Distributed Energy Resources and Dynamic Microgrid:

An Integrated Assessment

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Abstract of the Dissertation

Distributed Energy Resources and Dynamic Microgrid: An Integrated Assessment

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The overall goal of this thesis is to improve understanding in terms of the benefit of DERs to both utility and to electricity end-users when integrated in power distribution system. To achieve this goal, a series of two studies was conducted to assess the value of DERs when integrated with new power paradigms.

First, the arbitrage value of DERs was examined in markets with time-variant electricity pricing rates (e.g., time of use, real time pricing) under a smart grid distribution paradigm. This study uses a stochastic optimization model to estimate the potential profit from electricity price arbitrage over a five-year period. The optimization process involves two types of PHEVs (PHEV-10, and PHEV-40) under three scenarios with different assumptions on technology performance, electricity market and PHEV owner types. The simulation results indicate that expected arbitrage profit is not a viable option to engage PHEVs in dispatching and in providing ancillary services without more favorable policy and PHEV battery technologies. Subsidy or change in electricity tariff or both are needed.

Second, it examined the concept of dynamic microgrid as a measure to improve distribution resilience, and estimates the prices of this emerging service. An economic load dispatch (ELD) model is developed to estimate the market-clearing price in a hypothetical community with single bid auction electricity market. The results show that the electricity market clearing price on the dynamic microgrid is predominantly decided by power output and cost of electricity of each type of DGs. At circumstances where CHP is the only source, the electricity market clearing price in the island is even cheaper than the on-grid electricity price at normal times. Integration of PHEVs in the dynamic microgrid will increase electricity market clearing prices. It demonstrates that dynamic microgrid is an economically viable alternative to enhance grid resilience.

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List of Abbreviations

AMI/AMR: Advanced Metering Infrastructure/Reading

CD: Charge Depleting

CHP: Combined Heat and Power

COE: Cost of Electricity

CS: Charge Sustaining

DERs: Distributed Energy Resources

DG: Distributed Generator

DOD: Depth of Discharge

DSO: Distribution System Operator

ELD: Economic Load Dispatch

HEV: Hybrid Electric Vehicle

O&M: Operation and Management

PHEV: Plug-in Hybrid Electric Vehicle

RTP: Real Time Pricing

SOC: State of Charge

TOU: Time of Use

TSO: Transmission System Operator

V2G: Vehicle to Grid

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Chapter 1 Introduction

1.1 Motivation, research strategy, and organization of the dissertation

The thesis is motivated by the promising future of distributed energy resources (DERs), and its role played in power industry when coexists with conventional sources as primary energy sources in the future power systems (Poudineh & Jamasb, 2014). DERs are usually directly connected to the distribution network or are on the customer site of the meter (Georgilakis & Hatziargyriou, 2013). DERs are consisted of distributed generator (DG), energy storage, load control, and, for certain systems, advanced power electronic interfaces between the DGs and bulk power providers (Lasseter et al., 2002). Integration of DERs is evolving as an emerging power scenario for electric power system infrastructure based on the significant issues, such as reducing heavy dependence on fossil fuel, widespread deployment of advanced DERs technologies, deregulation of electric utility industry, and enhancing environmental awareness of low carbon society from public (Basak, Chowdhury, nee Dey, & Chowdhury, 2012).

Customers, utilities, and society can gain many benefits from the applications of DERs (Corey, Iannucci, & Eyer, 2004; KEMA, February 2012; Mohd, Ortjohann, Schmelter, Hamsic, & Morton, 2008; Zogg, Lawrence, Ofer, & Brodrick, 2007). When integrated with electric gird, DERs can: (1) increase energy efficiency, reduce energy costs and pollutant emissions; (2) improve power quality and reliability of the grid; (3) relieve transmission and distribution congestion and avoid or defer investment in the upgrade of transmission and distribution system; and (4) improve system resilience, especially to critical loads and vital services; and (5) increase generation diversity.

Traditional distribution configuration is not designed to accommodate much DER integration (Zhenhua, 2006). The integration of DERs for the current distribution grid system is a critical and complex issue, which requires both technical and economic changes to make current distribution networks more adaptive to DERs (Poudineh & Jamasb, 2014). There have been numerous endeavors to address these issues. Technically, system has to be more intelligent with higher flexibility to absorb the intermittent DER sources. From an economic viewpoint, the adoption of distributed resources requires extending the traditional business model of distribution utilities in a consistent manner within the unbundled sectors (Poudineh & Jamasb, 2014). When integration of DERs in the emerging power paradigm can provide new services for customers, previous assessment tool is not adequate enough to fully understand the value of DER technology (Lasseter et al., 2002). Hence, new tools of assessment should be conducted under the evolving technical and economic models of distribution system(Poudineh & Jamasb, 2014).

The overall objective of this dissertation is to improve understanding DERs' benefit to both utility and electricity end-users in the emerging grid paradigms. These benefits will be calculated and reflected in a couple of innovative economic models in a future distribution system. Addressing technical barriers of facilitating DER integration is not the aim of this thesis, and it's assumed that the emerging power paradigms are functioning well in the defined distribution system. To achieve the overall objective, several specific sub-objectives shall be accomplished. The first sub-objective is to understand the arbitrage value of DERs in the application of energy storage. The financial benefit from arbitrage will help DER owners offset the operation cost of vehicle and encourage more adoption of emerging technologies. Next, the economics of DERs in islanded situation shall be examined. This provide an evidence of DERs as emergent energy sources to improve system resilience to extreme outage events. Finally, the policy implications of utilizing DERs shall be concluded.

Plug-in hybrid electric vehicle (PHEV), as one type of DERs with both electric and chemical energy and having been widely discussed as one of the primary future transportation candidates, is primarily studied in this dissertation. It can discharge power from both electric and chemical energy sources, and the power output from PHEV battery discharging can be utilized without considering the complex intermittency issues that some of DERs may process. The value of PHEV as DERs is impacted by various factors, including technology performance, economic market design, and customer's preferences of emerging technology, etc. Any changes or the inherit uncertainties of these factors will impact the successfulness of integration of DERs (Kassakian & Schmalensee, 2011). To eliminate uncertainty issues in terms of future DER technology improvement, this research not only considers the state-of-the-art DERs technologies, but also predicts the improvements of these technologies. Other uncertainties are interpreted in forms of probability distributions to represent the stochastic nature of these factors.

Each chapter explains an independent research topic, and aims to achieve the overall and sub-objectives of this thesis. PHEVs as the studied DER are tested in various circumstances to reduce the impact of parameters with uncertainty. Operation of PHEVs is optimized to minimize its overall operation cost. Since the chapters of this dissertation were written separately, each chapter may exist some conceptual redundancy throughout the body of work. The chapters, however, are intended for academic publication, and therefore can be read separately.

