25}$$

In order to bring future values to present, a discount rate is defined based on inflation rates. Capital costs are capped by the total savings during the life span of the project.

$$\text{Capital Costs} \leq Savings \tag{3.26}$$

Microgrid Electricity Bill

The final electricity bill for microgrid is the difference of costs and revenues, given as follows:

$$Microgrid\_Bill = \sum_{t=1}^{T} (Operational\_Costs) - Revenue \tag{3.27}$$

Obviously, a negative electricity bill means revenues obtained are larger than operational costs and the microgrid is profitable.

Constraints

Important factors need to be considered in microgrid operation to ensure the reliability of the system. The reliable and economic operation of the microgrid is limited by many important constraints. These factors may be equality or inequality terms.

- *Power balance*

  This item is the most important constraint in microgrid formulations which must be held at any cost. Equation 3.28 formulates the power balance. This equation ensures the supply of the demand considering battery charge/discharge and power exchange with grid.

$$P_{Buy,Grid} + P_{Discharge}(t) + P_{PV}(t) + P_{MT}(t) = P_{Demand}(t) + P_{Sell,Grid}(t) + P_{Charge}(t) \quad \forall \quad (t) \tag{3.28}$$

- *Available area for PV modules*

  One limiting factor related to the PV modules is the available area for the installation of PV modules. This item is specially important in the campus microgrid design which the available land is very limited due to the location of campuses in cities.

$$0 \leq n_{PV} \leq \frac{Available \quad area \quad for \quad PV}{PV \quad module \quad area} \quad \forall \quad n_{PV} \in \mathbb{Z} \tag{3.29}$$

- *Power Exchange with the Grid*

  As discussed in transmission charges section, the power bought from the grid or sold to it is limited by the billing capacity.

$$0 \leq P_{Buy,Grid}(t) \leq B_{Cap} \quad \forall \quad (t) \tag{3.30}$$

$$0 \leq P_{Sell,Grid}(t) \leq B_{Cap} \quad \forall \quad (t) \tag{3.31}$$

Scenarios and Objective Functions

The microgrid sizing can be formulated considering different objective functions. The objective function can be minimizing the Microgrid_Bill under different circumstances such as reduced carbon emissions or carbon free microgrid design or maximizing the green energy production.

3.3 Microgrid Scheduling

After obtaining the optimal sizes of the microgrid components, an efficient energy management algorithm is needed to ensure microgrid reliable and economic operation. Hence, a DRTO algorithm is developed to mitigate the adverse impacts of uncertainty in electricity prices, load and solar power generation on optimal scheduling. DRTO is a proactive energy management algorithm which extends the accessible system states in the scheduling horizon.

3.3.1 Problem Formulation

This section formulates the DRTO problem. In each iteration, all equations are solved from t^0 to t^h which is the optimization horizon, assuming that all the future system states are available up to t^h. The current point t^0 is extended to T which is the project total time span equal to 8760 hours. Since the operation of microgrid technologies is similar to the sizing, equations are not discussed extensively. For more detailed discussions on equations, please refer to the sizing section.

Battery Operation

The energy storage operation is similar to the sizing algorithm. SOC will be calculated based on the energy stored in the battery from previous hour and the energy charged or discharged from the battery. $P_{Charge}(t)$ and $P_{Discharge}(t)$ are the decision variables in this equation. The new batteries offer the usable capacity of battery which is different for each battery technology. So, for the consistency, the usable capacity of battery is set as the maximum battery capacity in MWh, while the minimum is zero.

$$SOC(t+1) = SOC(t) + \eta_c * P_{Charge}(t) - \frac{P_{Discharge}(t)}{\eta_d} \quad \forall \quad t \in \{t^0, ..., t^h\}, t^0 \in \{1, ..., T\} \tag{3.32}$$

Operational Costs

The operational costs in the optimal scheduling, are similar to operational costs in the sizing algorithm. However, in scheduling algorithm all the costs are calculated hourly and are not accumulated during the project horizon.

$$\begin{aligned} Operational\_Costs(t) = {} & Cost_{O\&M,PV}(t) + Cost_{O\&M,MT}(t) + Cost_{O\&M,Batt}(t) + \\ & Cost_{Buy,Grid}(t) + Cost_{Transmission}(t) + Cost_{Distribution}(t) \\ & \forall \quad t \in \{t^0, ..., t^h\}, t^0 \in \{1, ..., T\} \end{aligned} \tag{3.33}$$

- *Solar Energy O&M*

  This item will formulate the hourly operational costs of PV which is proportional to the solar power generation.

$$Cost_{O\&M,PV}(t) = P_{PV}(t) * O\&M_{PV} \quad \forall \quad t \in \{t^0, ..., t^h\}, t^0 \in \{1, ..., T\} \tag{3.34}$$

- *Microturbine O&M*

  Similar to the sizing algorithm, operational costs of the microturbine are calculated based on equation 3.35.

$$\begin{aligned} Cost_{O\&M,MT}(t) = P_{MT}(t) * (O\&M_{MT} + V_{Fuel} * (Cost_{Fuel}(t) + E_{Fuel} * Tax_{Fuel})) \\ \forall \quad t \in \{t^0, ..., t^h\}, t^0 \in \{1, ..., T\} \end{aligned} \tag{3.35}$$

- *Battery O&M*

  The O&M cost of battery is proportional to the discharged energy from battery.

$$Cost_{O\&M,batt}(t) = P_{Discharge}(t) * O\&M_{Batt} \quad \forall \quad t \in \{t^0, ..., t^h\}, t^0 \in \{1, ..., T\} \tag{3.36}$$

- *Power Purchase Costs*

  Power purchase costs are a product of energy bought from the grid and electricity price at the same hour.

$$Cost_{Buy,Grid}(t) = P_{Buy,Grid}(t) * Price_{Electricity}(t) \quad \forall \quad t \in \{t^0, ..., t^h\}, t^0 \in \{1, ..., T\} \tag{3.37}$$

- *Transmission Charges*

  As discussed before, DTS charges are usually inevitable since they are related to the reliability of the system. The most important term of cost that can be avoided is the coincident metered demand charge.

$$\begin{aligned} Cost_{Tranmission}(t) = (B_{Cap} * BCC + Sub_{Frac} + Sub_{Charge}) * Billing(t) + (TCRCE+ \\ BSC + RSC + VCC + ORC * Price\_Electricity(t)) * P_{Buy,Grid}(t) + PeakLoad(t)* \\ PC * P_{Buy,Grid}(t) \quad \forall \quad t \in \{t^0, ..., t^h\}, t^0 \in \{1, ..., T\} \end{aligned} \tag{3.38}$$

  Since $PeakLoad(t)$ is unknown during scheduling, different representaions are tested to investigate the impact of each approach. First, the forecasted daily PL hour is used which creates a framework to avoid the most probable PL hour of each day and consequently the PL hour of the month. Other approaches then test the efficacy of the proposed forecast. A perfect knowledge of the system load is assumed and the actual monthly PL hour is also extracted to represent $PeakLoad(t)$. In order to determine the impact of daily PL versus the monthly PL, a comparison of scheduling results with actual PL hour information on both daily and monthly basis is done.

- *Distribution Charges*

  Distribution charges will be simply given by the following equation.

$$Cost_{Distribution}(t) = Service\_Charge * Distribution\_Billing(t) \quad \forall \quad t \in \{t^0, ..., t^h\}, t^0 \in \{1, ..., T\} \tag{3.39}$$

Revenue

The revenue in the scheduling algorithm also comes from selling energy to the grid on regular basis and monthly PL hour.

$$Revenue(t) = P_{Sell,Grid}(t) * Price_{Electricity}(t) + PeakLoad(t) * P_{Sell,Grid}(t) * PC \quad \forall \quad t \in \{t^0, ..., t^h\}, t^0 \in \{1, ..., T\} \tag{3.40}$$

Constraints

- *Power Balance*

  Power balance constraint ensures the reliable operation of the microgrid.

$$P_{Buy,Grid} + P_{Discharge}(t) + P_{PV}(t) + P_{MT}(t) = P_{Demand}(t) + P_{Sell,Grid}(t) + P_{Charge}(t) \quad \forall \quad t \in \{t^0, ..., t^h\}, t^0 \in \{1, ..., T\} \tag{3.41}$$

- *Power Exchange with the Grid*

  Power exchange with the grid must be less than or equal to the billing capacity.

$$0 \leq P_{Buy,Grid} \leq B_{Cap} \quad \forall \quad t \in \{t^0, ..., t^h\}, t^0 \in \{1, ..., T\} \tag{3.42}$$

$$0 \leq P_{Sell,Grid} \leq B_{Cap} \quad \forall \quad t \in \{t^0, ..., t^h\}, t^0 \in \{1, ..., T\} \tag{3.43}$$

- *Microturbine Output Limits*

  This constraint enables the partial dispatch of the MT along with efficiency considerations. Also, the maximum output of the MT must be less than the MT size which is found by sizing algorithm.

$$0.5 * Size_{MT} < P_{MT}(t) < Size_{MT} \quad \forall \quad t \in \{t^0,...,t^h\}, t^0 \in \{1,...,T\} \tag{3.44}$$

- *Battery Level Limits*

  Battery level must be less than the usable capacity of the battery.

$$0 < SOC(t+1) < DoD * Size_{Batt} \quad \forall \quad t \in \{t^0,...,t^h\}, t^0 \in \{1,...,T\} \tag{3.45}$$

Objective function

The hourly electricity bill includes operational costs minus revenues. The total bill for one year of microgrid operation is formulated by equation 3.47.

$$Bill(t) = Operational\_Costs(t) - Revenue(t) \quad \forall \quad t \in \{t^0,...,t^h\}, t^0 \in \{1,...,T\} \tag{3.46}$$

$$Total\_Bill = \sum_{t=1}^{T} Bill(t) \quad \forall \quad t \in \{t^0,...,t^h\}, t^0 \in \{1,...,T\} \tag{3.47}$$

The main objective function considered in this study is minimizing the electricity bill.

$$Objective = Minimize(Total\_Bill) \quad \forall \quad t \in \{t^0,...,t^h\}, t^0 \in \{1,...,T\} \tag{3.48}$$

The MILP problem for optimal sizing and MINLP problem for optimal scheduling were solved in GAMS/MATLAB enviornment using CPLEX and BARON solvers, respectively. GAMS®(License 24.3.3) and MATLAB®R2016b softwares were installed on a 64-bit HP laptop with Intel(R) Core(TM)i7-8550U @ 1.80GHz processor and 16 GB RAM to run the optimization models.

Chapter 4

Results and Discussion

This chapter represents the proposed methodology results for a campus microgrid. First, the case study is introduced and relative information is provided. Next, the sizing algorithm results with the available data are discussed. Moving forward to the scheduling algorithm, first the statistical results for PL hour forecast are given and finally, the scheduling results for the specified sizing scenarios are discussed.

4.1 Case Study - University of Calgary

The studied campus is *University of Calgary (UofC)* main campus located in the northwest area of Calgary in the province of Alberta. The University of Calgary was established in 1966, with 170,000+ alumni and more than 30,000 current students. The total main campus area is around 2.13 km^2. The maximum campus electricity consumption is approximately 14 MW. A base load of approximately 8 MW also exists which mostly accounts for research facilities and labs. Figure 4.1 shows the load profile of the main campus over one year. The different load profile in the very beginning and very end of the data set is due to the new year holidays which university is almost closed.

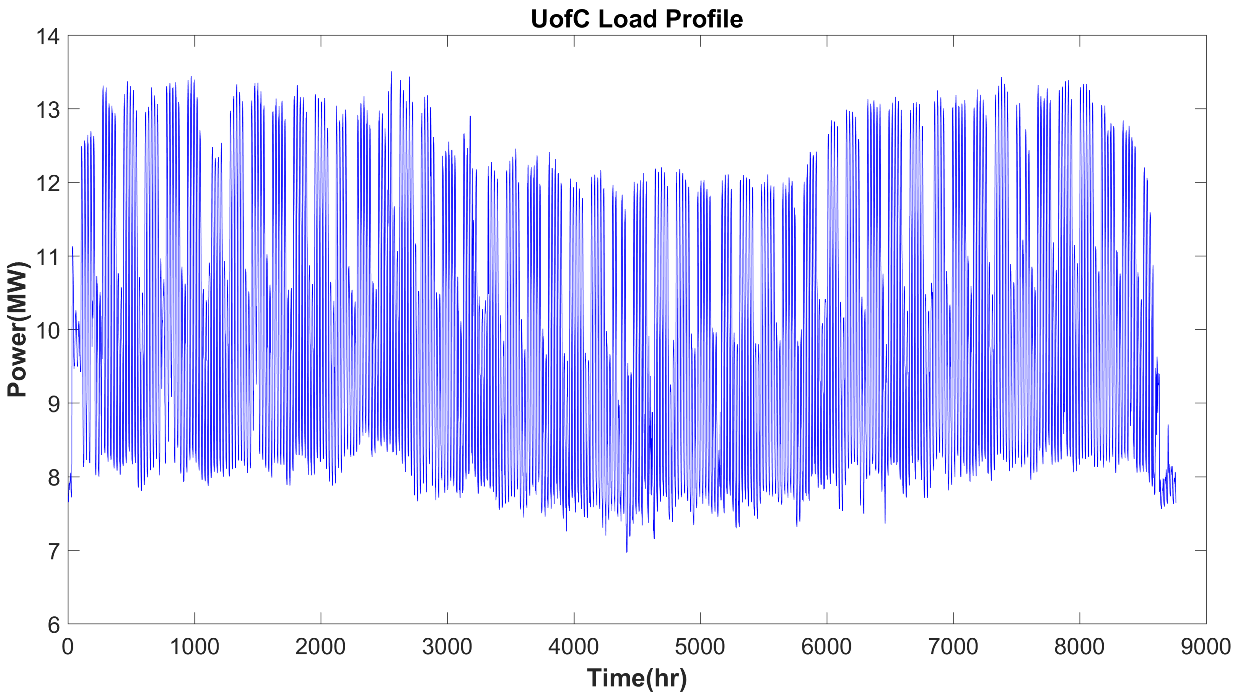

Figure 4.1: UofC 2015 total electricity demand

The UofC electricity consumption is obtained by adding the energy flowing in the university grid through six main feeders. However, there is also a *Central Heating and Cooling Plant (CHP)* onsite with 12 MW output. A part of this CHP plant output is consumed onsite and the metering data for the supplied buildings by CHP is not available. To resolve this issue, it is assumed that the CHP size is 8 MW with an average output of 6.5 MW. For security reasons, more detailed information regarding the electricity grid in campus can not be provided.

Figure 4.2 illustrates UofC map with all the information regarding the buildings and parking lots. Cogeneration plant is located in HP building denoted by the red arrow. Hence this is the location that MT is assumed to be installed. Battery energy storage is also assumed to be installed next to the cogeneration facility.

The area devoted to the placement of PV modules includes the rooftops of buildings. Also, by constructing ceilings for the parking lots these areas can also be used for installing PV modules.

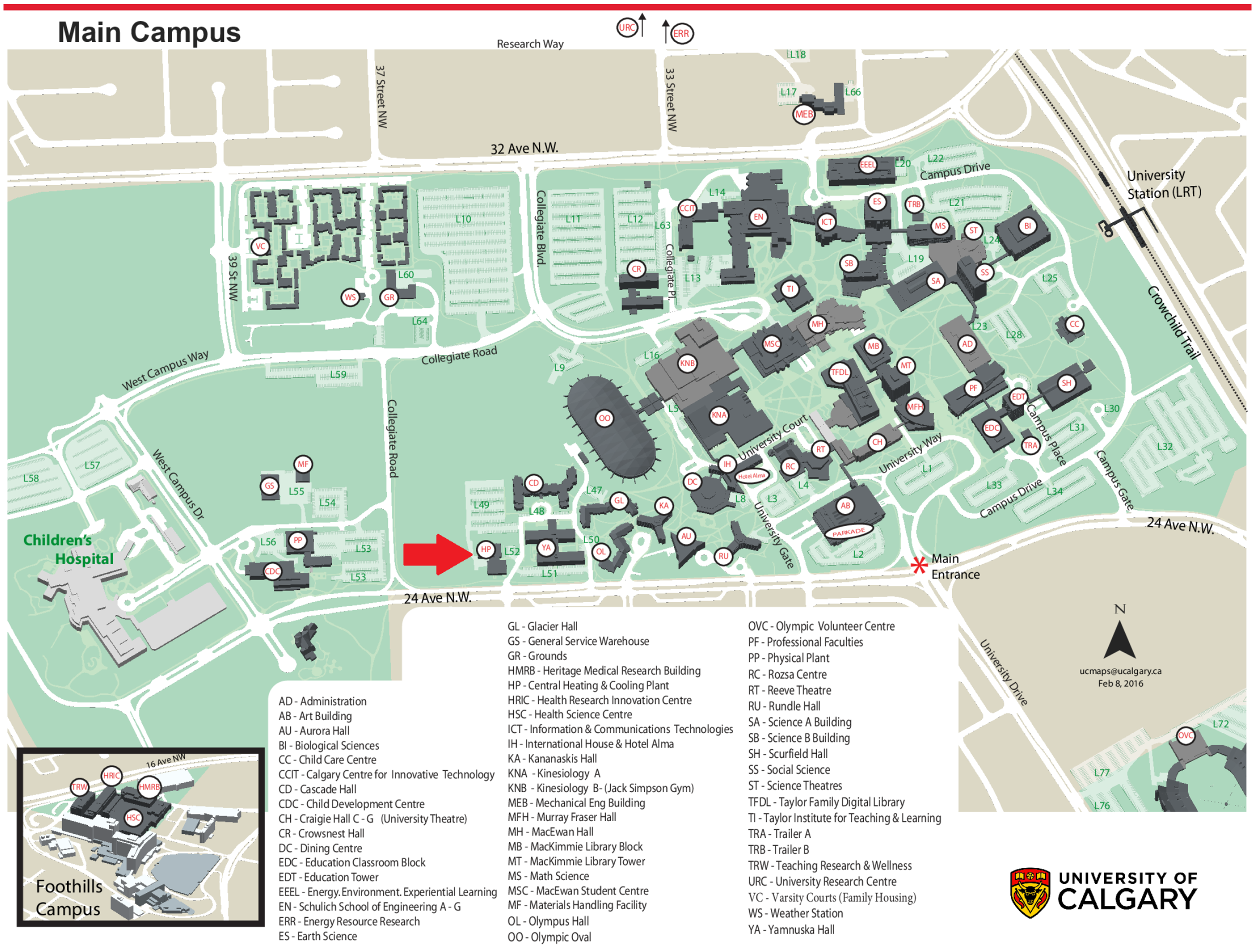

Figure 4.2: University of Calgary Map

4.2 Sizing Results

4.2.1 General Assumptions

In this section, the sizing results are provided. The designed scenarios will run under the general assumptions listed in table 4.1. General assumptions are the considered sizes and prices for purchasing, maintenance and operation of equipments. All prices are in Canadian dollars.

Parameter	Value
Capital Costs	PV $\frac{\$451.75}{Module}$ $Battery$ $\frac{\$450{,}000}{MWh}$ MT $\frac{\$2{,}100{,}000}{MW}$
Operational Costs	PV $\frac{\$6.08}{MWh}$ MT $\frac{\$12.60}{MWh}$
Natural Gas Volume of Fuel/Energy Ratio	$117.36\frac{m^3}{MWh}$
Natural Gas Emission /Volume of Fuel Ratio	$2.2\frac{kg}{m^3}$
Carbon Taxation	$0.031\frac{\$}{Kg}$
Annual Growth of Costs & Revenue	$OperationalCosts$ %4 $Revenue$ %4 $ElectricityBill$ %4
Discount Rate	%2.5
Service_Charge	$23\frac{\$}{day}$
Alberta Carbon Emission Factor	$0.82\frac{TonCO_2}{MWh}$

Table 4.1: General Assumptions

The purchasing cost of the battery is based on the values found in [144]. Purchasing costs and the specifications for the MT were provided by *Vergent Power Solutions* for a Low-Pressure Natural Gas Capston 200 kW microturbine. The aggregated cost for 1 MW units is used in this study. The operational costs of MT include the O&M costs, fuel purchasing costs and carbon taxation costs. O&M cost of MT is an average of values published by *National Institute of Building Sciences*. Natural gas fuel prices are a monthly average of historical prices reported in *Gas Alberta Inc* website. The CO_2 emission factor for natural gas accounts for the amount of CO_2 produced from burning 1 m^3 of natural gas and is obtained from *Natural Resources Canada*. Carbon taxation rates in Alberta are reported on the government website.

Two sources of CO_2 emissions is considered in this study. First, the carbon emissions directly produced from the installed microgrid and second, the carbon emissions of imported energy from the grid. Depending on the carbon intensity of primary electricity generation resources, each province has a specific emission factor. Alberta has the carbon emission factor of 0.82 Ton/MWh which is the highest emission factor for grid electricity in Canada.

Allesun Industries Inc in Canada provides cost of purchasing PV modules. The price reported for one module, includes the cost of the panel, inverter, racks, cable and *DC_AC* boxes in addition to the installation costs. The O&M costs used in this study are obtained from [145, 146].

Discount rates are based on the inflation rates reported by *Statistics Canada*. Rate DTS for years 2015 and 2017 listed in table 4.2 are published by *AESO*. The detailed discussion of all DTS components is given in section 1.1.4. Rate DTS is applied to all the scenarios evaluated in this study.

Clusters	Rate component	2015 Charge Rate	2017 Charge Rate
Bulk System Charge	Coincident Metered Demand	$ 9,305 /MW/month	$ 10,670 /MW/month
	Metered Energy	$1.09 /MWh	$1.25 /MWh
Local System Charge	Billing Capacity	$ 2,162 /MW/month	$ 2,356 /MW/month
	Metered Energy	$0.76 /MWh	$0.87 /MWh
Point of Delivery Charge	Substation fraction	$ 7,865 /month	$ 8,789 /month
	First (7.5 SF) MW of billing capacity	$ 3,184 /MW/month	$ 3,559 /MW/month
	Next (9.5 SF) MW of billing capacity	$ 1,994 /MW/month	$ 2,229 /MW/month
	Next (23 SF) MW of billing capacity	$ 1,391 /MW/month	$1,555 /MW/month
	all remaining MW of billing capacity	$ 901 /MW/month	$ 1,007 /MW/month
Operating reserve charge	Metered Energy	Pool Price * 6.41%	Pool Price * 6.99%
Tranmission Constraint	Metered Energy	$ 0 /MWh	$ 0.07 /MWh
Voltage Control Charge	Metered Energy	$ 0.05 /MWh	$ 0.07 /MWh

Table 4.2: Rate DTS for the years 2015 and 2017

4.2.2 Scenarios

Base case scenario

For the base case scenario, MT size and billing capacity are considered to be free variables in the optimization problem. However, a 20 MWh maximum size for battery is still considered. The microgrid is assumed to be transmission connected and the objective is to minimize electricity bill. Since the base case scenario is very general, other scenarios are designed to investigate the impact of regulations and limitations in the sizing project.

Case #1 : Reduced Carbon Emissions

Renewable energy and reduced carbon emissions are of the main motivations to microgrid projects. This case scenario aims to reduce the base case MT carbon emission by 50% since moving to zero carbon emission microgrid may not be instantly feasible for every microgrid owner in terms of both economical and also operational aspects. The rest of the parameters are considered to be the same as base case scenario.

Case #2 : Zero Carbon Emission

Many communities and campuses are on the way of shutting down all the fossil fuel energy production resources in longterm. This case scenario intends to investigate the optimal size and number of energy storage and PV modules in a carbon-free microgrid. Compared to the base case scenario, only the carbon emissions are forced to be zero for this evaluation.

Case #3 : Maximize Green Energy Resource Installation

The most economic operation is not the objective in every microgrid project. The third additional scenario takes into account environmental concerns and green energy production. This case is similar to the base case, but instead of minimizing the electricity bill, the optimizer maximizes the green energy installation. MT size and energy storage size are optimized accordingly.

Case #4 : Existing MT onsite

In the last additional scenario, sizing results are obtained considering the existing MT in the UofC campus. In this case, the MT size is set to 8 MW and the rest of microgrid components are optimized accordingly. To calculate the normal electricity bill prior to microgrid installation, MT output is considered to be 6.5 MW constantly while the rest of the energy demand will be bought from the grid. Similar to the base case, the objective of the microgrid is minimizing the electricity bill.

4.2.3 Sizing Results

In this section, sizing results for the proposed scenarios are provided and discussed. All the results are provided for years 2015 and 2017. In average, 2015 electricity prices are about 11 $\$/MWh$ higher than 2017 electricity prices. Also, according to Figure 4.3, 2015 electricity prices are more volatile than 2017 electricity prices in general. The volatility of prices profoundly impacts the microgrid operation and component sizes. Also, the effect of carbon taxation will be investigated by comparing results under taxation and ignoring it.

Economic results indicate that although 2017 electricity prices are lower than 2015 electricity prices in average, 2017 microgrid utility bill is higher for all the scenarios compared to the 2015 microgrid utility bill. This is due to the lower regular campus utility bill in low prices and consequently less savings available for being invested in purchasing microgrid components. Also, flat electricity prices result in less arbitrage opportunities and consequently lower revenues. In general, introducing carbon tax to all the scenarios makes the microgrid less profitable due to the higher operational costs.

In the Base Case scenario, there is no limitation on carbon emissions and the optimizer is free to choose the MT size and dispatch it frequently in order to minimize the electricity bill. No carbon taxation 2015 scenario is the most profitable case among all the scenarios. Introducing carbon tax to 2015 and 2017 scenarios results in a slightly smaller MT size, more number of PV modules and less carbon emissions while the maximum battery size is chosen. Although MT size has not reduced noticeably after carbon taxation is introduced, carbon emissions are decreased 15% and 27% for years 2015 and 2017, respectively. However, the energy bought from the grid has increased under carbon tax and according to electricity generation emission factor in Alberta, net CO_2 emissions from on site MT and grid does not vary much considering carbon tax. All sub-scenarios are profitable, while 2015 sub-scenarios are more profitable due to more available revenue streams from arbitrage opportunities.

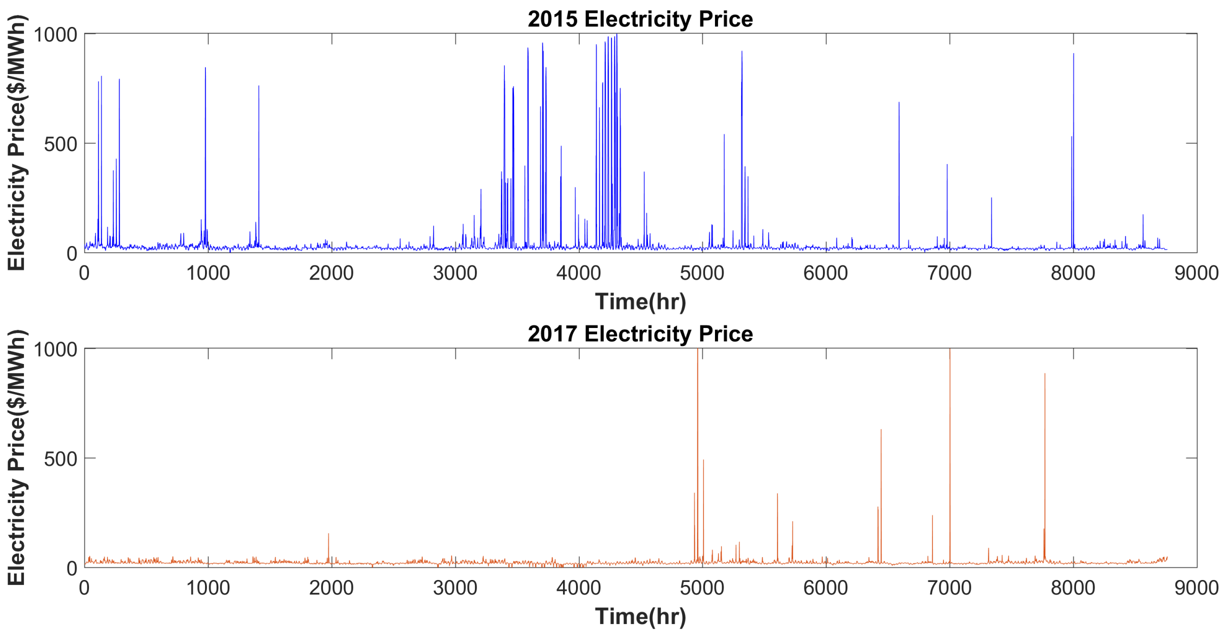

Figure 4.3: 2015 and 2017 Electricity Price Profiles

The economic results are provided in Table 4.3 followed by sizing results in Table 4.4. The difference between the regular bill and microgrid bill gives the annual savings on electricity bill which will be invested in capital costs of the microgrid components. A negative bill means that grid owes the microgrid and microgrid is profitable.

Scenario #1 cuts the MT carbon emissions in the base case scenarios by 50%. This constraint has encouraged the solar energy production and all sub-scenarios have reached the maximum number of PV modules that can be installed. The reduction in MT size is more for carbon taxed sub-scenarios. Since the maximum battery size is chosen and there is not more area for installing PV modules, the required energy must be supplied from the grid. The net CO_2 emissions has increased

Scenarios	***Year***	***Tax***	***NPV***	***Cost PV***	***Cost Batt***	***Cost MT***	***Revenue***	***Op Cost***	***Microgrid DTS***	***Microgrid Bill***	***Regular Bill***
BaseCase	2015	No	$-39.27MM	$31.41MM	$9.00MM	$31.08MM	$5.40MM	$3.46MM	$1.16MM	$-1.93MM	$5.47MM
		Yes	$-48.68MM	$31.63MM	$9.00MM	$30.41MM	$5.16MM	$3.82MM	$1.17MM	$-1.34MM	$5.47MM
	2017	No	$-59.54MM	$30.77MM	$9.00MM	$30.14MM	$4.12MM	$3.49MM	$1.25MM	$-0.62MM	$4.75MM
		Yes	$-68.00MM	$31.57MM	$9.00MM	$27.74MM	$3.75MM	$3.73MM	$1.30MM	$-0.01MM	$4.75MM
Case #1	2015	No	$-37.18MM	$34.47MM	$9.00MM	$18.84MM	$4.52MM	$3.01MM	$1.19MM	$-1.51MM	$5.47MM
		Yes	$-40.79MM	$34.47MM	$9.00MM	$15.90MM	$4.35MM	$3.23MM	$1.19MM	$-1.11MM	$5.47MM
	2017	No	$-57.92MM	$34.47MM	$9.00MM	$19.68MM	$3.41MM	$3.10MM	$1.33MM	$-0.31MM	$4.75MM
		Yes	$-59.81MM	$34.47MM	$9.00MM	$14.61MM	$3.12MM	$3.22MM	$1.30MM	$0.10MM	$4.75MM
Case #2	2015	No	$-33.65MM	$34.47MM	$9.00MM	$0MM	$3.33MM	$2.74MM	$1.20MM	$-0.58MM	$5.47MM
		Yes	$-33.65MM	$34.47MM	$9.00MM	$0MM	$3.33MM	$2.74MM	$1.20MM	$-0.58MM	$5.47MM
	2017	No	$-49.96MM	$34.47MM	$9.00MM	$0MM	$2.38MM	$2.77MM	$1.35MM	$0.39MM	$4.75MM
		Yes	$-49.96MM	$34.47MM	$9.00MM	$0MM	$2.38MM	$2.77MM	$1.35MM	$0.39MM	$4.75MM
Case #3	2015	No	$-91.13MM	$34.47MM	$1.99MM	$18.12MM	$3.40MM	$3.21MM	$1.36MM	$-0.19MM	$5.47MM
		Yes	$-91.13MM	$34.47MM	$1.99MM	$18.12MM	$3.40MM	$3.67MM	$1.36MM	$0.26MM	$5.47MM
	2017	No	$-79.03MM	$34.47MM	$2.37MM	$18.23MM	$2.23MM	$3.14MM	$1.38MM	$0.90MM	$4.75MM
		Yes	$-79.03MM	$34.47MM	$3.49MM	$18.02MM	$2.23MM	$3.58MM	$1.35MM	$1.34MM	$4.75MM
Case #4	2015	No	$-66.55MM	$34.47MM	$9.00MM	$0MM	$4.52MM	$3.04MM	$1.18MM	$-1.40MM	$4.00MM
		Yes	$-74.14MM	$34.47MM	$9.00MM	$0MM	$4.44MM	$3.29MM	$1.19MM	$-1.14MM	$4.45MM
	2017	No	$-61.56MM	$34.47MM	$9.00MM	$0MM	$3.36MM	$3.07MM	$1.28MM	$-0.28MM	$3.69MM
		Yes	$-69.14MM	$34.47MM	$9.00MM	$0MM	$3.26MM	$3.32MM	$1.30MM	$0.05MM	$4.15MM

Table 4.3: Economic Results for the Microgrid Design Algorithm

Scenarios	***Year***	***Tax***	n_{PV} ***modules***	***Green Installed***	***BattSize***	***MTSize***	***B-Cap***	***MT*** CO_2 ***Emissions***	***Grid*** CO_2 ***Emissions***	***Net*** CO_2 ***Emissions***
BaseCase	2015	No	69,538	22.59 MW	20.00 MW	14.80 MW	19.53 MW	20,910 Ton	5,176 Ton	26,086 Ton
		Yes	70,028	22.75 MW	20.00 MW	14.48 MW	19.53 MW	17,670 Ton	8,156 Ton	25,826 Ton
	2017	No	68,133	22.14 MW	20.00 MW	14.35 MW	19.45 MW	21,980 Ton	3,867 Ton	25,847 Ton
		Yes	69,902	22.71 MW	20.00 MW	13.20 MW	19.45 MW	16,010 Ton	10,070 Ton	26,080 Ton
Case #1	2015	No	76,310	24.80 MW	20.00 MW	8.97 MW	19.23 MW	10,450 Ton	20,208 Ton	30,658 Ton
		Yes	76,310	24.80 MW	20.00 MW	7.57 MW	19.02 MW	8,800 Ton	23,478 Ton	32,278 Ton
	2017	No	76,310	24.80 MW	20.00 MW	9.37 MW	19.68 MW	10,990 Ton	18,122 Ton	29,112 Ton
		Yes	76,310	24.80 MW	20.00 MW	6.96 MW	18.68 MW	8,005 Ton	23,733 Ton	31,738 Ton
Case #2	2015	No	76,310	24.80 MW	20.00 MW	0 MW	18.20 MW	0 Ton	41,832 Ton	41,832 Ton
		Yes	76,310	24.80 MW	20.00 MW	0 MW	18.20 MW	0 Ton	41,832 Ton	41,832 Ton
	2017	No	76,310	24.80 MW	20.00 MW	0 MW	18.68 MW	0 Ton	39,833 Ton	39,833 Ton
		Yes	76,310	24.80 MW	20.00 MW	0 MW	18.68 MW	0 Ton	39,833 Ton	39,833 Ton
Case #3	2015	No	76,310	24.80 MW	4.43 MW	8.63 MW	20.45 MW	15,080 Ton	2,938 Ton	18,018 Ton
		Yes	76,310	24.80 MW	4.43 MW	8.63 MW	20.45 MW	15,080 Ton	2,938 Ton	18,018 Ton
	2017	No	76,310	24.80 MW	5.28 MW	8.68 MW	20.52 MW	15,000 Ton	2,886 Ton	17,886 Ton
		Yes	76,310	24.80 MW	7.77 MW	8.58 MW	20.18 MW	14,840 Ton	3,088 Ton	17,928 Ton
Case #4	2015	No	76,310	24.80 MW	20.00 MW	8.00 MW	19.22 MW	12,310 Ton	16,231 Ton	28,541 Ton
		Yes	76,310	24.80 MW	20.00 MW	8.00 MW	19.14 MW	9,970 Ton	21,408 Ton	31,378 Ton
	2017	No	76,310	24.80 MW	20.00 MW	8.00 MW	18.88 MW	13,300 Ton	12,409 Ton	25,709 Ton
		Yes	76,310	24.80 MW	20.00 MW	8.00 MW	18.88 MW	9,880 Ton	20,003 Ton	29,883 Ton

Table 4.4: Sizing Results for the Microgrid Design Algorithm

around 20% in all sub-scenarios compared to their respective sub-scenarios in Base Case. Moreover, carbon taxation has increased net CO_2 emissions for both years. In terms of utility bill, there is a relatively small increase in electricity bill, however, sub-scenarios are still profitable in general.