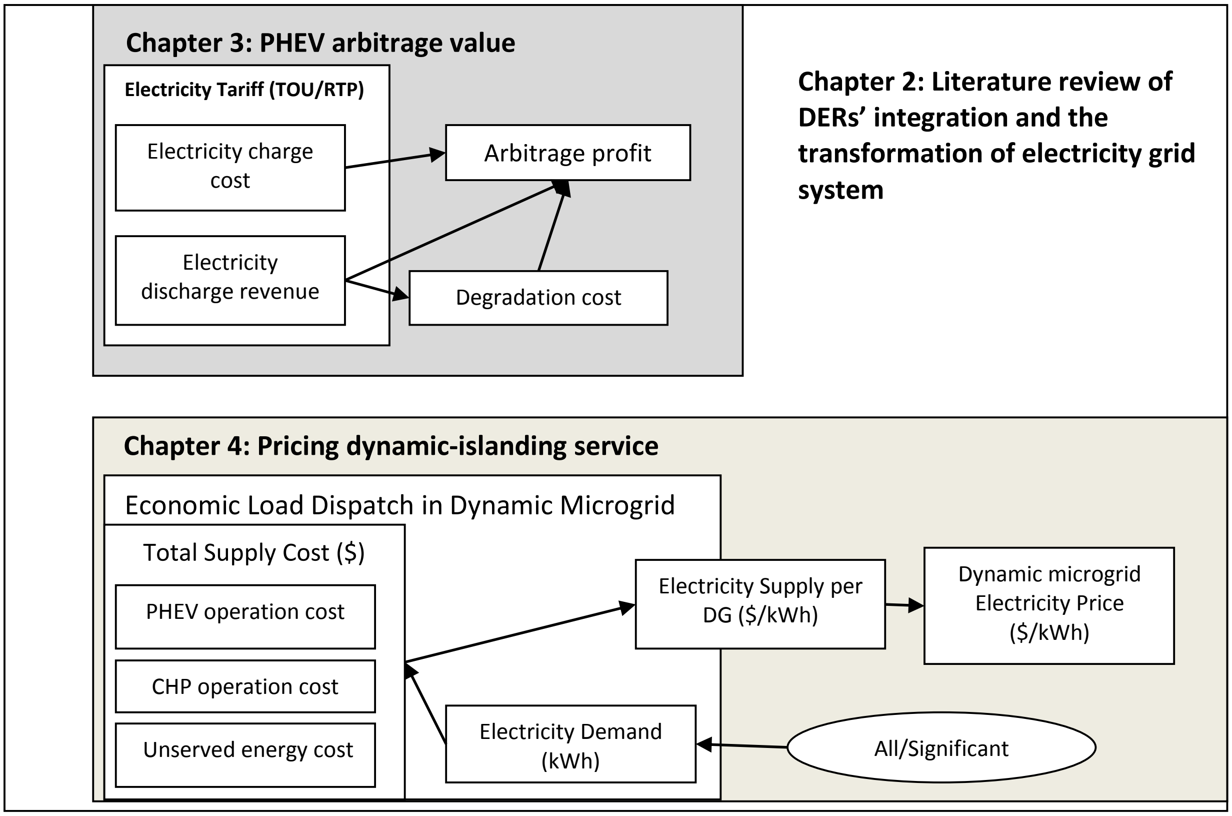

Figure 1.1 Thesis Structure

Figure 1.1 shows the overall structure of the primary researches. Each node in this structure represents the significant elements and their relationships in each study and the arrow demonstrates how the models in each research are formulated to achieve each objective. Chapter 2 comprehensively reviewed the benefit and challenge of DERs' integration, and the transformation process of electricity power grid to better adopt DERs integration from various perspectives. Chapter 3 and 4 are the two major research studies of DER technologies and their application in the emerging power grid paradigms. Chapter 3 used a stochastic optimization method to optimize PHEV battery charging and discharging behavior. Arbitrage profit equals to the revenue of PHEV discharging after taking off the electricity charging cost and the degradation cost resulted from battery discharging. Chapter 4 examined an innovative concept of power grid paradigm as a measure improving grid resilience. An economic load dispatch (ELD) model is developed to estimate the market clearing price in a hypothetical community with single bid auction electricity market.

Specifically, Chapter 2, “Distributed Energy Resources: status and benefits”, first summarized the benefits of DERs to customers and utilities when integrated with electricity distribution system. The integration process, however, is not as intuitive as a simple plug-and-play process during which residents plug electric appliances onto the wall. Traditional grid (distribution) system is controlled and operated in a passive way, and it’s not designed to adopt large integration of DERs. The intermittency essence of some DERs complicates the voltage regulation across the length of distribution feeders and are deemed as “dirty power” since it may have adverse impact to the distribution system. When largely integrated, DERs will bring catastrophic impact on the U.S. bulk power system. A couple of changes are required to make current grid system more adaptive to large DERs integration. Technically, power system has to be more intelligent, evolving from passive to active management and control, and enhancing system flexibility to absorb DERs intermittent output. Storage technology plays a critical role when deployed close to intermittent DGs. Economically, an evolving economic market is required to expand new businesses other than from DG connection and distribution system usage charges. Smart grid and microgrid are introduced as the future power paradigm candidates to address the issue of large integration of DERs.

Chapter 3, “Electricity-price Arbitrage with Plug-in Hybrid Electric Vehicles (PHEV): Gain or Loss”, evaluates the value of battery on PHEV in the electricity arbitrage implications. Battery can serve as distributed energy storage device which brings PHEV owner financial benefit when doing active arbitrage. The magnitude of the arbitrage benefit will be answered by a quantitative assessment, which examines PHEVs financial benefit when deployed in different time-based electricity markets in a smart grid paradigm. This study implemented a stochastic optimization model to optimize PHEV owners' charging and discharging behavior. The model estimates the financial benefit from electricity price arbitrage of two types of PHEVs (PHEV-10, and PHEV-40) under three designed scenarios. The scenarios are consisted of different electricity market designs with various PHEV owner types over a five-year period. The impact of DERs technology improvement is also reflected on the scenarios. The results indicate that under current market conditions, even with significant improvement in battery technologies (e.g., higher efficiency, lower cost), PHEV owners can't achieve a positive arbitrage profit. This finding implies that expected arbitrage profit is not a viable option to engage PHEVs in dispatching and in providing ancillary services without more favorable policies and PHEV technologies. Subsidy or changing electricity tariff or both from government are needed.

Chapter 4, "Pricing Dynamic Microgrid Service as Way Enhancing Distribution Resilience" examined the concept of dynamic microgrid as a measure improving system resilience to extreme weather events and accelerating grid restoration process. The electricity market clearing prices in dynamic microgrid are estimated. This research implements an economic load dispatch (ELD) model to estimate the market clearing price of electricity in a hypothetical community with single-bid auction electricity market. The model is further tested under four scenarios with two DER types included in this study: a combined heat and power (CHP) plant and a fleet of plug-in hybrid electric vehicles (PHEVs The results show that the electricity market clearing price on the dynamic microgrid is predominantly decided by power output and cost of electricity of each type of DGs. At circumstances where CHP is the only source, the electricity market clearing price in the island is even cheaper than the on-grid electricity price at normal times. Integration of PHEVs in the dynamic microgrid will increase electricity market clearing prices. It demonstrates that dynamic microgrid is an economically viable alternative to enhance grid resilience.

Finally, Chapter 5, “Summary of major findings, policy implications, and future research needs”, summarizes major findings and provides their policy implications from the previous conducted researches. The last section in this chapter states the future work to be accomplished to address some simplified parameters or omitted uncertain factors in the primary researches.

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Chapter 2 Distributed Energy Resources: Status and Benefits

-- Comprehensive literature review of DERs integration, with focus on the status and benefit

2.1. Benefit of Distributed Energy Resources

Distributed energy resources (DERs) are rapidly becoming attractive because it produces electrical power with immense benefits to customers, utilities and societies (Basak, Chowdhury, nee Dey, & Chowdhury, 2012). The recent shift towards utility restructuring renewed interest in the distribution (and transmission) side of the business, which helps expanding the integration of distributed energy resource (Masters, 2013).