Case #2 is the same as the base case, but the optimizer is forced to make the emissions zero. Since there are no carbon emissions, there is no impact by carbon taxation. So, results for 2015 and 2017 sub-scenarios has been replicated. The optimizer chose the maximum battery size and also the maximum number of PV modules allowed for both years. In other words, microgrid uses all the available resources to supply the demand while minimizing the utility bill. Interactions with the main grid are inevitable in this scenario and although microgrid has no direct carbon emissions, the net carbon emissions for both years is around 60% more than the Base Case net emissions. Compared to previous cases, utility bill has increased due to the reduced low cost on-site generation. 2015 sub-scenarios are still profitable under the forced constraint on carbon emissions.

Case #3 favours the environmental policies and green energy installation over economic aspects of microgrid planning. Hence, maximizing the green energy production is the objective of this scenario while there is no limitation on carbon emissions. The maximum number of allowed PV modules is chosen along with battery and MT. The MT size is similar to the base load of campus. For 2015, the results are replicated for the two sub-scenarios. Carbon taxation has encouraged the battery installation for 2017. The maximum battery size is not selected, because the selected battery size is able to fulfill the investments required for purchasing maximum number of PV modules. The relatively higher utility bill is a good indicative of the objective of this case. The energy bought from the grid has decreased due to smaller size of the battery and this reduction is reflected in the very low level of grid CO_2 emissions. This scenario has the lowest net CO_2 emissions among all the discussed scenarios.

Case #4 considers the existing MT at UofC campus. The MT size is set to 8 MW and the optimizer finds the battery size and number of PV modules accordingly. Regular bill for Case #4 sub-cases is less than other cases since 6.5 MW of the campus load is supplied by MT and only the remaining demand is bought from the grid. For all sub-scenarios, the maximum number of PV modules is selected along with the maximum battery size. In terms of carbon emissions, carbon taxation enforces a reduction in MT dispatch, however, it also results in increased power purchase from the main grid and consequently increased net carbon emissions. This scenario demonstrates that with the existing MT on campus and smart energy management strategies, profitable microgrids can be installed and maximum solar energy can be exploited.

Among all the scenarios discussed, maximized green energy production scenario seems more realistic and in line with the motivations of microgrid installation. First, in terms of the environmental impact, this scenario aims for maximum exploitation of renewable resources along with minimum carbon emissions among the studied scenarios. Also, MT installation is considered which is very beneficial for campus microgrids where supplying the heat accounts for a big share of energy consumption. So, upgrading the MT to co-generation facility is very beneficial. In general, the on-site MT is environmentally preferred due to the high emission factor for electricity generation in Alberta.

Based on DTS rates, noticeable charges apply to billing capacity in local system charge and point of delivery charge sections. Referring to the results, there is a 20 MWh battery, 15 MW MT and 22 MW of solar electricity generation but only around 14MW of demand on campus. Billing capacity restricts the amount of power exchange with the main grid in the optimization problem. In general, billing capacity column results imply the importance of optimal billing capacity for different sizes of microgrid components. These results also emphasize that higher bounds for energy exchange with the grid do not necessarily yield to lower electricity bills.

According to Figures 4.4 and 4.5 revenue out of selling power to the grid in the monthly PL hour is a primary source of revenue in all cases specifically for year 2017. For all the evaluated scenarios, the revenue out of selling energy to the grid for the year 2017, is reduced noticeably compared to the year 2015. The zero carbon emission and maximized green energy scenarios have the lowest revenues for both years which is resulted from lower on-site generation and smaller battery size, respectively.

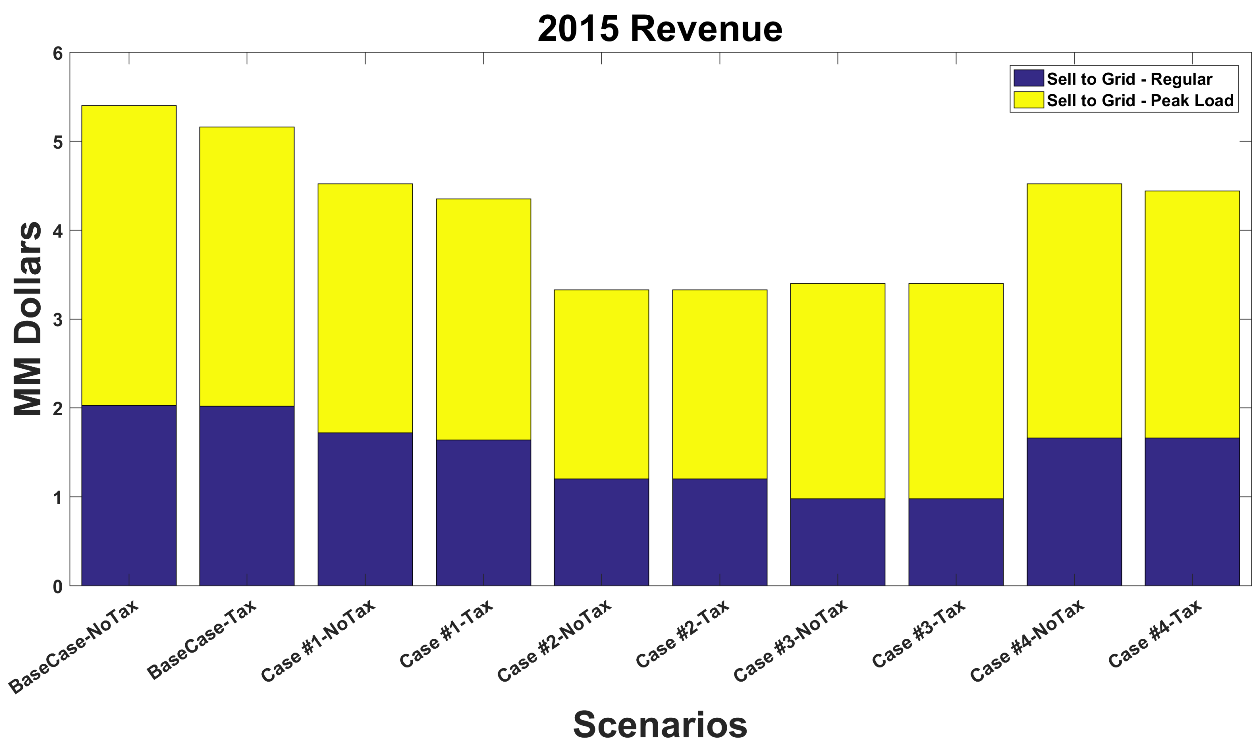

Figure 4.4: 2015 Revenues for the Scenarios Evaluated

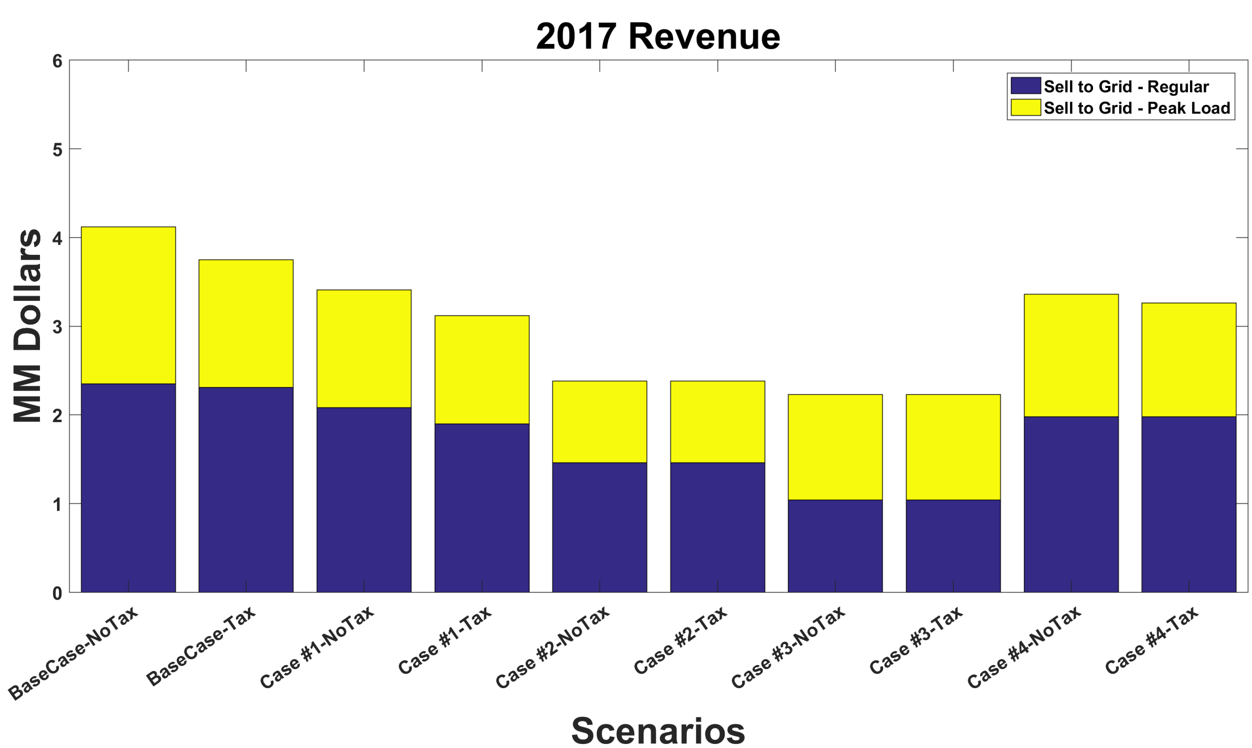

Figure 4.5: 2017 Revenues for the Scenarios Evaluated

Figures 4.6 and 4.7 give graphical representation of the DTS charges for years 2015 and 2017. In all the cases, DTS charges are reduced significantly except for the case that an existing microgrid is considered. Generally, DTS charges are higher for 2017 due to higher Rate DTS for 2017 compared to 2015. Usually, in scenarios under taxation, a higher DTS charge is resulted. This slight difference may be due to the lower MT size under carbon taxation scenarios which will eventually result in more power purchase from the grid and higher metered energy and consequent DTS charges.

Billing capacity is one of the major charges associated to DTS. It must be noted that billing capacity for all scenarios is comparably higher than the regular billing capacity when no microgrid is installed. In other words, although the optimally determined billing capacity increases the DTS charges, the optimal power exchange level with the grid reduces the utility bill overally.

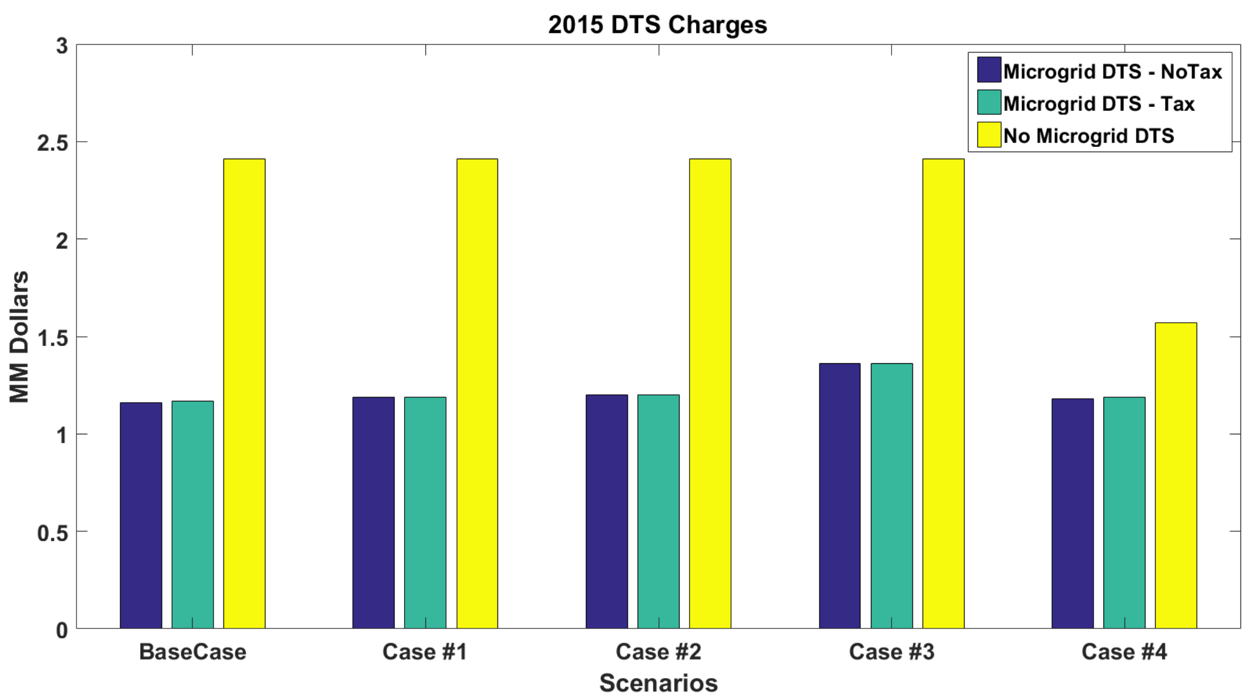

Figure 4.6: 2015 DTS Charges for Microgrid Scenarios Compared to Regular DTS Bill

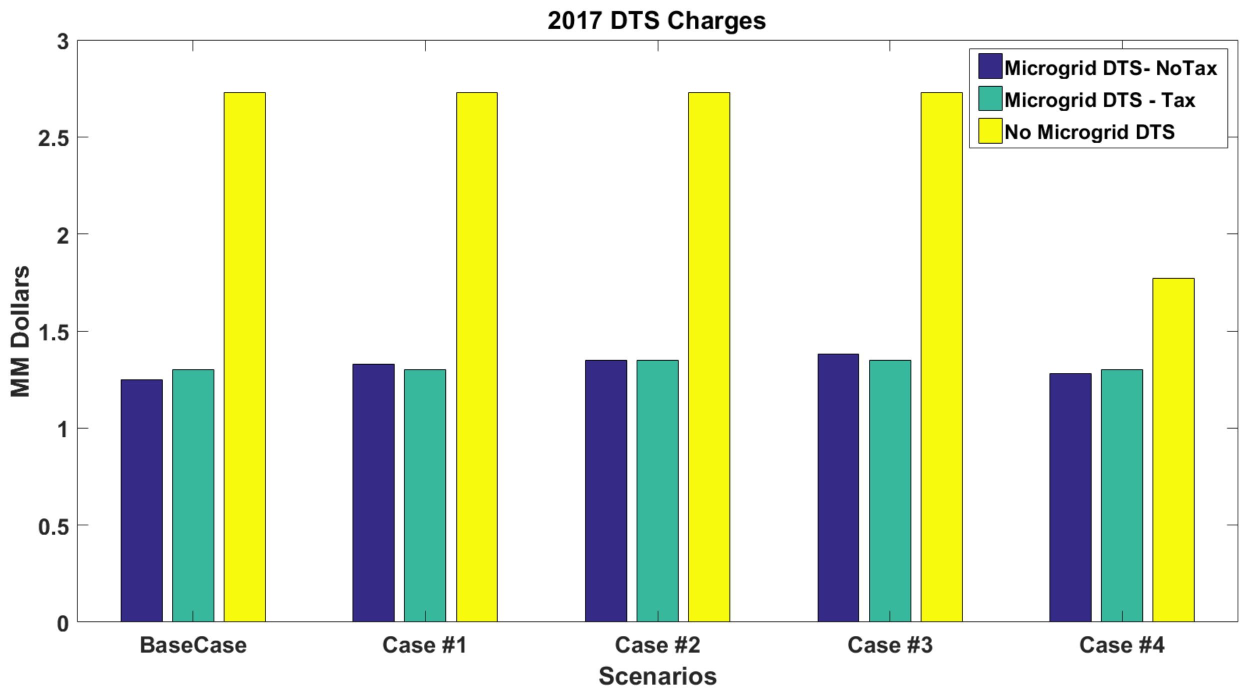

Figure 4.7: 2017 DTS Charges for Microgrid Scenarios Compared to Regular DTS Bill

4.3 Peak Load Hour Forecast

This section investigates the PL hour forecast results. As explained before, monthly PL hour usually has a repeating pattern. Table 4.5 introduces the most frequent daily PL hour for each month as the most probable monthly PL hour.

For each month PL hour estimation, all the calculations are applied to historical data for the same month. For example, for January, historical data column means previous load data for January up to four years in the past. Different amount of data is used in the statistical analysis to demonstrate the robust nature of daily PL hour. Results show that after using two years of past data, the PL hour does not change much as the historical data amount increase. Consequently, the accuracy of the results compared to the actual PL hour does not vary much for different amount of data.

Although, only taking the previous year load data could forecast PL hour with reasonable or even high accuracy, the PL hour forecast using four years of historical data is favoured in this study.

Year	***Historical Data***	***Jan***	***Feb***	***Mar***	***Apr***	***May***	***Jun***	***Jul***	***Aug***	***Sep***	***Oct***	***Nov***	***Dec***	***Accuracy***
2015	2014	18	19	21	12	12	17	17	17	17	20	18	18	58.3%
	2013 to 2014	18	19	21	12	17	17	17	17	17	20	18	18	66.6%
	2012 to 2014	18	19	21	12	17	17	17	17	17	20	18	18	66.6%
	2011 to 2014	18	19	21	12	17	17	17	17	17	20	18	18	66.6%
2016	2015	18	19	21	12	17	17	17	18	21	20	18	18	41.6%
	2014 to 2015	18	19	21	12	12	17	17	18	21	20	18	18	33.3%
	2013 to 2015	18	19	21	12	17	17	17	17	21	20	18	18	41.6%
	2012 to 2015	18	19	21	12	17	17	17	17	17	20	18	18	41.6%
2017	2016	18	19	20	12	17	17	17	17	21	20	18	18	75.0%
	2015 to 2016	18	19	21	12	17	17	17	18	21	20	18	18	58.3%
	2014 to 2016	18	19	21	12	17	17	17	18	21	20	18	18	58.3%
	2013 to 2016	18	19	21	12	17	17	17	17	21	20	18	18	66.6%

Table 4.5: Peak Load Hour Forecast Results

This is due to the fact that in general, more historical data represents the PL hour characteristics better.

PL governing factors are temperature, lighting hour, electricity price and after work hours. Usually, when people arrive home after work around 16:00 to 21:00, they will turn on heating or air conditioning, lights and other household appliances. This justifies the daily PL hour mostly happening between 16:00 and 21:00.

However, actual PL hour results show that PL does not always follow the reasoning mentioned above. Other factors such as electricity price can impact the load consumption significantly. When electricity price is low during on-peak hours (8:00 to 21:00), price sensitive industrial loads do not go offline leading to very high demands in hours other than the daily usual PL hour.

4.4 Optimal Scheduling - DRTO

The optimal sizes of microgrid components are imported to an efficient scheduling algorithm. The DRTO is done for years 2015 and 2017. Electricity prices, UofC campus demand and solar irradiation, are assumed to be known 4 hours in the future. All the parameters for operational costs and DTS rates are similar to the values used in the sizing algorithm. To avoid the coincident metered demand charge, the forecasted daily PL hours in section 4.3 and also perfect monthly PL hours are used and the efficiency of the proposed daily PL hour forecast is discussed.

4.4.1 Microgrid Operation Under Forecasted Daily Peak Load Hour

Microgrid Utility Bill Under Forecasted Daily Peak Load Hour

This section provides the electricity bill under various sizing scenarios evaluated. All results show the accumulated electricity bill over one year (8760 hours). At the monthly billing hour which is the ending hour of each month, constant charges affiliated with local system charge and point of delivery charge will take place. Moreover, at the monthly PL hour, there may be a step increase or decrease in the electricity bill depending on the accuracy of the daily PL hour forecast and available energy to be sold to the grid. The step decrease in the electricity bill is a result of selling energy to the grid in the monthly PL hour.

Figure 4.8 illustrates the electricity bill associated to four base case sub-scenarios. In all cases, taxation contributes to a higher electricity bill due to higher operational costs. Also, the slope of the electricity bill increase is higher in scenarios under taxation. This is due to the smaller size of MT and less internal generation. Although the Starting May to end of July, a steep reduction in utility bill is observed for 2015 sub-scenarios. This steep decrease in the bill is incited by very volatile and high electricity prices during the proposed hours which is coincident to the maximum solar energy production and higher export capacities. Revenues obtained by battery arbitrage operation also reduced the utility bill during volatile electricity prices period. 2017 utility bill is ever increasing except for the accurately forecasted monthly PL hours and also the month of August when volatile electricity prices are triggered.

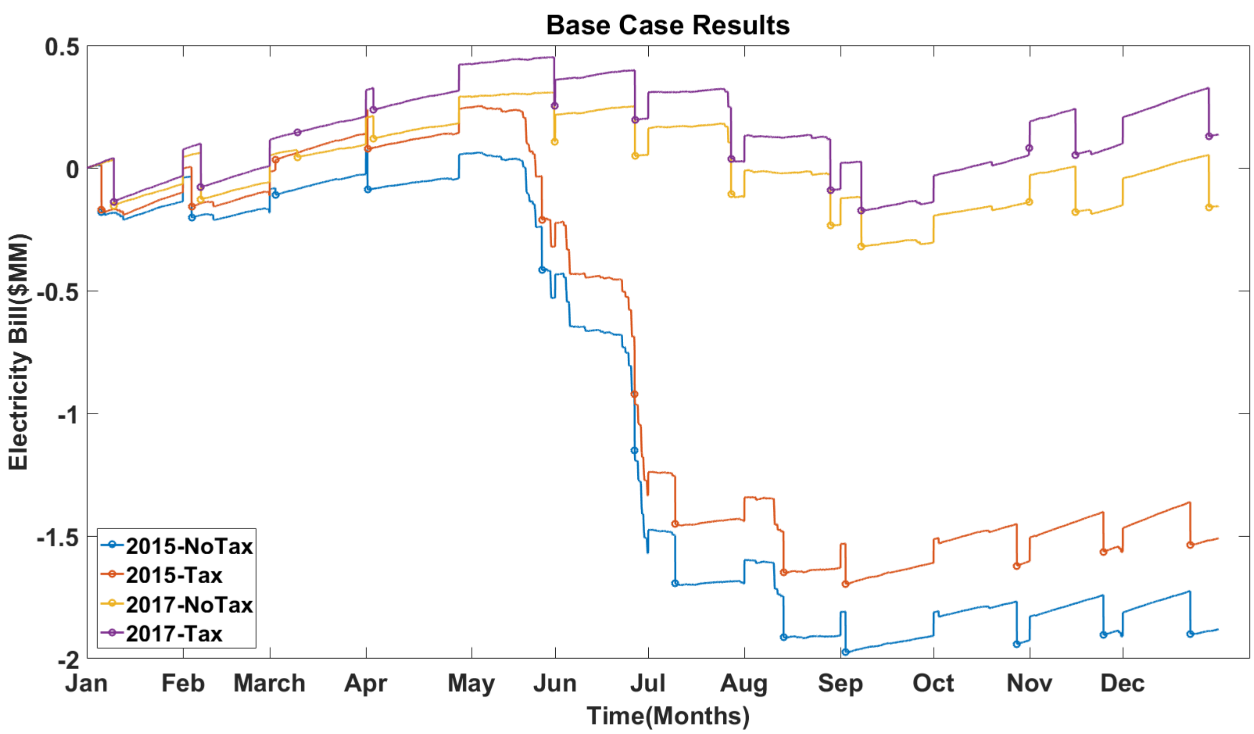

Figure 4.8: Utility Bill for Base Case

Figure 4.9 illustrates the scheduling results for Case #1 sub-scenarios. As discussed previously, this scenario cuts the carbon emissions in Base Case by 50%. The same trend as Base Case holds for Case #1 results; however, the electricity bill is increased for all sub-scenarios. This general increase is again addressed by the smaller MT size due to the carbon emission reduction.

The next results depicted in Figure 4.10 provide the electricity bill for Case #2 sub-scenarios. Since Case #2 forces the carbon emissions and accordingly MT size to zero, the sub-scenarios are narrated to two sub-scenarios based on years regardless of the carbon taxation. Loss of the dispatchable on-site generation by MT resulted in smaller step reductions in accurately forecasted PL hour compared to the Base Case and consequently higher utility bill for both years is obtained.

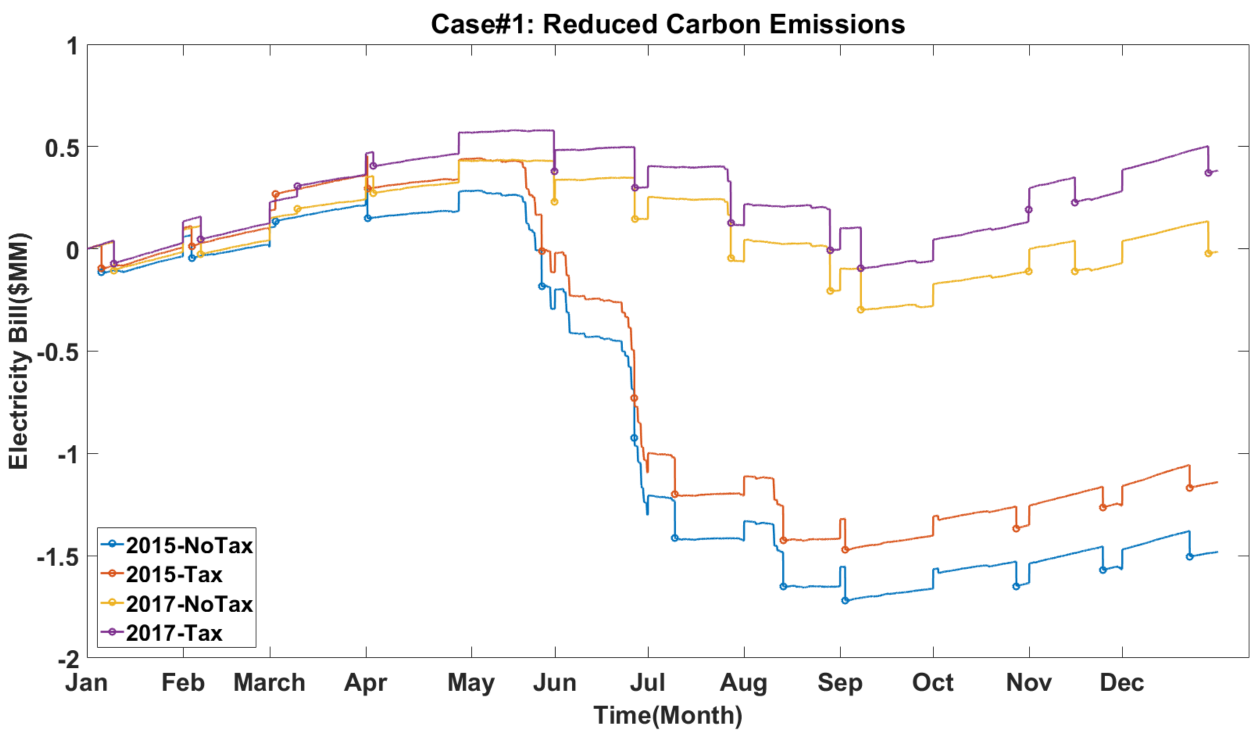

Figure 4.9: Utility Bill for Case1 : Reduced Carbon Emissions

Figure 4.11 demonstrates the electricity bill for Case #3 sub-scenarios. The objective of sizing algorithm is to maximize the green energy production for case #3. Whereof the 2015 sub-scenarios acquire the same size of microgrid components regardless of the carbon taxation, the utility bill is higher for the taxed sub-scenario due to the higher operational costs. It is observed that 2015 scenarios could be profitable although the environmental concerns are prioritized.

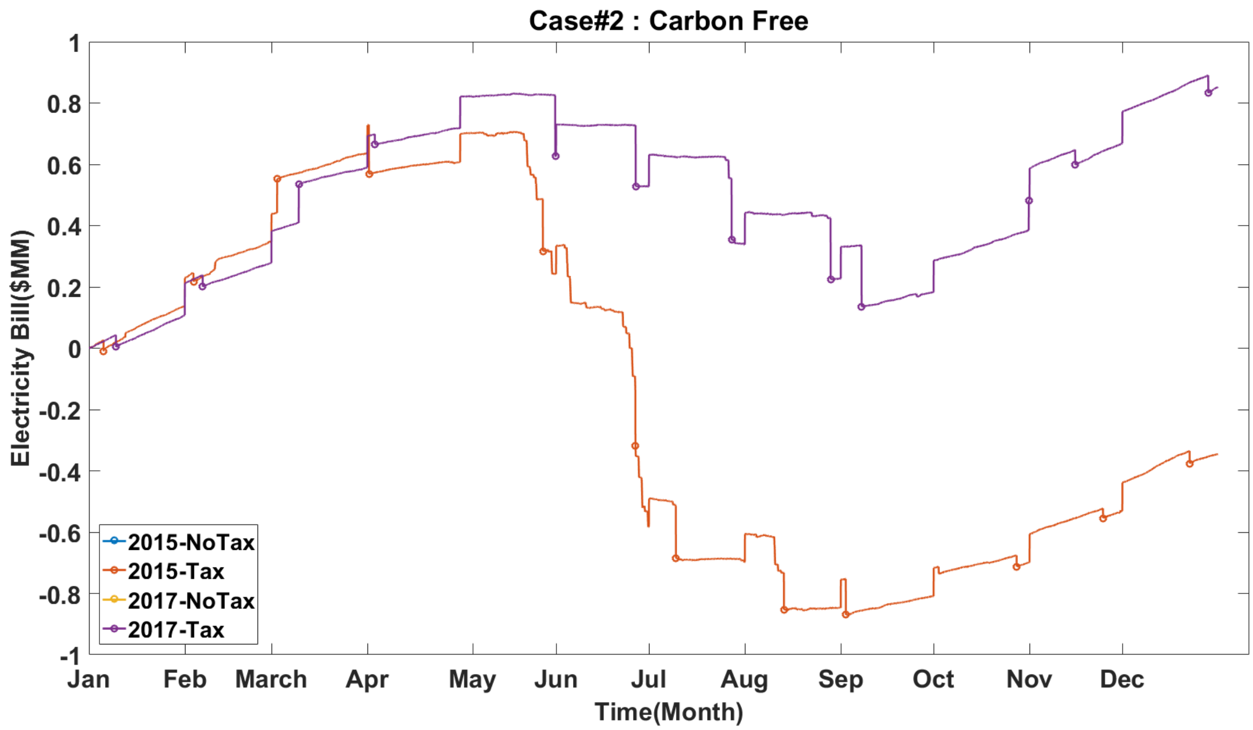

Figure 4.10: Utility Bill for Case2 : Zero Carbon Emissions

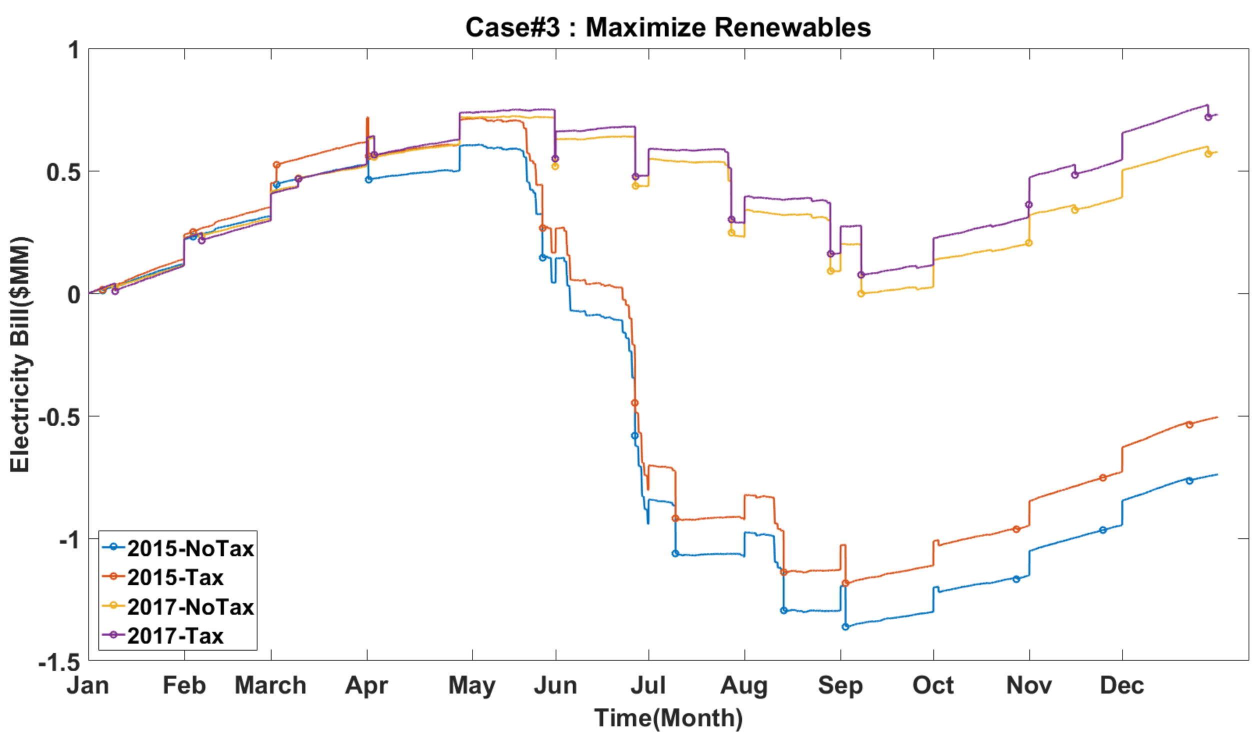

Figure 4.11: Utility Bill for Case3 : Maximize Green Energy Resource Installation

The scheduling results for the last case is depicted in Figure 4.12. Case #4 minimizes the electricity bill based on an existing MT at UofC campus and accordingly optimized size and number of other microgrid components and parameters. The electricity bill trends for the same year sub-scenarios are very similar, however carbon taxation induced a higher MT operational cost and therefore less frequently dispatching of MT. Similar to previously discussed scenarios, a steep reduction in 2015 electricity bills occur form May to August along of high and volatile electricity prices.