Literatures summarized the benefits of DER when integrated in the grid system DERs (Corey, Iannucci, & Eyer, 2004; KEMA, February 2012; Mohd, Ortjohann, Schmelter, Hamsic, & Morton, 2008; Zogg, Lawrence, Ofer, & Brodrick, 2007). The integration of distributed generators (DGs) based on renewable energy reduced green house gas emission and dependency on conventional fossil fuels. A diversification of electricity sources also reduces energy security risk. Small scale of DGs is easy and flexible to install. DERs can serve as ancillary services which help voltage regulation, supply emergency power at outages, and manage demand response etc. The ancillary services can serve customers with better power efficiency and improved reliability.

In addition, the integration of DERs is going to change the way of energy transmission through utility grid. Consumers are enabled to have some scale of flexible energy utilizations. By integrating these distributed sources from consumers, power system can be converted into small distributed energy integrated system. This change will relief the existing power system from congestion on transmission and distribution system and defers the investment on upgrading generation and transmission systems.

2.2. Challenge of grid integration of distributed energy resources

2.2.1. Development dilemma of traditional distribution system

A conventional electric power distribution system refers to the networks where the lines carry medium voltage power from the end of transmission and deliver it to individual power consumers. It's either a three-phase system which serves urban and suburban residential, or a single phase system primarily serving for rural areas.

The basic configuration and operation of existing electric grid has remained unchanged in the past century. It's a strictly hierarchical system in which centralized power plants at the top of the chain ensure power delivery to customers' loads at the bottom of the chain via transmission and distribution (Farhangi, 2010). Current distribution system is controlled and operated in a passive way which relies on manual and paper-based systems with little real-time circuit and customer data (Fan & Borlase, 2009). Primarily, the distribution system is essentially a one-way pipeline, where the configuration of power lines and protective relaying assume a "unidirectional power flow". While the physical wires and transformers can carry power flow in the reverse direction, DG nonetheless can have adverse impacts on system reliability, power quality, and safety (Ipakchi & Albuyeh, 2009). Therefore, current distribution grid is not designed to accommodate much DER integration(Zhenhua, 2006).

It's been argued that the current centralized power system architecture may not be sustainable for the power needs in a foreseeable future (Lasseter et al., 2002). First, since peak demand is an infrequent occurrence, the system operation is inherently inefficient (Farhangi, 2010). Then, an unprecedented rising power demand coupled with lagging investments in the electrical power infrastructure decreases system stability (Farhangi, 2010). Under the current scale of grid distribution, however, investments on expanding and repairing of aged grid facility may not be cost effective (Kassakian & Schmalensee, 2011). A dwindling available sites, and a general NIMBY (not in my backyard) or BANANA (build absolutely nothing anywhere near anybody) suspicion of power facilities also make the current centralized generating paradigm incapable of adequate expansion (Lasseter et al., 2002). Furthermore, current centralized generation hardly satisfies future end-use need since power quality and reliability have been a great concern to end users. Increasing small-scale generations close to loads has emerged as a desire to addressing increased demand and unsatisfied power quality and reliability issues (Lasseter et al., 2002). Last, in the traditional distribution system, the installment of DER has been focused on connection rather than integration, which makes DER invisible to the system(Pudjianto, Ramsay, & Strbac, 2007). DER lacks the functionality required for system support and security activities.

2.2.2. Impact of DER integration on the U.S. bulk power system

When considering grid integration of DERs, technically, a primary issue is to address the impact of some DERs as intermittent generation sources. Intermittency of a power source refers to the extent to which a power source may exhibit undesired and uncontrolled changes in output (Sinden, 2005). When DG sources are intermittent energy resource (e.g. solar, wind, etc.), it complicates the regulation of voltage across the length of distribution feeders. In addition, the loss of DG units at the same time will induce voltage sag and fast drop in frequency, and recovery could be slow.

The current deployment of DERs has very little impacts to the U.S. bulk power system because they have accounted for only a small fraction of energy supply (Kassakian & Schmalensee, 2011). The impact, however, could make system aggravated or destructive when higher penetration of

DER being applied (Kassakian & Schmalensee, 2011). Since modern infrastructure systems are highly interconnected, a change in conditions at any one location can have immediate impacts over a wide area (Amin & Wollenberg, 2005). Large-scale cascade failures can occur almost instantaneously and with consequences in remote regions or seemingly unrelated businesses (Amin & Wollenberg, 2005). System could suffer a large shortage of generation when DERs are largely integrated in the network (Bollen & Häger, 2005).

From economic perspective, when integrating intermittent DERs, fossil fuel plants must bear the expenses of more frequent regulation by additional start-ups and shut-downs. More frequent start-ups and shut-downs (and ramping up and downs) can increase mechanical stress on generation plants, potentially resulting in higher maintenance costs and reduced life" (Kassakian & Schmalensee, 2011).

2.3. Pathway of power distribution network to adopt large integration of DERs

When penetration rate of DERs is beyond a certain point, more sophisticated challenges urge necessary changes of distribution system in terms of system planning and operations (Houwing, Ajah, Heihnen, Bouwmans, & Herder, 2008; Houwing, Heijnen, & Bouwmans, 2006; Mendez et al., 2006). This section states the changes needed for conventional distribution network to enhance its capability of adopting large integration of DERs. This is further illustrated from technical and economic perspectives of changes, and a couple of future promising paradigms of power distribution system are discussed in the end of this section.

2.3.1. Changes of power distribution from technical perspective

Technically, network management needs to evolve from passive to active by using real time control and management of DERs and network equipment based on real time measurement of primary system parameters (i.e. voltage and current) (Zhang, Cheng, & Wang, 2009). To maintain power system reliability after DER integration, it requires a more flexible power system, in which additional operational costs is incurred to cover for the variability and high uncertainty associated with DG output (Alarcon-Rodriguez, Haesen, Ault, Driesen, & Belmans, 2009; Energy, 2010). To reach that flexibility, power system must have enough response capacity, from interconnections, demand response, storage, and backup supply to maintain reliability standards (Holttinen et al., 2011).

There have been endeavors to overcome the technological challenges from a potential future explosion of DER integration. For example, upgrading to bidirectional power flow distribution system will enable DER owners dispatching power back to the grid as an alternative of expanding power capacity; by aggregating a geographically diverse collection of DERs, rapid changes in the outputs of individual DERs will be replaced by the slower output variations of the aggregated resource (Laughton, 2007). The industry also has collaborated with the Institute of Electrical and Electronics Engineers (IEEE) to create IEEE Standard 1547 to ensure that DG units won't do harm to other customers or equipment connected to the grid (Kassakian & Schmalensee, 2011).

Energy storage is a primary key to the intermittency issue. When installed closed to DGs (as part of the DER components), it enriches the value of DERs. Several financial benefits of energy storage have been summarized in (Mohd et al., 2008). The stochastic nature and sudden deficiencies of DGs will be compensated by energy saved in storage without suffering loss of load events or expenses for starting new generation units (Hamsic et al., 2006). Energy storage combining with advanced power electronics would allow utilization of the DG powers after smoothing and voltage regulation at the remote point of connection.

2.3.2. Change of power distribution from economic perspective

Economically, the business model of distribution market is required to evolve and expand beyond the current revenue source of DG connection and distribution system usage charges (Poudineh & Jamasb, 2014). This is because large integration of DERs close to loads reduces the volume of energy transmission in the grid and consequently shrinks the revenue base of utility companies (van Werven & Scheepers, 2005).