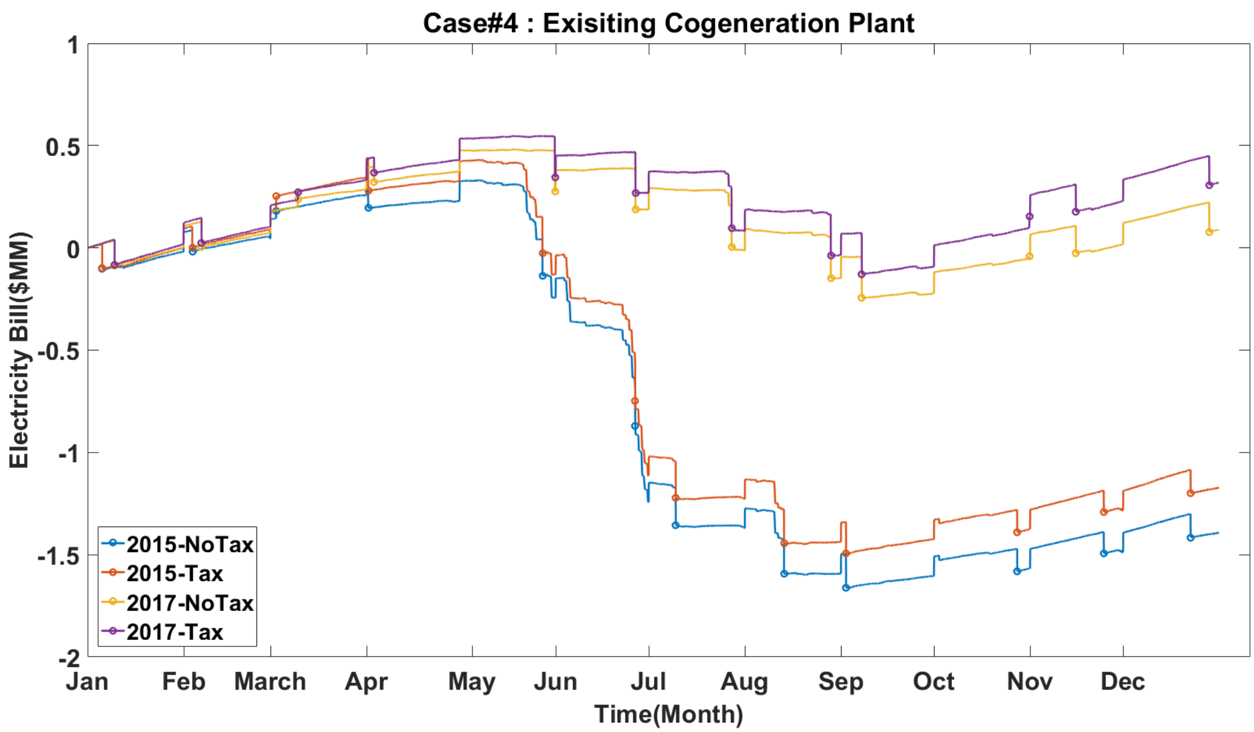

Figure 4.12: Utility Bill for Case4 : Existing MT Onsite

Optimal Operation of Microgrid Components

This section discusses the optimal policies for microgrid components and also exchanged power with the main grid. The Base Case scenario results are shown for two specific days in 2015 and 2017. To investigate the operation of microgrid in monthly PL hour two specific days are selected. The monthly PL occurrence day in the month of July is the first sample while the PL is correctly forecasted. Also, the PL occurrence day in March is chosen to discuss the operation of microgrid when PL hour is not correctly forecasted.

The operation of battery depicted in Figure 4.13 shows that in winter months battery is dispatched more frequently. This is justified by the less solar irradiation and duration in cold months and consequently less solar power generation. hence, the discharged energy from the battery is the primary source of energy sold to the grid in cold months . While in warmer months, the excess solar power generation is sold to the grid and battery is dispatched less regularly. Although, during the high and volatile electricity prices in May, June and July the battery operation has increased.

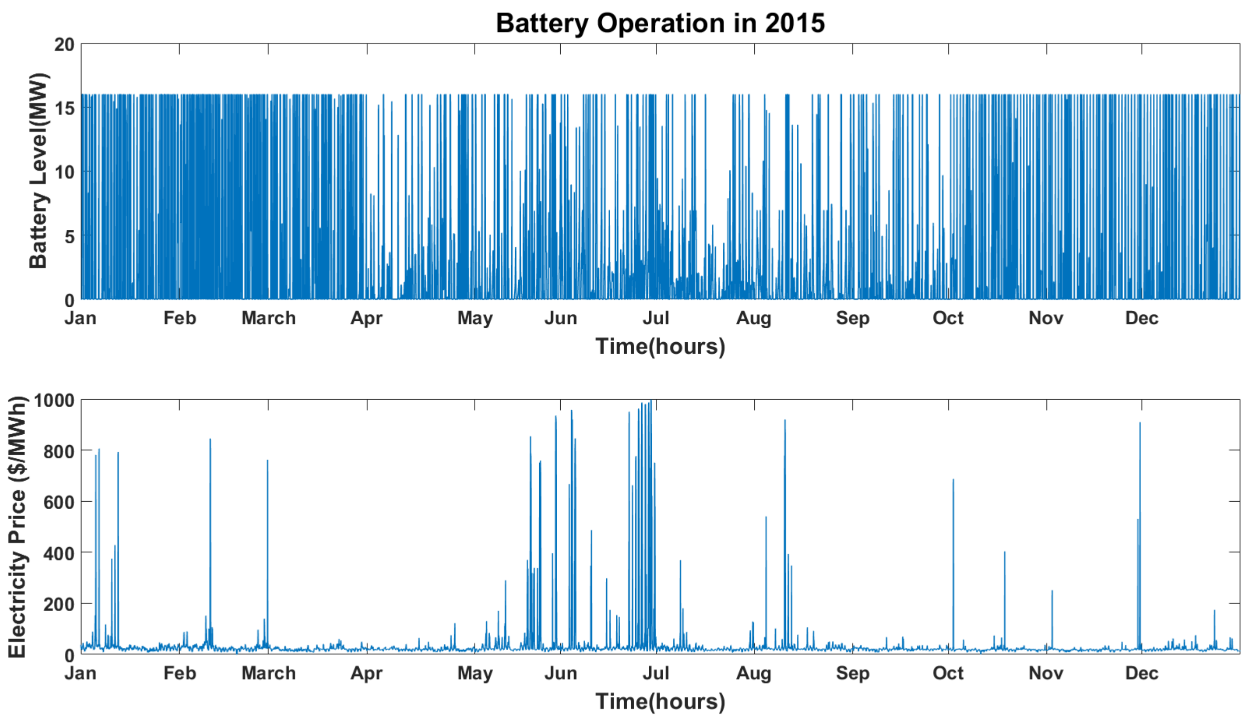

Figure 4.13: Battery Operation in Year 2015

The detailed operation of microgrid components for March 2nd, 2015 is shown in Figure 4.14 along with respective electricity prices. In general, during the sun hours microgrid sells the excess on-site generation to the main grid. In this month, hour 20:00 is the actual monthly Pl hour, while the proposed forecast estimated hour 21:00. In the forecasted PL hour microgrid avoids buying energy and sells the surplus energy from the MT and battery to the main grid. Although the PL hour revenue is missed, the electricity price relative to forecasted PL hour is high and compensates a part of coincident metered demand charge. It also must be noted that the electricity price for forecasted PL hour is higher than the actual PL hour, which indicates that electricity price and bulk system demand are not fully correlated.

Figure 4.15 gives the optimal policies of microgrid components for July 9th, 2015. In the specified day, monthly PL hour occurs at hour 17:00 similar to the proposed forecast result. Due to the longer hours of solar irradiation, more energy is sold to the grid, however the power exchange is capped to the billing capacity. The remaining produced energy is charged to the battery. At hour 8:00 electricity prices start increasing, hence, battery is charged at 7:00 with the energy bought from the grid. MT is generally dispatched at 8MW, but the dispatch level increased at the high electricity price triggered at 13:00 and also hour 22:00 when the solar energy is declining and electricity price is relatively high.

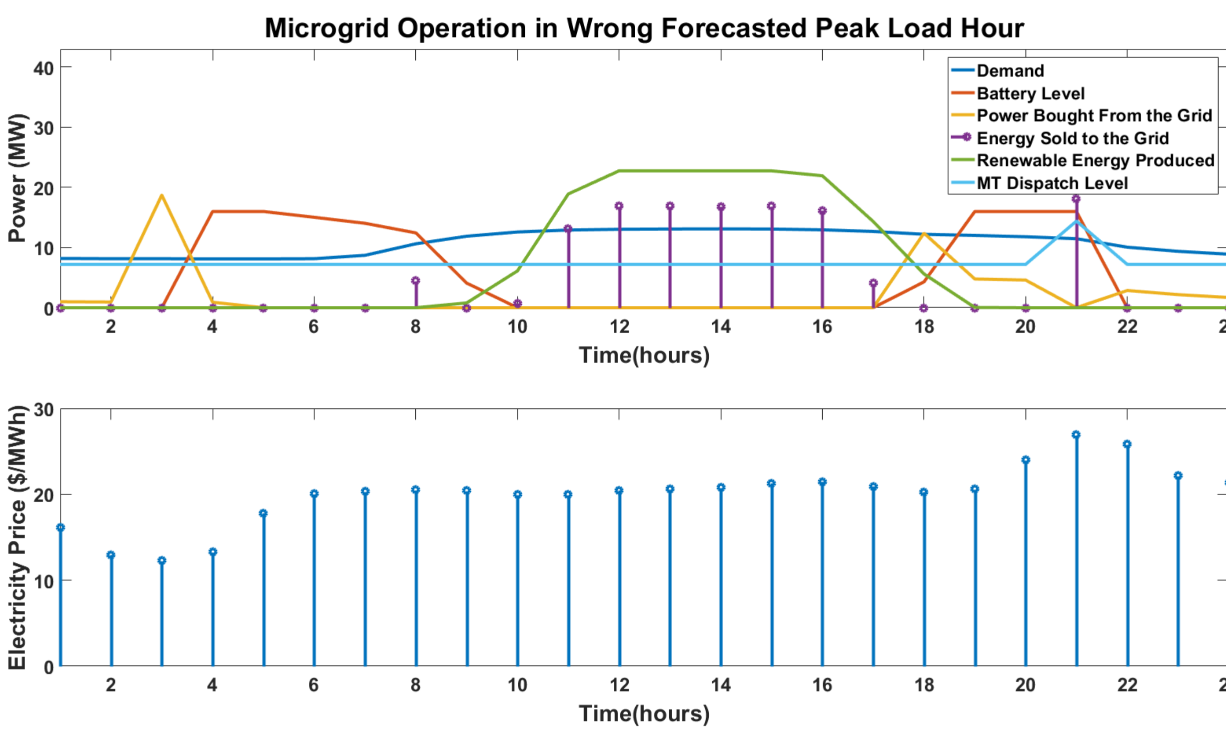

Figure 4.14: Microgrid Operation on March 2nd, 2015

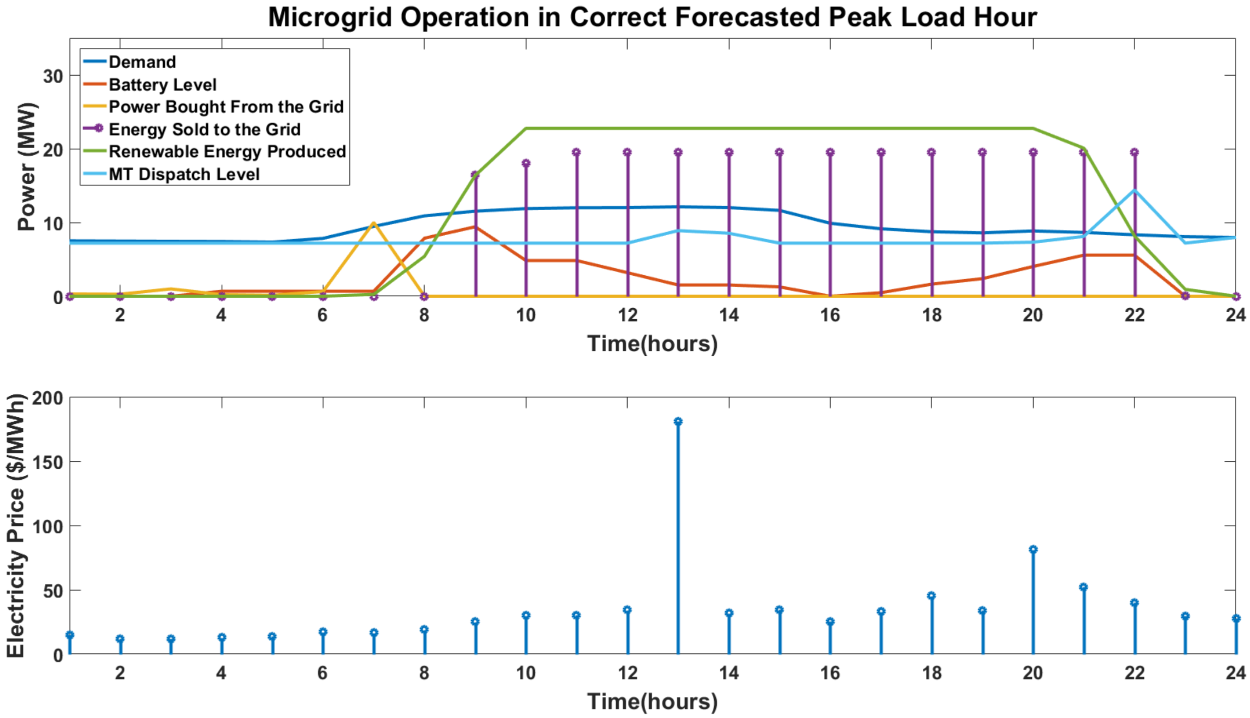

Figure 4.15: Microgrid Operation on July 9th, 2015

The battery operation for year 2017 is shown in Figure 4.16 which follows the same reasoning for year 2015.

Microgrid operation under wrong forecasted PL hour is given by 4.17 for March 9th, 2017. Again the monthly PL hour is 20:00 while the forecasted PL hour considers hour 21:00. Due to this error, battery retains its energy for hour 21:00 to sell it to the grid. However, the relative high electricity price for hour 20:00 results in avoiding power purchase from the grid. It is also observed that at hour 7:00, a high electricity price is triggered and battery is fully discharged.

In Figure 4.18, microgrid operates optimally under the accurate forecasted PL hour on July 27th, 2017. The power purchase from the grid is minimized to zero during the sun hours and all the excess energy capped to the billing capacity is sold to the grid. Although high electricity prices are triggered for hours 11:00 and 12:00, battery is not discharged and all the energy sold is from solar energy and MT.