The extended business mode comes from interaction of distribution system operator (DSO) with more stakeholders in distribution system, which include the well-defined electricity end-user types, transmission system operator (TSO), DER operators/owners, and retail suppliers (Poudineh & Jamasb, 2014). DSO provides services to extend revenue sources and pays services from certain customers that consists of partial cost. These new services are stated in the literature (Poudineh & Jamasb, 2014), which include supplying power with premium quality and reliability for demanding commercial and industrial end-users whose production processes are sensitive to the electricity quality. Other services include offering system data to the DGs operators and retail energy suppliers since DSO maintains the source of customer data, and services of load balancing and ancillary services through dispatchable DG operators which will be reimbursed by the upstream TSO, etc.

An important extended economic model that hasn't been fully understood and well developed is for the integration of DERs as alternatives to grid capacity enhancement (Poudineh & Jamasb, 2014). This economic model must be consistent with regulatory framework of unbundled sectors, and will facilitate DSOs to procure DERs efficiently and ensure physical compliances by resource providers

2.4. New paradigms as solutions for DER integration

From power system perspective, power grid with advanced technologies will have a better adaption to the integration of DERs. Smart grid and microgrid are the two promising power paradigm candidates that are best suitable for large DERs integration in the future. The two paradigms are not on the same scale of power distribution system. Microgrid can be collectively treated by the utility grid as a controllable load or generation unit in a distribution system which may implement the smart grid technology.

2.4.1. Smart grid

The smart grid paradigm is a modern electric power grid infrastructure, which collects all technologies, concepts, topologies, and approaches, that allow the traditional architecture of power system to be replaced with an end-to-end, organically intelligent, fully integrated environment where the business process, objectives, and needs of all stakeholders are supported by the efficient exchange of data, service, and transactions (Farhangi, 2010; Gungor et al., 2011). The smart grid paradigm has been widely discussed because it's expected to address the major shortcomings of the existing grid and to define a new way of engagement with energy transactions among various stakeholders(Farhangi, 2010). There're more features that differentiate smart grid from an existing grid, and the comparison has been summarized in a table below (Farhangi, 2010).

Table 2-1 Comparison between existing grid and smart grid

Existing Grid	**Smart Grid**
Electromechanically	Digital
One-way Communication	Two-way Communication
Centralized Generation	Distributed Generation
Hierarchical	Network
Few Sensors	Sensors Throughout
Blind	Self-monitoring
Manual Restoration	Self-healing
Failures and Blackouts	Adaptive and Islanding
Manual Check/Test	Remote Check/Test
Limited Control	Pervasive Control
Few Customer Choice	Many Customer Choices

One of the designated feature of smart grid is to "accommodate a wide variety of distributed generation and storage operations" (Brown, 2008). Through real-time advanced tele-communication and surveillance, DER units will be observable to system operators and will be involved into the grid operation process. The integration of DERs also benefits smart grid by helping minimize the operation and maintenance expenses, since a higher reliable and qualified power will be reachable after integrations. Several applications of smart grid assist DER integration. The advanced metering infrastructure (AMI) is an advanced digital meters at all customer service locations. It's evolving from advanced metering reading (AMR) technique (Farhangi, 2010). It's a two-way communication meter system, which makes a large amount of data available to operations and planning in real time (Brown, 2008). At smart grid distribution feeders, the distribution automation units (DAs) monitor, control the power flow and communicate with end-users. The units resemble as intelligent nodes in the distribution system connecting each other. They are the fundamentals of constructing smart grid as a tree-shaped distribution network (Brown, 2008).

2.4.2. Microgrid

Microgrid is considered as a cluster of interconnected DGs, loads, and intermediate storage units that cooperate with each other to be collectively treated by the utility grid as a controllable load or generation unit in the distribution network(Pedrasa & Spooner, 2006). Microgrid can operate in grid-connected mode or in islanded mode. Whatever mode microgrid is running, balancing a balanced condition has to be maintained between supply and demand applicable to microgrid (Basak et al., 2012). Primary parameters that determine the balance condition is voltage and frequency.

When microgrid operates in grid connected mode, it either draws power from the grid or supply to the grid depending on the market policies. The voltage and frequency are determined by the grid at this mode. Were there abnormal conditions on main grid, microgrid should be shifted to islanded mode (Peng, Li, & Tolbert, 2009). At this mode, voltage and frequency of the islanded microgrid should be determined by one or more primary or intermediate energy sources within the microgrid (Basak et al., 2012). If the frequency reaches to a very low value, loads in the microgrid have to be shed.

Preparation for planned islanding is an important aspect in microgrid concept. It's used to maintain the continuity of supply during planned outages, like substation maintenance period, etc. (Hatziargyriou, Asano, Iravani, & Marnay, 2007). Energy storage device plays a critical role in the balancing operation during this period. The energy storage should be capable of reacting rapidly to frequency and voltage changes and exchanging large amounts of real or reactive power to maintain microgrid reliability. In addition, storage units are expected to offer spinning reserve assembled advantages for microsource control. Without spinning reserves like usual grid, DERs will have delayed responses when implementing secondary voltage and frequency control. Further control and operation details of microgrid will be illustrated in chapter four.

2.5. Reference

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Chapter 3 Electricity-price Arbitrage with Plug-in Hybrid Electric Vehicle: Gain or Loss?

3.1. Introduction

Customers, utilities, and society can gain many benefits from the applications of distributed energy resources (DERs). The ones include: (1) increase energy efficiency and reduce energy costs; (2) when integrated with grid, improve power quality and reliability of the grid; (3) avoid or defer investment in the expansion of transmission and distribution system; and (4) improve system resilience, especially to critical loads and vital services. Time-based pricing mechanisms (e.g., time of use, real time pricing or dynamic pricing) have been used by many utilities to shift load demand. Customers who are sensitive to electricity price will shift load demand from peak to off-peak periods. These mechanisms allow DER owners to gain financial benefits by using DERs to hedge price risk, to sell power to the grid, or to provide ancillary services. Plug-in hybrid electric vehicle, with both battery and gas tank, can serve as a distributed energy storage device of both electric and chemical energy. From owner's perspective, the potential financial benefits from arbitraging and from providing ancillary services can offset some of the operation costs. For utilities and societies, PHEVs connecting with a smart grid can bring many of the benefits that DERs can. An Oakridge National Lab (ONL) study found that wide penetration of PHEVs can significantly improve the demand curves and that current U.S. power grid can accommodate these new loads (Hadley & Tsvetkova, 2009). A demonstration project that tests the feasibility of using PHEVs to provide ancillary services is also undergoing in the Pennsylvania-Jersey-Maryland (PJM) system (Sioshansi, Denholm, Jenkin, & Weiss, 2009).

These potential benefits have been studied under a variety of scenarios of battery and market conditions. Williams and Lipman (Williams & Lipman, 2010) estimated the potential arbitrage gain of a PHEV-15 in the California electric market with real-time pricing tariff, and the result is estimated $114 per year per vehicle. In their study, the PHEV battery is treated as a stationery storage device and degradation is not considered as the PHEV operation cost. Peterson (Peterson, Whitacre, & Apt, 2010) examined the impact of electricity price prediction mechanism on the arbitrage profits under two scenarios, and reported similar estimates. White and Zhang (White & Zhang, 2011), however, found that arbitrage profit is negative in near term when degradation cost is included. The arbitrage profit could be positive in a long term when more PHEVs are deployed in the vehicle market. Their major assumptions and findings are summarized in Table 3.1.

This study is different with previous studies in several ways. First, two PHEV cases, PHEV-10 and PHEV-40, are tested. Second, previous studies are based on the state-of-the-art battery technologies of their times, which did not reflect recent and future progresses. Li-ion battery has experienced a rapid progress in recent years, and this trend will continue in the future because enormous efforts have been invested in its innovation. A National Research Council study (Council, 2010) predicts that the costs of Li-ion battery will gradually decline with improved performance. For instance, it predicts the number of cycles will rise from 3000 in 2010 to 7500 by 2030. The energy and power density will improve, too. These progresses will have significant impacts on the arbitrage profit.

Table 3.1 Previous PHEV arbitrage project summary

	Vehicle & battery	Market design	Arbitrage profit per year
Peterson(Peterson, Whitacre, et al., 2010)	PHEV-20 Capacity: 16 kWh Charging time: 2.2 hours	Real time pricing perfect information two-weeks ahead prediction	No degradation: \$142-249 * With degradation: \$12-118 * \$6-72 # Note: *: perfect price prediction #: price prediction based on fortnight data
White and Zhang (White & Zhang, 2011)	PHEV-40 (Volt) Capacity: 16 kWh Depth of discharge: 95% Charging time: 6 hours	Real time pricing (Hour ahead Market)	Low Penetration (10%): -\$110 to -\$126 (life cycles: 1500; degradation cost: 26.25 cents/kWh) -\$17 to -\$33 (life cycles: 5300; degradation cost: 6.45 cents/kWh) High penetration: 25%: \$29 50%: \$27
Williams and Lipman (Williams & Lipman, 2010)	PHEV-15 Capacity: 6 kWh Depth of discharge: 80% Battery as a stationary storage No degradation	Real time pricing (California market)	\$114

Previous studies assumed that PHEV batteries are solely used for vehicle to grid (V2G) service. This assumption neglects the impacts of driving-related discharge on both the state of charge (SOC) and battery degradation (i.e., capacity drop). Another problem of not including driving discharge is that the state of charge at the beginning of arbitrage is not accurate. Battery degradation resulted from driving is an important factor impacting the battery capacity. First, arbitrage discharging causes less battery degradation than driving discharge (Peterson, Apt, & Whitacre, 2010). When driving discharge is factored in, the battery lifespan will be shorter. Previous studies overestimated the life span, and hence underestimated the degradation cost.

Current literature of PHEV arbitrage studies assumes that PHEV owners are rational decision makers with identical and fixed time preferences. Early adopters of a new technology (e.g., PHEV), however, have different time preferences with those of late followers. This difference implies that the expected values of the financial profit from price arbitrage are different to various types of buyers.

Assuming PHEV owners as price takers, this study estimates the value of a single PHEV (PHEV-10 or PHEV-40) under three scenarios. The research question is, what is the financial benefit that PHEV owner can gain if the battery is used as distributed energy storage (DES) device that can arbitrage electricity prices, in addition to as a source of vehicle power?

3.2. Model description

3.2.1. General description

A stochastic optimization model is developed to estimate the arbitrage profit of PHEV under three scenarios of electricity market and owner behavior. The arbitrage profit is measured as difference between the baseline and arbitrage cases. The cost in the arbitrage case is the sum of charging cost and battery degradation cost, minuses the revenue from V2G discharging. In the baseline case, PHEV does not participate arbitrage. The cost consists of only charging cost and degradation cost from PHEV driving.

This model has three major modules: (1) arbitrage module; (2) battery depletion module; and (3) battery degradation module. Figure 3.1 shows the model structure.

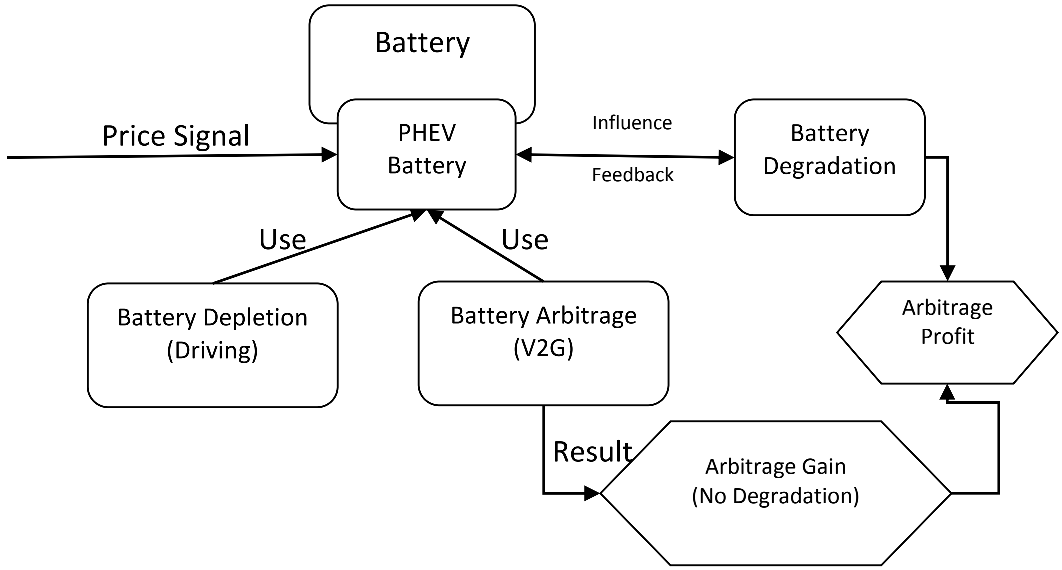


Figure 3.1 PHEV Battery Arbitrage Model Structure

3.2.2. Arbitrage module

The arbitrage module calculates the revenue from electricity arbitrage. This study assumes that 1) V2G is immediately available when PHEV arrives at home, and 2) V2G occurs only at home. The charging and discharging of the battery is optimized to minimize the net electricity cost during a 24-hour period, and the optimization is repeated for 1,827 times (five years) with real electricity price data. The daily electricity price profile with the electricity prices of every hour, is provided by the utility one day in advance. PHEV charges when the hourly prices are at the lowest levels, and, in the arbitraging case, conducts discharging (e.g. sell electricity back to the grid) when the prices are at the highest levels. It is also assumed that the arbitrage costs are only consisted of 1) the electricity cost that the utility charges the PHEV owner, and 2) the battery degradation cost.

The operation of electricity price arbitrage has to comply with the technical constrains of the battery and V2G devices. The first limit is the rated capacity of the battery. In real practice, only a portion, not all of the rated capacity, is available for discharging. SOC window must be within a range between 80% (i.e., 80% of the full capacity) and 30% (Council, 2010; Nelson, Amine, Rousseau, & Yomoto, 2007). 80% of the full capacity as the estimated upper threshold is because the battery needs free capacity to accept the power from regenerative braking. The lower limit of SOC is normally set as 30% of full capacity to protect vehicle battery (Council, 2010).

The round circuit efficiency, a combination of charging and discharging efficiency, is a key factor influencing the arbitrage profit. Lithium-ion batteries for PHEV have an efficiency window ranging from 80% to 85%; and may improve to a window of 95% to 97% with a high-power battery systems (Nelson et al., 2007; Storage, 1993).