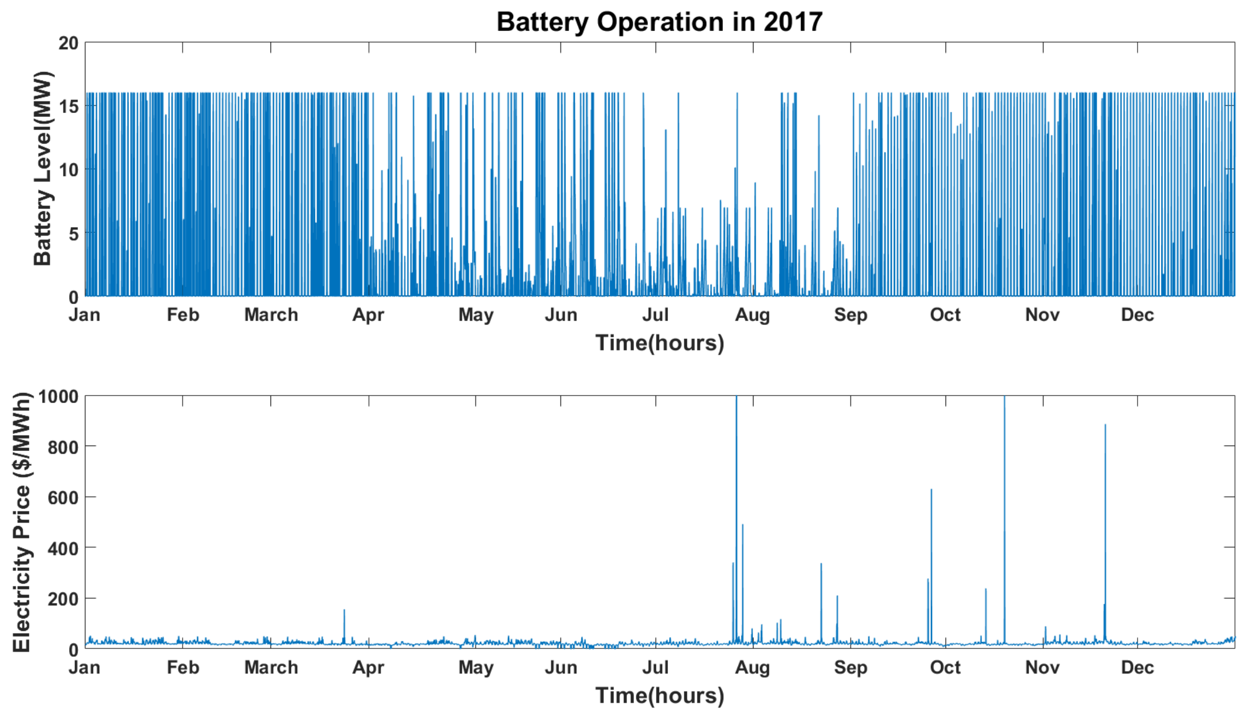

Figure 4.16: Battery Operation in Year 2017

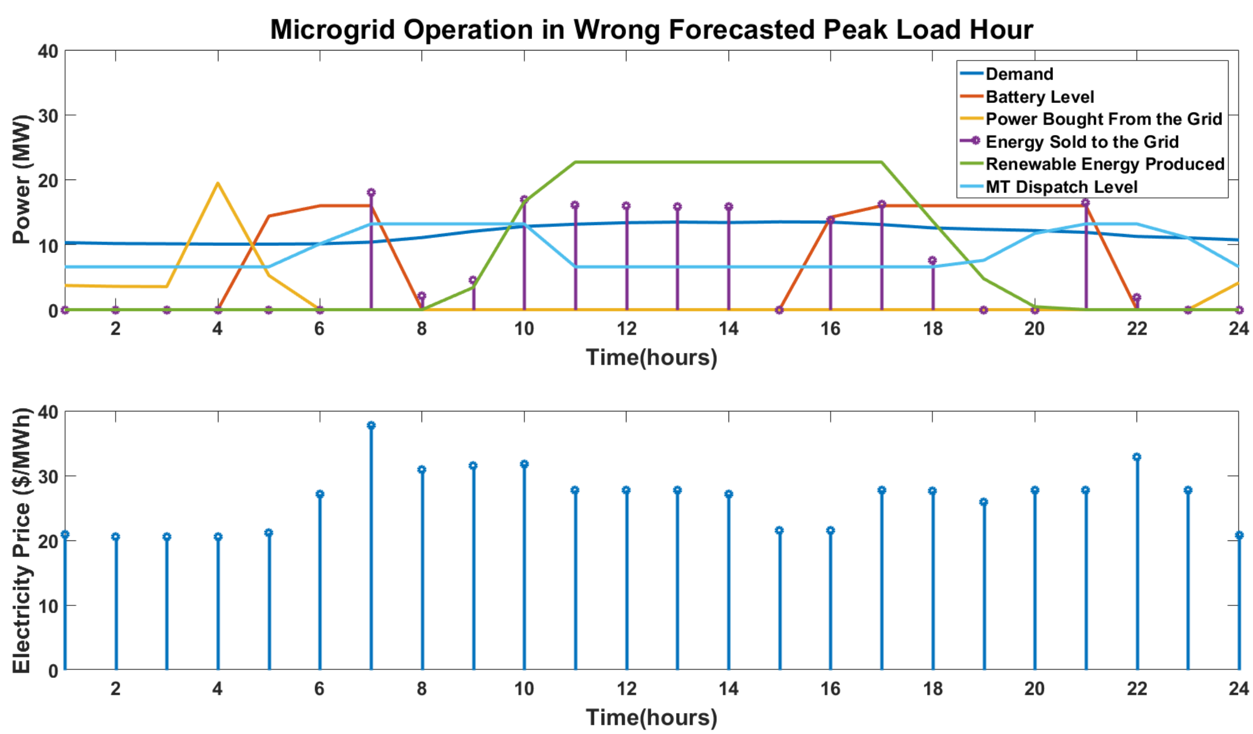

Figure 4.17: Microgrid Operation on March 9th, 2017

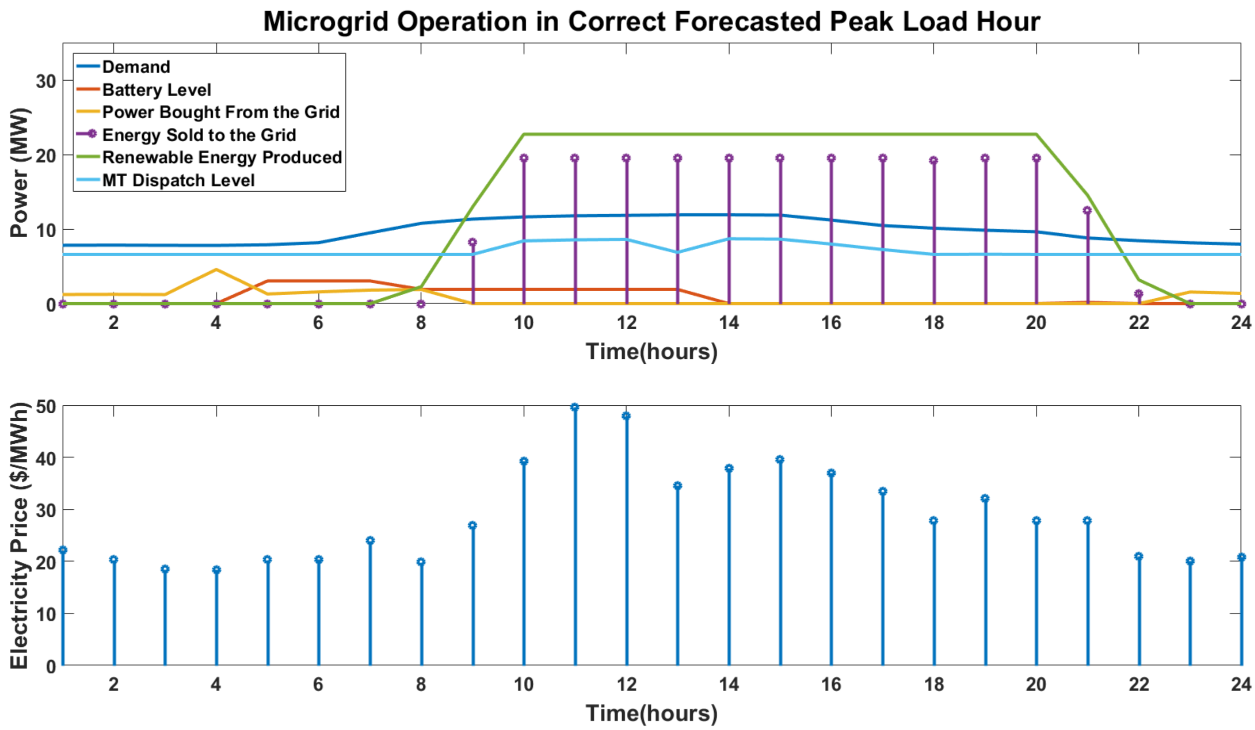

Figure 4.18: Microgrid Operation on July 27th, 2017

4.4.2 Daily Peak Load Hour Forecast Error Impact on Electricity Bill

In this section, the utility bills using actual monthly PL hour and also forecasted daily PL hour are provided in Figure 4.19 for Base Case sub-scenarios. Results show although the daily PL hour forecast accuracy for years 2015 and 2017 is 66.66% similarly, the difference in electricity bills using the daily PL hour forecast and perfectly known monthly PL hour is higher for 2017 compared to 2015. The level of internal power generation can explain this. Based on sizing results, 2015 sub-scenarios have more installed PV modules and also bigger MT sizes. Hence, more resources are available for selling energy to the grid at the accurately forecasted PL hours. Consequently, these revenues flattened the forecast error impact for 2015. In addition, 2017 has a higher rate for coincident metered demand charge, hence the forecast error induced a higher utility bill. Also, for scenarios under taxation a relatively higher utility bill is eventuated. This difference is also due to the smaller MT size and dispatch level which leads to lower revenues in PL hour.

nevertheless, the coincident metered demand charges are reduced 66.66% for both years and considering the DTS revenues, the proposed forecast has noticeably reduced the overall utility bill.

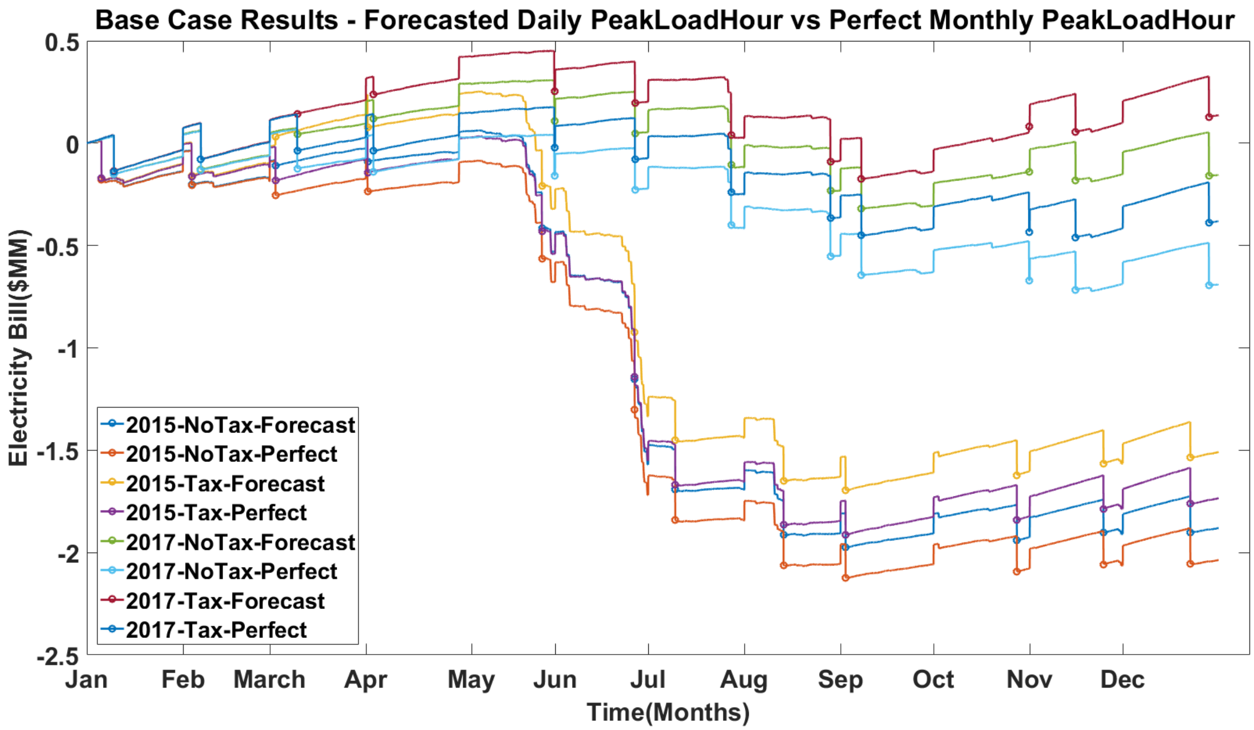

Figure 4.19: Efficiency of the Forecasted Daily Peak Load Hour for Base Case Scenarios

4.4.3 Daily Peak Load hour vs Monthly Peak Load Hour Electricity Bill

Predicting the hour of monthly PL may be possible to an accuracy, but the monthly PL hour is a posteriori event and forecasting the exact day of PL occurrence is impossible with the available data. This may impact the scheduling results since for 29 or 30 days of each month, a wrong assumption associated with coincident metered demand charge is impacting the optimal microgrid policies. In order to quantify the effect of daily PL hour versus monthly PL hour, two approaches have been investigated.

In the first approach, only the PL hour is assumed to be perfectly known. Hence, the PL hour is assumed to happen every day and the optimal policies are found resulting in the provided electricity bills in Figure 4.20. Alternatively, in the next approach, the exact day and hour of monthly

PL are assumed to be known and the optimal policies are found accordingly. The difference of the respective sub-scenarios quantifies the deficiency of daily PL hour forecast compared to the perfectly known monthly PL hour.

It is observed that the difference is negligible since the PL hour generally happens in the evening hours when the electricity prices are relatively high. Hence, the wrong assumption regarding the PL occurrence does not impact the optimal operation negatively.

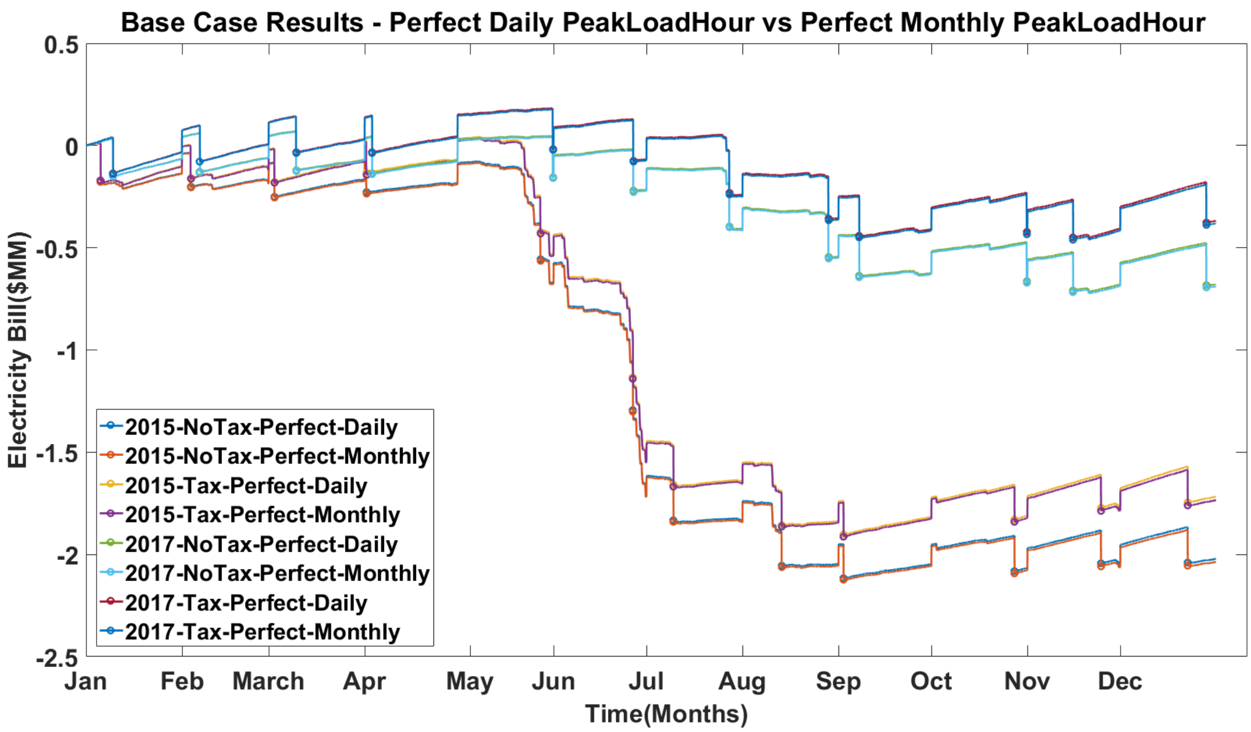

Figure 4.20: Impact of the Wrong Assumption on Monthly Peak Load Hour

Chapter 5

Conclusion and Recommendations

5.1 Conclusion

The evermore growing global electricity demand, international efforts for GHG emissions reduction and the necessity for green energy production along with technological advancement, has led to the move toward decentralized power systems. Microgrids have emerged as the best possible way to exploit the benefits of distributed generation resources. This hybrid structure comprising of wind turbines, PV panels, microturbines and batteries ensures the reliable and efficient supply of the demand. One of the major issues associated with microgrid projects is the interactions with the main grid regarding energy exchange and also receiving transmission services. This is the first time that transmission charges are implemented in the design and operation of microgrid projects. Compared to energy-only approaches, this study considers the electricity bill more realistically. Moreover, the transmission charges such as billing capacity and coincident metered demand charge are minimized.

The focus of this study is on campus/institutional microgrids. This tight geographical category of microgrids are usually placed in urban areas where the implementation of DERs such as wind turbines are impossible due to social, environmental and technological policies. Also, the installation of PV panels is bounded with the available area. Due to the limitations of renewable energy resources, on-site green energy production may not be able to supply all the demand. Hence, power exchange with the main grid is very crucial. The case study investigated in this thesis is University of Calgary main campus located in the northwest area of Calgary.

The optimal sizing and scheduling of the proposed microgrid are accomplished by implementing a two-stage optimization algorithm. In the first stage of the problem, the optimal number and size of DERs including PV panels, microturbine and battery and billing capacity are found considering the transmission service parameters. The economic assessment of installed DERs, power exchange and transmission charges are also acquired. This MIP model was solved for different scenarios to explore the impact of reduced CO_2 emissions, maximum green energy production and electricity pool prices on the final electricity bill. Moreover, installing a microgrid considering the existing microturbine in the University of Calgary main campus is considered.

The assessment of optimal sizing problem demonstrates that although 2017 electricity prices are less than 2015 electricity prices in general, 2017 scenarios resulted in higher utility bill compared to the respective 2015 scenarios. Moreover, introducing carbon taxation resulted in smaller MT size, lower CO_2 emissions, higher operational costs and lower profit in all the evaluated scenarios. The evaluation of DTS charges proves that implementation of transmission service parameters has significantly reduced the DTS charges. Also, revenues obtained in monthly PL hour, account for the primary revenue stream in most of the evaluated scenarios.

In the next stage of the optimization problem, the sizing results are fed to a DRTO algorithm designed for the optimal operation of the microgrid components. Load, solar irradiation and electricity prices are assumed to be perfectly known. Daily PL hour forecast by statistical analysis of historical bulk system load data, demonstrates up to 75% accuracy. The scheduling results confirm that under the optimal sizes of components, microgrid have enough resources to not only avoid coincident metered demand charge but also sell energy to the grid and make revenue. Comparison of the utility bill under daily PL hour forecast and actual monthly PL hour, affirm the efficacy of the proposed forecast. Moreover, the electricity bill profile under 2015 and 2017 prices demonstrates that predictive energy management strategies enable the microgrid to take advantage of high electricity prices and reduce the electricity bill.

Overall, this novel strategy introduces transmission service charges as another potential benefit of microgrid projects to reduce the electricity bill. The optimal sizing methodology allows the consideration of economic and environmental objectives based on the priorities of the microgrid owner. The sophisticated proposed scheduling algorithm confirms the effectuality of sizing results. It is also concluded that University of Calgary has enough resources to install profitable microgrids.

5.2 Recommendations and Future Work

As regards the study proposed in this thesis is based on perfect knowledge on stochastic variables including demand, solar irradiation, natural gas prices and most importantly, electricity prices, future work may be extended to develop forecasting methods for the aforementioned stochastic variables. Forecasts are specifically required in optimal scheduling of the energy storage.

Moreover, the MT considered in the design and operation of the proposed microgrid is used only for power generation. Since the buildings in campuses are located very closely and considering the extreme cold weather in North America, combined heat and power(CHP) operation of the MT would be very efficient.

Furthermore, all the data, policies and tariffs in this study are based on the Alberta electricity market. It would be interesting to consider the impact of microgrid projects on transmission charges in other deregulated market environments.

Bibliography

[1] IEA, "Key world energy statistics," *International Energy Agency: Paris, France*, 2017. [Online]. Available: https://www.iea.org/publications/freepublications/publication/KeyWorld2017.pdf

[2] EIA, "International Energy Outlook 2017," *Energy Information Administration*, 2017. [Online]. Available: https://www.eia.gov/outlooks/ieo/pdf/0484(2017).pdf

[3] IEA, "World Energy Outlook 2017," *International Energy Agency: Paris, France*, 2017. [Online]. Available: https://www.oecd-ilibrary.org/content/publication/weo-2017-en

[4] F.-Y. Liang, M. Ryvak, S. Sayeed, and N. Zhao, "The role of natural gas as a primary fuel in the near future, including comparisons of acquisition, transmission and waste handling costs of as with competitive alternatives," *Chemistry Central Journal*, vol. 6, no. S1, p. S4, 2012.

[5] N. R. Canada, "Energy Fact Book 2018-2019," 2018. [Online]. Available: https://www.nrcan.gc.ca/sites/www.nrcan.gc.ca/files/energy/pdf/energy-factbook-oct2-2018%20(1).pdf

[6] UNFCCC. Conference of the Parties (COP), "Paris Climate Change Conference-November 2015, COP 21," *Adoption of the Paris Agreement. Proposal by the President.*, vol. 21932, no. December, p. 32, 2015. [Online]. Available: http://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf

[7] G. o. Canada, *Canada's mid-century long-term low-greenhouse gas development strategy*, 2016. [Online]. Available: https://unfccc.int/files/focus/long-term_strategies/application/pdf/canadas_mid-century_long-term_strategy.pdf

[8] G. o. Canada, *Pan-Canadian Framework on Clean Growth and Climate Change : Canada's plan to address climate change and grow the economy*, 2016. [Online]. Available: https://www.canada.ca/en/services/environment/weather/climatechange/pan-canadian-framework/climate-change-plan.html

[9] A. Leach, A. Adams, S. Cairns, L. Coady, G. Lambert, "Climate Leadership - Report to Minister," 2015. [Online]. Available: https://www.alberta.ca/documents/climate/climate-leadership-report-to-minister.pdf

[10] G. o. Canada, *Overview of Reported 2015 Emissions*, 2016. [Online]. Available: http://www.ec.gc.ca/ges-ghg/82BA1E22-9653-45F1-8EC2-9BF8A2151555/ECCC_GHGRP_OverviewOfReported2015Emissions.pdf

[11] G. o. Ontario, *The End of Coal*. [Online]. Available: https://www.ontario.ca/page/end-coal

[12] C. Blake and L. Graydon, "Overview of electricity regulation in canada," *Retrieved on February*, vol. 9, p. 2009, 2008.

[13] IEA, "Energy Policies of IEA Countries-Canada 2015 Review," *International Energy Agency: Paris, France*, 2016. [Online]. Available: https://www.iea.org/publications/freepublications/publication/EnergyPoliciesofIEACountriesCanada2015Review.pdf

[14] AUC, "Alberta Electric Distribution System-Connected Generation Inquiry Final Report," *Alberta Utilities Commission*, 2017. [Online]. Available: http://www.auc.ab.ca/regulatory_documents/Consultations/DistributionGenerationReport.pdf

[15] AESO, "Alberta Capacity Market," *Alberta Electric System Operator*, 2017. [Online]. Available: https://www.aeso.ca/assets/Uploads/CMD-2.0-Rationales-CONSOLIDATED-Final.pdf

[16] MSA, "Alberta Wholesale Electricity Market," *Market Surveillance Administrator*, 2010. [Online]. Available: https://albertamsa.ca/uploads/pdf/Reports/Reports/Alberta%20Wholesale%20Electricity%20Market%20Report%20092910.pdf

[17] AESO, "AESO 2017 Long-term Transmission Plan," *Alberta Electric System Operator*, 2018. [Online]. Available: https://www.aeso.ca/assets/Uploads/AESO-2017-Long-termTransmissionPlan-Final.pdf

[18] MSA, "Alberta Retail Markets for Electricity and Natural Gas - A description of basic structural features," *Market Surveillance Administrator*, 2014. [Online]. Available: https://albertamsa.ca/uploads/pdf/Archive/00-2014/Alberta%20Retail%20Markets%20for%20Electricity%20and%20Natural%20Gas%20071714..pdf

[19] M. F. Akorede, H. Hizam, and E. Pouresmaeil, "Distributed energy resources and benefits to the environment," *Renewable and sustainable energy reviews*, vol. 14, no. 2, pp. 724–734, 2010.

[20] W. El-Khattam and M. M. Salama, "Distributed generation technologies, definitions and benefits," *Electric power systems research*, vol. 71, no. 2, pp. 119–128, 2004.

[21] J. Driesen and F. Katiraei, "Design for distributed energy resources," *IEEE Power and Energy Magazine*, vol. 6, no. 3, 2008.

[22] R. Lasseter, A. Akhil, C. Marnay, J. Stephens, J. Dagle, R. Guttromson, A. S. Meliopoulous, R. Yinger, and J. Eto, "Integration of distributed energy resources. the certs microgrid concept," 2002.

[23] R. H. Lasseter and P. Paigi, "Microgrid: A conceptual solution," in *Power Electronics Specialists Conference, 2004. PESC 04. 2004 IEEE 35th Annual*, vol. 6. IEEE, 2004, pp. 4285–4290.

[24] R. H. Lasseter, "Microgrids," in *Power Engineering Society Winter Meeting, 2002. IEEE*, vol. 1. IEEE, 2002, pp. 305–308.

[25] H. Jiayi, J. Chuanwen, and X. Rong, "A review on distributed energy resources and microgrid," *Renewable and Sustainable Energy Reviews*, vol. 12, no. 9, pp. 2472–2483, 2008.

[26] S. S. Rao, *Engineering optimization: theory and practice*. John Wiley & Sons, 2009.

[27] R. K. Arora, *Optimization: algorithms and applications*. Chapman and Hall/CRC, 2015.

[28] L. T. Biegler and I. E. Grossmann, "Retrospective on optimization," *Computers & Chemical Engineering*, vol. 28, no. 8, pp. 1169–1192, 2004.

[29] D. Bertsimas and J. N. Tsitsiklis, *Introduction to linear optimization*. Athena Scientific Belmont, MA, 1997, vol. 6.

[30] D. Solow, *Linear programming: An introduction to finite improvement algorithms*. Courier Corporation, 2014.

[31] S. Boyd and L. Vandenberghe, *Convex optimization*. Cambridge university press, 2004.

[32] G. Dantzig, *Linear programming and extensions*. Princeton university press, 2016.

[33] G. B. Dantzig and M. N. Thapa, *Linear programming 1: introduction*. Springer Science & Business Media, 2006.

[34] N. Karmarkar, "A new polynomial-time algorithm for linear programming," in *Proceedings of the sixteenth annual ACM symposium on Theory of computing*. ACM, 1984, pp. 302–311.

[35] F. A. Potra and S. J. Wright, "Interior-point methods," *Journal of Computational and Applied Mathematics*, vol. 124, no. 1-2, pp. 281–302, 2000.

[36] R. H. Byrd, M. E. Hribar, and J. Nocedal, "An interior point algorithm for large-scale nonlinear programming," *SIAM Journal on Optimization*, vol. 9, no. 4, pp. 877–900, 1999.

[37] A. P. Ruszczyński and A. Ruszczynski, *Nonlinear optimization*. Princeton university press, 2006, vol. 13.

[38] A. H. Land and A. G. Doig, "An automatic method of solving discrete programming problems," *Econometrica: Journal of the Econometric Society*, pp. 497–520, 1960.

[39] H. W. Kuhn and A. W. Tucker, "Nonlinear programming," in *Proceedings of the Second Berkeley Symposium on Mathematical Statistics and Probability*. Berkeley, Calif.: University of California Press, 1951, pp. 481–492. [Online]. Available: https://projecteuclid.org/euclid.bsmsp/1200500249

[40] R. Gomory, "An algorithm for the mixed integer problem," RAND CORP SANTA MONICA CA, Tech. Rep., 1960.

[41] J. E. Kelley, Jr, "The cutting-plane method for solving convex programs," *Journal of the society for Industrial and Applied Mathematics*, vol. 8, no. 4, pp. 703–712, 1960.

[42] M. Padberg and G. Rinaldi, "A branch-and-cut algorithm for the resolution of large-scale symmetric traveling salesman problems," *SIAM review*, vol. 33, no. 1, pp. 60–100, 1991.

[43] B. Borchers and J. E. Mitchell, "An improved branch and bound algorithm for mixed integer nonlinear programs," *Computers & Operations Research*, vol. 21, no. 4, pp. 359–367, 1994.

[44] T. Westerlund and F. Pettersson, "An extended cutting plane method for solving convex minlp problems," *Computers & Chemical Engineering*, vol. 19, pp. 131–136, 1995.

[45] T. Westerlund, H. Skrifvars, I. Harjunkoski, and R. Pörn, "An extended cutting plane method for a class of non-convex minlp problems," *Computers & Chemical Engineering*, vol. 22, no. 3, pp. 357–365, 1998.

[46] M. A. Duran and I. E. Grossmann, "An outer-approximation algorithm for a class of mixed-integer nonlinear programs," *Mathematical programming*, vol. 36, no. 3, pp. 307–339, 1986.

[47] A. M. Geoffrion, "Generalized benders decomposition," *Journal of optimization theory and applications*, vol. 10, no. 4, pp. 237–260, 1972.

[48] D. P. Bertsekas, *Dynamic programming and optimal control*. Athena scientific Belmont, MA, 2005, vol. 1, no. 3.

[49] M. Held and R. M. Karp, "A dynamic programming approach to sequencing problems," *Journal of the Society for Industrial and Applied Mathematics*, vol. 10, no. 1, pp. 196–210, 1962.

[50] M. Trifkovic, W. A. Marvin, P. Daoutidis, and M. Sheikhzadeh, "Dynamic real-time optimization and control of a hybrid energy system," *AIChE Journal*, vol. 60, no. 7, pp. 2546–2556, 2014.

[51] R. Bellman, "The theory of dynamic programming," RAND Corp Santa Monica CA, Tech. Rep., 1954.

[52] H. C. Tijms, *Stochastic models: an algorithmic approach*. John Wiley & Sons Chichester, 1994, vol. 994.

[53] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.

[54] J. C. Spall, *Introduction to stochastic search and optimization: estimation, simulation, and control*. John Wiley & Sons, 2005, vol. 65.

[55] N. V. Sahinidis, "Optimization under uncertainty: state-of-the-art and opportunities," *Computers & Chemical Engineering*, vol. 28, no. 6-7, pp. 971–983, 2004.

[56] A. Ben-Tal, L. El Ghaoui, and A. Nemirovski, *Robust optimization*. Princeton University Press, 2009, vol. 28.

[57] D. Bertsimas, D. B. Brown, and C. Caramanis, "Theory and applications of robust optimization," *SIAM review*, vol. 53, no. 3, pp. 464–501, 2011.

[58] A. Ben-Tal and A. Nemirovski, "Robust optimization–methodology and applications," *Mathematical Programming*, vol. 92, no. 3, pp. 453–480, 2002.

[59] H.-G. Beyer and B. Sendhoff, "Robust optimization–a comprehensive survey," *Computer methods in applied mechanics and engineering*, vol. 196, no. 33-34, pp. 3190–3218, 2007.

[60] C. Carlsson and R. Fuller, *Fuzzy reasoning in decision making and optimization*. Physica, 2012, vol. 82.

[61] A. Yazenin, "Fuzzy and stochastic programming," *Fuzzy sets and systems*, vol. 22, no. 1-2, pp. 171–180, 1987.

[62] M. Inuiguchi and J. Ramık, "Possibilistic linear programming: a brief review of fuzzy mathematical programming and a comparison with stochastic programming in portfolio selection problem," *Fuzzy sets and systems*, vol. 111, no. 1, pp. 3–28, 2000.

[63] R. T. Rockafellar and R. J.-B. Wets, "Scenarios and policy aggregation in optimization under uncertainty," *Mathematics of operations research*, vol. 16, no. 1, pp. 119–147, 1991.

[64] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, "Optimization by simulated annealing," *science*, vol. 220, no. 4598, pp. 671–680, 1983.

[65] X.-S. Yang and S. Deb, "Cuckoo search via lévy flights," in *Nature & Biologically Inspired Computing, 2009. NaBIC 2009. World Congress on*. IEEE, 2009, pp. 210–214.

[66] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: optimization by a colony of cooperating agents," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 26, no. 1, pp. 29–41, 1996.

[67] M. Dorigo and G. Di Caro, "Ant colony optimization: a new meta-heuristic," in *Proceedings of the 1999 congress on evolutionary computation-CEC99 (Cat. No. 99TH8406)*, vol. 2. IEEE, 1999, pp. 1470–1477.

[68] M. Gen and R. Cheng, *Genetic algorithms and engineering optimization*. John Wiley & Sons, 2000, vol. 7.

[69] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in *Micro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on*. IEEE, 1995, pp. 39–43.

[70] R. Atia and N. Yamada, "Sizing and analysis of renewable energy and battery systems in residential microgrids," *IEEE Transactions on Smart Grid*, vol. 7, no. 3, pp. 1204–1213, 2016.

[71] B. Zhao, X. Zhang, P. Li, K. Wang, M. Xue, and C. Wang, "Optimal sizing, operating strategy and operational experience of a stand-alone microgrid on dongfushan island," *Applied Energy*, vol. 113, pp. 1656–1666, 2014.

[72] I. Zenginis, J. S. Vardakas, C. Echave, M. Morató, J. Abadal, and C. V. Verikoukis, "Cooperation in microgrids through power exchange: An optimal sizing and operation approach," *Applied Energy*, vol. 203, pp. 972–981, 2017.

[73] C. Yuan, M. S. Illindala, and A. S. Khalsa, "Co-optimization scheme for distributed energy resource planning in community microgrids," *IEEE Transactions on Sustainable Energy*, vol. 8, no. 4, pp. 1351–1360, 2017.