The objective functions are listed below:

Cost of electricity (baseline case): min $Z_{Baseline} = \sum_{t \in T} P_t * E_{1t}^B$

Cost of electricity (arbitrage case): min $Z_{Arbitrage} = \sum_{t \in T} (P_t * E_{1t}^A - P_t * E_{2t})$

Total cost in the baseline case: $TC_{Baseline} = Z_{Baseline} + D_{Baseline}$

Total cost in the arbitrage case: $TC_{Arbitrage} = Z_{Arbitrage} + D_{Arbitrage}$

Arbitrage profit = $TC_{Arbitrage} - TC_{Baseline}$

Where

1. $Z_{Baseline}$: Electricity cost in the baseline case ($)
2. $Z_{Arbitrage}$: Net electricity cost in the arbitrage case ($)
3. $D_{Baseline}$ and $D_{Arbitrage}$: Battery degradation cost ($) in the baseline and arbitrage

case, respectively

4. P_t: electricity spot price at time t ($/kWh)

5. E_{1t}: the extent of electricity charged at time t (kWh)

6. E_{2t}: the extent of electricity discharged via V2G at time t (kWh)

The charging and discharging equations are subjected to the following constraints:

1. The state of charge of the battery must be between maximum and minimum allowable SOC.

2. The charging and discharging rates depend on the chargers. Slow charger for household use has a peak power of about 3.3 kW (Morrow, Karner, & Francfort, 2008). Charging power is reversely proportional with time required to fully charge an empty battery. "C" is used as a measure of charging and discharging limit. This study assumes the discharging rate is "1C", which means that battery completely depleting from its full capacity needs one hour. This limit is designed to protect charging facilities and battery (Vytelingum, Voice, Ramchurn, Rogers, & Jennings, 2010).

3. The battery is charged to the maximum level (e.g. 80% of the full capacity) before the first trip of a day.

When constraints are represented as constraint functions:

$$E_{1t} \geq 0$$

$$E_{2t} \geq 0$$

$$E_{1t} \leq \min\left(Pw_{1max} * \frac{1}{2}h,\ (SOC_{max} * C - E_{battery\_t})\right)$$

$$E_{2t} \leq \min\left(Pw_{2max} * \frac{1}{2}h,\ (E_{battery\_t} - SOC_{min} * C)\right)$$

$$SOC_{t=0} = SOC_{max}$$

Where

1. $E_{battery\_t} = SOC_0 * C + \sum_{i=1}^{t-1}(\propto * E_{1i} - E_{2i})$, the total electricity in the battery at time t;
2. Pw_{1max} and Pw_{2max}: the maximum charging and discharging rate, respectively (kW)
3. T: 48 half-hour time periods (1-48)
4. SOC_{max} and SOC_{min}: the maximum SOC (80% in this study) and minimum SOC (30% in this study)
5. SOC_0: SOC at the beginning of a trip
6. α : round circuit efficiency of battery
7. C: maximum capacity of the battery (kWh, degradation considered)

3.2.3. Battery depletion module

This module simulates the state of charge of PHEV battery from the beginning to the end of a trip. The remaining electricity is available for V2G service. Electricity used for driving depends on several factors including mode of operation, driving distance, and driving conditions. With given initial SOC (i.e., SOC at the beginning of a trip), the SOC at the end of a trip can be estimated through this depletion module.

Electric vehicles including PHEV have two major operation modes when driving: the charge depleting mode (or CD mode), and the charge sustaining mode (or CS mode). At charge depleting mode, the vehicle is exclusively, or almost exclusively, powered by the battery until the SOC reaches a specific threshold level. After that, PHEV switches to the charge sustaining mode, where chemical energy becomes the primary source of power (Zhang, 2010).

Battery driving efficiency is a measure of PHEV's energy efficiency. It is defined as the energy consumed for one mile when a PHEV drives at pure electric mode. It is a similar measure as the fuel economy--miles per gallon--for a car with internal combustion engine. Peterson et al.(Peterson, Apt, et al., 2010) estimated that the average battery driving efficiency is about 0.28 kWh/mile assuming the PHEV has a National Household Travel Survey (NHTS) trip profile from (DoT, 2001). EPRI estimated the battery driving efficiency was about 0.26 kWh/mile for a compact sedan (Duvall, 2002). A test at University of California Davis found that the efficiency is between 0.12 and 0.30 kWh/mile (Jonn Axsen, Kurani, & Burke, 2010). A truncated normal distribution (mean=0.21; standard deviation=0.03) is used to appropriate the battery driving efficiency. It is truncated at 0.12 and 0.30, which are assumed to be the lower and upper bounds of the 99.7% confidential interval.

The distance of each trip is estimated based on a national household travel survey of 2009 (Santos, McGuckin, Nakamoto, Gray, & Liss, 2011). This survey shows that average number of trips per vehicle is 3.02 trips (3.21 trips per day on weekdays and 2.53 trips per day during weekends), and that the average distance per vehicle per day is 28.97 miles (9.72 miles per trip). Table 3.2 shows an average daily trip profile used in Peterson's study (Peterson, Apt, et al., 2010), which includes the starting time, duration, and distance of each trip. This study uses an exponential distribution to appropriate the miles a PHEV travels during a day, with a coefficient λ of 0.0296 (Shiau et al., 2010).

Table 3.2 Daily PHEV driving profile

Trip	Start Time	Duration (minutes)	Distance (%)
1	8:45	15	27.8%
2	12:16	12	22.2%
3	16:30	10	22.2%
4	17:20	15	27.8%

3.2.4. Battery degradation module

This module estimates the battery degradation process. The lifespan of a battery, either calendar life or cycle life, is an important factor influencing the battery economics, and hence that of the PHEV. Calendar life measures the time that a battery degrades to a specific level, and is an indicator of its ability to withstand degradation over time without factoring in how the battery is used (Jonn Axsen, Burke, & Kurani, 2008). Cycle life, the number of charging and discharging cycles a battery can have before it degrades to a specific level, is influenced by the depth of discharge (DOD), current, and temperature of charging/discharging (Köhler, Kümpers, & Ullrich, 2002; Omar, Van Mierlo, Verbrugge, & Van den Bossche, 2010; Ritchie, 2004). The charging and discharging involve chemical reactions. The reactivity of chemicals declines, and the resistance increases, as the number of charging/discharging cycle increases. The impact of DOD, however, is less significant on the degradation of next generation battery (Jonn Axsen et al., 2008). Peterson et al. found that DOD per cycle has no significant impact on the degradation rate for

LiFePO4/graphite battery (Peterson, Apt, et al., 2010). The battery degrades faster at higher charging/discharging temperature (Jonn Axsen et al., 2008). Battery degradation leads to declined voltage and capacity. When the voltage and capacity drop below a certain level (normally 80% of the original level), the battery needs to be replaced as it cannot power the vehicle safely and functionally (Meissner & Richter, 2003). The battery usually reaches cycle life first before the calendar life.

The total amount of electricity charged and discharged is the most important determinant of battery degradation. For the same amount of electricity discharged, V2G causes less degradation than driving discharging (Peterson, Apt, et al., 2010).

Table 3.3 PHEV battery degradation coefficients (Peterson, Apt, et al., 2010)

Coefficient	**Value**	**95% Confidence Interval**
Driving discharge, γ_d	−5.99E−5	1.71E−6
V2G discharge, γ_{V2G}	−2.71E−5	1.85E−6

The degradation coefficients, γ_d and γ_{V2G} are different because PHEV battery has more frequent and transient discharging in driving mode than in V2G behaviors. Table 3.3 shows the respective degradation coefficients, γ, and their ranges.