[74] A. Ogunjuyigbe, T. Ayodele, and O. Akinola, “Optimal allocation and sizing of pv/wind/split-diesel/battery hybrid energy system for minimizing life cycle cost, carbon emission and dump energy of remote residential building,” *Applied Energy*, vol. 171, pp. 153–171, 2016.

[75] O. Daskalou, M. Karanastasi, Y. Markonis, P. Dimitriadis, A. Koukouvinos, A. Efstratiadis, and D. Koutsoyiannis, “Gis-based approach for optimal siting and sizing of renewables considering techno-environmental constraints and the stochastic nature of meteorological inputs,” in *EGU General Assembly Conference Abstracts*, vol. 18, 2016, p. 12044.

[76] R. Margolis, P. Gagnon, J. Melius, C. Phillips, and R. Elmore, “Using gis-based methods and lidar data to estimate rooftop solar technical potential in us cities,” *Environmental Research Letters*, vol. 12, no. 7, p. 074013, 2017.

[77] A. Maleki, F. Pourfayaz, H. Hafeznia, and M. A. Rosen, “A novel framework for optimal photovoltaic size and location in remote areas using a hybrid method: A case study of eastern iran,” *Energy Conversion and Management*, vol. 153, pp. 129–143, 2017.

[78] D. Latinopoulos and K. Kechagia, “A gis-based multi-criteria evaluation for wind farm site selection. a regional scale application in greece,” *Renewable Energy*, vol. 78, pp. 550–560, 2015.

[79] E. J. Molina Bacca, “Optimal sizing and geographic placement of the components of a microgrid,” Master’s thesis, Schulich School of Engineering, 2018.

[80] S. Moghaddas-Tafreshi and E. Mashhour, “Distributed generation modeling for power flow studies and a three-phase unbalanced power flow solution for radial distribution systems considering distributed generation,” *Electric Power Systems Research*, vol. 79, no. 4, pp. 680–686, 2009.

[81] F. Amini and R. Kazemzadeh, "Distributed generations optimal placement and sizing in unbalanced distribution systems with respect to uncertainties"," *International Journal of Renewable Energy Research*, vol. 7, no. 2, pp. 1–11, 2017.

[82] W. Sheng, K.-Y. Liu, Y. Liu, X. Meng, and Y. Li, "Optimal placement and sizing of distributed generation via an improved nondominated sorting genetic algorithm ii," *IEEE Transactions on Power Delivery*, vol. 30, no. 2, pp. 569–578, 2015.

[83] C. Li, S. K. Chaudhary, M. Savaghebi, J. C. Vasquez, and J. M. Guerrero, "Power flow analysis for low-voltage ac and dc microgrids considering droop control and virtual impedance," *IEEE Transactions on Smart Grid*, vol. 8, no. 6, pp. 2754–2764, 2017.

[84] Z. Wang and M. Lemmon, "Stability analysis of weak rural electrification microgrids with droop-controlled rotational and electronic distributed generators," in *Power & Energy Society General Meeting, 2015 IEEE*. IEEE, 2015, pp. 1–5.

[85] H. Abdi, S. D. Beigvand, and M. La Scala, "A review of optimal power flow studies applied to smart grids and microgrids," *Renewable and Sustainable Energy Reviews*, vol. 71, pp. 742–766, 2017.

[86] A. Soroudi and M. Ehsan, "A distribution network expansion planning model considering distributed generation options and techo-economical issues," *Energy*, vol. 35, no. 8, pp. 3364–3374, 2010.

[87] A. Arabali, M. Ghofrani, M. Etezadi-Amoli, and M. S. Fadali, "Stochastic performance assessment and sizing for a hybrid power system of solar/wind/energy storage," *IEEE Transactions on Sustainable Energy*, vol. 5, no. 2, pp. 363–371, 2014.

[88] M. T. Wishart, M. Dewadasa, I. Ziari, G. Ledwich, and A. Ghosh, "Intelligent distribution planning and control incorporating microgrids," in *Power and Energy Society General Meeting, 2011 IEEE*. IEEE, 2011, pp. 1–8.

[89] B. Zhao, X. Zhang, J. Chen, C. Wang, and L. Guo, "Operation optimization of standalone microgrids considering lifetime characteristics of battery energy storage system," *IEEE transactions on sustainable energy*, vol. 4, no. 4, pp. 934–943, 2013.

[90] M. H. Moradi, M. Eskandari, and S. M. Hosseinian, "Operational strategy optimization in an optimal sized smart microgrid," *IEEE Transactions on Smart Grid*, vol. 6, no. 3, pp. 1087–1095, 2015.

[91] M. L. Di Silvestre, G. Graditi, and E. R. Sanseverino, "A generalized framework for optimal sizing of distributed energy resources in micro-grids using an indicator-based swarm approach," *IEEE Transactions on Industrial Informatics*, vol. 10, no. 1, pp. 152–162, 2014.

[92] L. Guo, W. Liu, J. Cai, B. Hong, and C. Wang, "A two-stage optimal planning and design method for combined cooling, heat and power microgrid system," *Energy Conversion and Management*, vol. 74, pp. 433–445, 2013.

[93] J. Chen, W. Zhang, J. Li, W. Zhang, Y. Liu, B. Zhao, and Y. Zhang, "Optimal sizing for grid-tied microgrids with consideration of joint optimization of planning and operation," *IEEE Transactions on Sustainable Energy*, vol. 9, no. 1, pp. 237–248, 2018.

[94] C. Chen, S. Duan, T. Cai, B. Liu, and G. Hu, "Smart energy management system for optimal microgrid economic operation," *IET renewable power generation*, vol. 5, no. 3, pp. 258–267, 2011.

[95] G. Osório, J. Lujano-Rojas, J. Matias, and J. Catalão, "A probabilistic approach to solve the economic dispatch problem with intermittent renewable energy sources," *Energy*, vol. 82, pp. 949–959, 2015.

[96] N. Augustine, S. Suresh, P. Moghe, and K. Sheikh, "Economic dispatch for a microgrid considering renewable energy cost functions," in *Innovative Smart Grid Technologies (ISGT), 2012 IEEE PES*. IEEE, 2012, pp. 1–7.

[97] A. Lorca and X. A. Sun, “Adaptive robust optimization with dynamic uncertainty sets for multi-period economic dispatch under significant wind,” *IEEE Transactions on Power Systems*, vol. 30, no. 4, pp. 1702–1713, 2015.

[98] L. Zhao and B. Zeng, “Robust unit commitment problem with demand response and wind energy,” in *Power and Energy Society General Meeting, 2012 IEEE*. IEEE, 2012, pp. 1–8.

[99] D. Bertsimas, E. Litvinov, X. A. Sun, J. Zhao, and T. Zheng, “Adaptive robust optimization for the security constrained unit commitment problem,” *IEEE Transactions on Power Systems*, vol. 28, no. 1, pp. 52–63, 2013.

[100] G. Osório, J. Lujano-Rojas, J. Matias, and J. Catalão, “A new scenario generation-based method to solve the unit commitment problem with high penetration of renewable energies,” *International Journal of Electrical Power & Energy Systems*, vol. 64, pp. 1063–1072, 2015.

[101] A. Brooke, D. Kendrick, A. Meeraus, R. Raman, and U. America, “The general algebraic modeling system,” *GAMS Development Corporation*, vol. 1050, 1998.

[102] R. Fourer, D. M. Gay, and B. Kernighan, *Ampl*. Boyd & Fraser Danvers, MA, 1993, vol. 117.

[103] R. Fourer, D. M. Gay, and B. W. Kernighan, “A modeling language for mathematical programming,” *Management Science*, vol. 36, no. 5, pp. 519–554, 1990.

[104] D. Tenfen and E. C. Finardi, “A mixed integer linear programming model for the energy management problem of microgrids,” *Electric Power Systems Research*, vol. 122, pp. 19–28, 2015.

[105] A. C. Luna, L. Meng, N. L. Diaz, M. Graells, J. C. Vasquez, and J. M. Guerrero, “Online energy management systems for microgrids: experimental validation and assessment framework,” *IEEE Transactions on Power Electronics*, vol. 33, no. 3, pp. 2201–2215, 2018.

[106] S. Helal, R. Najee, M. Hanna, M. Shaaban, A. Osman, and M. Hassan, "An energy management system for hybrid microgrids in remote communities," in *Electrical and Computer Engineering (CCECE), 2017 IEEE 30th Canadian Conference on*. IEEE, 2017, pp. 1–4.

[107] R. Palma-Behnke, C. Benavides, F. Lanas, B. Severino, L. Reyes, J. Llanos, and D. Sáez, "A microgrid energy management system based on the rolling horizon strategy," *IEEE Transactions on Smart Grid*, vol. 4, no. 2, pp. 996–1006, 2013.

[108] L. N. An and T. Quoc-Tuan, "Optimal energy management for grid connected microgrid by using dynamic programming method," in *Power & Energy Society General Meeting, 2015 IEEE*. IEEE, 2015, pp. 1–5.

[109] H. Chitsaz, H. Shaker, H. Zareipour, D. Wood, and N. Amjady, "Short-term electricity load forecasting of buildings in microgrids," *Energy and Buildings*, vol. 99, pp. 50–60, 2015.

[110] Y. Ren, P. N. Suganthan, N. Srikanth, and G. Amaratunga, "Random vector functional link network for short-term electricity load demand forecasting," *Information Sciences*, vol. 367, pp. 1078–1093, 2016.

[111] M. Q. Raza and A. Khosravi, "A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings," *Renewable and Sustainable Energy Reviews*, vol. 50, pp. 1352–1372, 2015.

[112] R. Azimi, M. Ghayekhloo, and M. Ghofrani, "A hybrid method based on a new clustering technique and multilayer perceptron neural networks for hourly solar radiation forecasting," *Energy Conversion and Management*, vol. 118, pp. 331–344, 2016.

[113] L. M. Aguiar, B. Pereira, P. Lauret, F. Díaz, and M. David, "Combining solar irradiance measurements, satellite-derived data and a numerical weather prediction model to improve intra-day solar forecasting," *Renewable Energy*, vol. 97, pp. 599–610, 2016.

[114] A. Yadav and K. Sahu, “Wind forecasting using artificial neural networks: A survey and taxonomy,” *International Journal of Research In Science & Engineering*, vol. 3, 2017.

[115] C. Feng, M. Cui, B.-M. Hodge, and J. Zhang, “A data-driven multi-model methodology with deep feature selection for short-term wind forecasting,” *Applied Energy*, vol. 190, pp. 1245–1257, 2017.

[116] H. Chitsaz, P. Zamani-Dehkordi, H. Zareipour, and P. P. Parikh, “Electricity price forecasting for operational scheduling of behind-the-meter storage systems,” *IEEE Transactions on Smart Grid*, vol. 9, no. 6, pp. 6612–6622, 2018.

[117] Z. Yang, L. Ce, and L. Lian, “Electricity price forecasting by a hybrid model, combining wavelet transform, arma and kernel-based extreme learning machine methods,” *Applied Energy*, vol. 190, pp. 291–305, 2017.

[118] I. P. Panapakidis and A. S. Dagoumas, “Day-ahead electricity price forecasting via the application of artificial neural network based models,” *Applied Energy*, vol. 172, pp. 132–151, 2016.

[119] E. Čeperić, S. Žiković, and V. Čeperić, “Short-term forecasting of natural gas prices using machine learning and feature selection algorithms,” *Energy*, vol. 140, pp. 893–900, 2017.

[120] W. Su, J. Wang, and J. Roh, “Stochastic energy scheduling in microgrids with intermittent renewable energy resources,” *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 1876–1883, 2014.

[121] S. Talari, M. Yazdaninejad, and M.-R. Haghifam, “Stochastic-based scheduling of the microgrid operation including wind turbines, photovoltaic cells, energy storages and responsive loads,” *IET Generation, Transmission & Distribution*, vol. 9, no. 12, pp. 1498–1509, 2015.

[122] M. Alipour, B. Mohammadi-Ivatloo, and K. Zare, “Stochastic scheduling of renewable and chp-based microgrids,” *IEEE Transactions on Industrial Informatics*, vol. 11, no. 5, pp. 1049–1058, 2015.

[123] A. Zakariazadeh, S. Jadid, and P. Siano, “Smart microgrid energy and reserve scheduling with demand response using stochastic optimization,” *International Journal of Electrical Power & Energy Systems*, vol. 63, pp. 523–533, 2014.

[124] J. Liu, H. Chen, W. Zhang, B. Yurkovich, and G. Rizzoni, “Energy management problems under uncertainties for grid-connected microgrids: a chance constrained programming approach,” *IEEE Transactions on Smart Grid*, vol. 8, no. 6, pp. 2585–2596, 2017.

[125] S. Mohammadi, S. Soleymani, and B. Mozafari, “Scenario-based stochastic operation management of microgrid including wind, photovoltaic, micro-turbine, fuel cell and energy storage devices,” *International Journal of Electrical Power & Energy Systems*, vol. 54, pp. 525–535, 2014.

[126] N. Nikmehr, S. Najafi-Ravadanegh, and A. Khodaei, “Probabilistic optimal scheduling of networked microgrids considering time-based demand response programs under uncertainty,” *Applied energy*, vol. 198, pp. 267–279, 2017.

[127] Y. Xiang, J. Liu, and Y. Liu, “Robust energy management of microgrid with uncertain renewable generation and load,” *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 1034–1043, 2016.

[128] Y. Zhang, N. Gatsis, and G. B. Giannakis, “Robust energy management for microgrids with high-penetration renewables,” *IEEE Transactions on Sustainable Energy*, vol. 4, no. 4, pp. 944–953, 2013.

[129] W. Hu, P. Wang, and H. B. Gooi, “Toward optimal energy management of microgrids via robust two-stage optimization,” *IEEE Transactions on Smart Grid*, vol. 9, no. 2, pp. 1161–1174, 2018.

[130] E. C. Umeozor and M. Trifkovic, "Operational scheduling of microgrids via parametric programming," *Applied Energy*, vol. 180, pp. 672–681, 2016.

[131] M. Elsied, A. Oukaour, T. Youssef, H. Gualous, and O. Mohammed, "An advanced real time energy management system for microgrids," *Energy*, vol. 114, pp. 742–752, 2016.

[132] S. Golshannavaz, S. Afsharnia, and P. Siano, "A comprehensive stochastic energy management system in reconfigurable microgrids," *International Journal of Energy Research*, vol. 40, no. 11, pp. 1518–1531, 2016.

[133] A. Askarzadeh, "A memory-based genetic algorithm for optimization of power generation in a microgrid," *IEEE transactions on sustainable energy*, vol. 9, no. 3, pp. 1081–1089, 2018.

[134] J. Radosavljević, M. Jevtić, and D. Klimenta, "Energy and operation management of a microgrid using particle swarm optimization," *Engineering Optimization*, vol. 48, no. 5, pp. 811–830, 2016.

[135] A. A. Moghaddam, A. Seifi, and T. Niknam, "Multi-operation management of a typical micro-grids using particle swarm optimization: A comparative study," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 2, pp. 1268–1281, 2012.

[136] M. Marzband, F. Azarinejadian, M. Savaghebi, and J. M. Guerrero, "An optimal energy management system for islanded microgrids based on multiperiod artificial bee colony combined with markov chain," *IEEE Systems Journal*, vol. 11, no. 3, pp. 1712–1722, 2017.

[137] W.-M. Lin, C.-S. Tu, and M.-T. Tsai, "Energy management strategy for microgrids by using enhanced bee colony optimization," *energies*, vol. 9, no. 1, p. 5, 2016.

[138] R. Velik and P. Nicolay, "Grid-price-dependent energy management in microgrids using a modified simulated annealing triple-optimizer," *Applied Energy*, vol. 130, pp. 384–395, 2014.

[139] B. Bahmani-Firouzi and R. Azizipanah-Abarghooee, "Optimal sizing of battery energy storage for micro-grid operation management using a new improved bat algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 56, pp. 42–54, 2014.

[140] PEMBINA, "Wind Energy in Alberta: Sustainable Communities, Sustainable Environment," 2017. [Online]. Available: https://www.pembina.org/reports/ab-wind-workshop-local-govt-capacity.pdf

[141] P. Toma, P. Dorin, E. Radu, and M. Daniel, "Sizing photovoltaic-wind smart microgrid with battery storage and grid connection," in *Automation, Quality and Testing, Robotics, 2014 IEEE International Conference on*. IEEE, 2014, pp. 1–5.

[142] A. Castillo and D. F. Gayme, "Grid-scale energy storage applications in renewable energy integration: A survey," *Energy Conversion and Management*, vol. 87, pp. 885–894, 2014.

[143] M. Aneke and M. Wang, "Energy storage technologies and real life applications–a state of the art review," *Applied Energy*, vol. 179, pp. 350–377, 2016.

[144] N. DiOrio, A. Dobos, S. Janzou *et al.*, *Economic analysis case studies of battery energy storage with SAM*. National Renewable Energy Laboratory Denver, CO, USA, 2015.

[145] ScottMaden, "Solar Photovoltaic Plant Operating and Maintenance Costs," 2010. [Online]. Available: https://www.scottmadden.com/insight/solar-photovoltaic-plant-operating-and-maintenance-costs/

[146] E. P. R. Institute, "Budgeting for Solar PV Plant Operations & Maintenance: Practices and Pricing," 2015. [Online]. Available: http://prod.sandia.gov/techlib/access-control.cgi/2016/160649r.pdf