This study assumes that PHEV battery is an A123 battery with ANR26650M1 cell (LiFePO4). To simplify the calculation, the battery degradation at CS mode was excluded since the extent of degradation is much less significant than the degradation at CD mode. Therefore, the degradation process of a battery is a function of the accumulated amount of electricity discharged over life time:

$$\Delta C = C_0 - C = E_d * \gamma_d + E_{V2G} * \gamma_{V2G}$$

where,

C_0: the nameplate capacity (kWh) of the battery

C: the battery capacity (kWh)

E_d : accumulated electricity discharged for driving

E_{V2G}: accumulated electricity discharged for V2G

γ_d: battery degradation coefficient of driving discharging process

γ_{V2G}: battery degradation coefficient of V2G process

When C is less than C_{min}, the battery needs to be replaced. Assuming replacement cost is K (in $), E is the total amount of electricity discharged for both driving and V2G (e.g. $E = E_d + E_{V2G}$), the degradation cost associated with 1 kWh of electricity discharged, D, is: D=K/E.

This study assumes that the battery is replaced with a new one when its capacity drops to 80% of the initial level. The specific cost of a new battery (in $/kWh) is represented with a truncated normal distribution. A NRC study presents three estimates of the future costs: conservative, probable, and optimistic (Council, 2010). This study assumes that the "probable" estimate is the mean of the normal distribution, and the "conservative" and "optimistic" estimates are the lower and upper limits of the 99.7% confidence interval of the mean, respectively. Labor cost of replacing the battery is not included.

3.2.5. Electricity price

The electricity tariff data is from Frontier Zone of National Grid (Buffalo, Niagara Falls, Olean, Angola, Lakewood, and Dunkirk). Real time price is calculated on a day-ahead basis and is determined by the supply and demand in each hour of a day. TOU price data is from the same region. Residential households have three different blocks of rates on a weekday: on-peak, shoulder, and off-peak; and a flat rate (i.e. off-peak rate) during the weekends and on holidays. The TOU hours are shown in Table 3.4.

A five-year electricity price data (from 2007 to 2012) is utilized to reduce the influences of weather variation or substantial demand spikes. The time interval of this model is 30 minute.

Table 3.4 TOU tariff periods (Grid, 2012)

TOU Period	Hours
Peak	12:00 p.m. to 8:00 p.m.
Shoulder	7:00 a.m. to 12:00 p.m. and 8:00 p.m. to 10:00 p.m.
Off-Peak	10:00 p.m. to 7:00 p.m. Weekdays, and all hours for Weekend and Holidays

3.2.6. Simulation environment

This model estimates the arbitrage profits of two types of PHEV: PHEV-10 with a 4-kWh battery pack and PHEV-40 with a 16-kWh battery pack. The numbers “10” and “40” are the number of pure electric miles that PHEV can travel with a fully charged battery. The model is built and executed in ANALYTICA with Optimizer.

3.3. Factors influencing PHEV arbitrage value

The roles of PHEVs in a future smart grid system, including potential arbitrage profits to owners, have uncertainties including those in the technology, market, and society.

3.3.1. Battery characteristics

Several types of battery (e.g. Lead-acid, Nickel-metal hybrid (NiMH), Lithium-ion, Nickel-Zinc (Ni-Zn), Nickel-Cadmium(Ni-Cd)) can be used to power PHEV (Khaligh & Li, 2010). Lithium-ion battery is the best among these technologies and has been widely adopted on PHEV. Lithium-ion battery has both high energy and high power density, and can maintain a good performance at extreme environment. There are several major tradeoffs among power density, capacity, and usable state-of-charge. They determine the cost, mass, volume, lifespan of battery, battery driving efficiency, and vehicle operation (Markel & Simpson, May 2006). Battery with larger capacity stores more electricity, hence is more capable of providing ancillary services. But it is also heavier at a given density, and usually costs more, and hence lowers the battery driving efficiency. The usable SOC window involves another major tradeoff. A large SOC window with deeper depth of discharge (DOD) can significantly reduce the costs. It, however, will shorten the battery lifespan (Markel & Simpson, May 2006).

In terms of future prediction of battery technology, some primary coefficients of battery are expected improved in 2025 and further. Battery unit cost will reduce significantly in 2030, where the unit cost of PHEV-10 battery reduced from average $825/kWh in 2010 to $475/kWh, and the unit cost of PHEV-40 battery reduced from average $875/kWh in 2010 to $500/kWh (Council, 2010). The uncertainty of battery improvement is considered in a truncated normal distribution. The truncated thresholds represent the worst and the best technology improvement scenarios published in the report (Council, 2010). Then, battery roundtrip efficiency is deemed as the other factor that may have significant improvement in the future. This study uses 90% as the average round circuit efficiency for today’s state-of-the-art battery, and 95% as the future improved battery round circuit efficiency in 2030 (Gerssen-Gondelach & Faaij, 2012).

3.3.2. Electricity market and tariff structure

Potential arbitrage profits depend on variation of electricity rates during a day. Flat rate is the simplest and most commonly used electricity tariff. It doesn't vary with load change or with the time. Inclining block rate (IBR) sets the marginal price increase based on the total amount of electricity consumed. When demand exceeds a specific level, an electricity rate spike will be expected (Reiss & White, 2005). Customers who are sensitive to electricity prices have to switch load demand to the less expensive times. Time-based pricing mechanisms (i.e., dynamic pricing) is another approach to reduce peak loads (Mohsenian-Rad & Leon-Garcia, 2010).

Time of use (TOU) is an easy and commonly used dynamic pricing mechanism. The 24 hours on a weekday is divided into three blocks: peak, shoulder, and off-peak hours, and different rates are set for each period of time (Fox-Penner, 2010). Consumers who are sensitive to price signals are likely to switch some loads from peak hours with higher rates to off-peak hours. TOU is also convenient for customers since they only need to know when rates change, and then adjust their electricity use behavior accordingly.

Real-time-pricing (RTP) is a more accurate but more complex form of dynamic pricing mechanism. Power system engineering uses the constantly changing marginal cost known as "system lambda" to calculate the present hourly prices and matches the demand with supply (Fox-Penner, 2010). The price that retail customers pay equals to these hourly wholesale prices plus several fixed fees. Compared with other tariffs, RTP can lower the average daily utility cost by 5 to 25% (Doostizadeh, Khanabadi, Esmaeilian, & Mohseninezhad, 2011; Mohsenian-Rad & Leon-Garcia, 2010).

Two barriers, however, impede the deployment of RTP: 1) lack of real-time forwarded price information to customers; and 2) low adoption rate of home automation systems (Doostizadeh et al., 2011). In a smart grid system, smart meters can receive real-time price information from the utilities. Smart meter also records real-time loads, and sends the records back to the utility, which can be used to improve load prediction.

Over long term under the time-based pricing schemes, however, the profit margin of arbitrage will decline as more people adjust their behavior in response to differentiated rates. Wide deployment of PHEVs introduces significant new challenges to the utility (Yuchen, Hess, & Edwards, 2007). Aggregated adjustment in electricity use behavior will lead to a demand curve with smaller difference between peak and off-peak. The change of load demands over long-term is not included in this research. Therefore, the electricity rate won't have apparent differences between short-term and long-term electricity market.

3.3.3. PHEV owner: technology adoption and time preference

The expected value of arbitrage profits depends on the types of technology buyers are, as they have different time preference reflected by their discount rates (Jonn Axsen & Kurani, 2012; Huijts, Molin, & Steg, 2012). Individual's belief and attitude influence their intention of accepting or rejecting a new technology (Huijts et al., 2012). From sociological perspectives, personal preference and attitude are also shaped by the social context (e.g. family, household, or work place). Three types of technology adopters are defined in this study. The innovators love new technologies, and are willing and have resources to pay a premium to own a new product. Late adopters are the majority population who are sensitive to purchasing price of the emerging technology product. Between them are early adopters. As a new technology, PHEV is first adopted by innovators, who then generate information about this technology, and share within their social network (Moore, 2002).

The diffusion of PHEV as an innovative technology takes time. During this time period, PHEV technology improves, its market share increases. First buyers of PHEV as a new product are innovators. They are followed by early adopters, and then late adopters. Study on the time preference of hybrid electric vehicle (HEV) buyer's reveals that as the market share rises, discount rates of potential buyers increases and they become more concerned about the vehicle price and less about the energy-saving benefit (Mau, Eyzaguirre, Jaccard, Collins-Dodd, & Tiedemann, 2008). Table 3.5 shows the discount rates of HEV buyers at different market-share levels. Assuming the discount rates of HEV buyers are indicative, this study uses them to approximate those of PHEV buyers.

Table 3.5 Discount rates and market share (Mau et al., 2008)

Market Share	0.03%	5%	10%	20%
Discount Rate	21%	28 %	35%	49%

3.4. Scenario Designs

Electricity tariff and PHEV-buyer type (and hence the discount rate) are the two most important uncertainty factors in estimating the arbitrage profit. They are used to define a two-by-two matrix with each quadrant representing a different combination of these two uncertainties, and a plausible scenario of the future. This study estimates the potential arbitrage profits under three scenarios. The technological uncertainty is also considered into the scenarios. For the market design, two tariff systems are considered: real time pricing, and time of use. Two types of PHEV buyers are considered: early adopter, and late adopter.

The table 3.6 shows a 2 X 2 matrix of scenarios. Scenario I may represent the current situation. Under this scenario, the electricity market uses a TOU tariff system, which requires no advanced metering instruments. PHEV is a new technology in the market. Potential buyers are considered as "early adopter". Since the market penetration of PHEV is still low, their aggregated influence on the power system is negligible. The battery represents today's state-of-art battery technology.

Table 3.6 Scenarios

PHEV Buyer / **Electricity Tariff**	Early adopter (low penetration)	Late adopter (high penetration)
Time of Use	Scenario I	(Excluded in this study)
Real Time Pricing	Scenario II	Scenario III

The only difference between Scenario and Scenario I is the electricity market. Under Scenario II, smart meters have been widely deployed, and a dynamic real time pricing mechanism is implemented. Under this scenario, the market penetration of PHEV is still low, and the number of commercial and residential PHEVs driving on road or charging at charging stations is low. PHEV owners in this electricity market will take advantage of the price gaps between the peak and off-peak prices, and the smart meters and other electronic systems help PHEV owners optimize the charging and discharging behavior to maximize the arbitrage profits.

Scenario III represents a future market where battery cost drops to a much lower level as a result of technology progress and economy of scale. This study assumes that the load curve in Scenario III is as same as that in Scenario II. The market penetration level of PHEV is assumed as high as the HEVs' today.

This study does not consider Scenario IV because the TOU scheme is assumed to be gradually replaced by RTP in the future.

3.5. Result and Analysis

3.5.1. Battery SOC and electricity price

Figure 3.2 shows the state of charge of a PHEV-40 battery over 24 hours (i.e., 48 half-hour periods), and the electricity price profile under Scenario II. Figure 3.3 shows the charging and discharging behaviors of the battery during a 24-hour period on a sample day. The PHEV is assumed driving at the 2nd, 9th, 18th, and 20th time interval, which represent four transportation trips. The PHEV returned home at the 21st period, and immediately became available for V2G service. The charging and discharging were controlled by an optimization algorithm. In this example, PHEV discharged electricity back to house at the 22nd and 33rd time intervals when prices were the highest, and recharged from the grid at the 31st, 32nd, and 38th to 44th periods when the prices were relatively low.

Figure 3.2 SOC of a sample PHEV-40 battery and corresponding electricity price

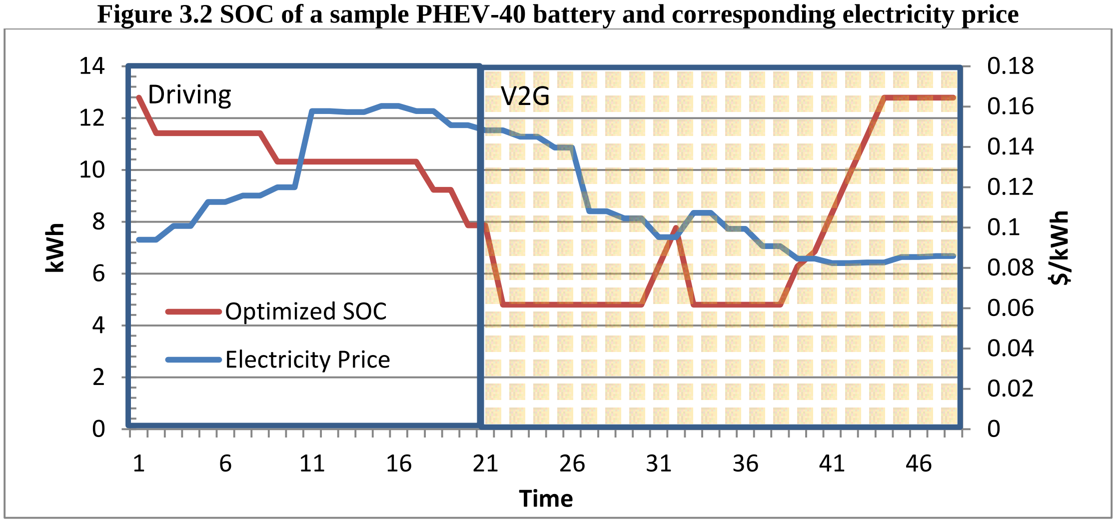
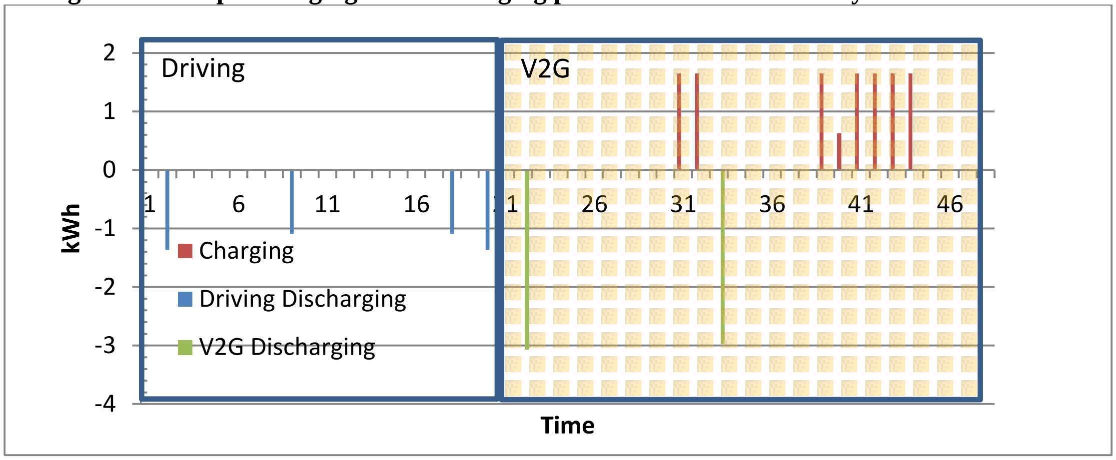


Figure 3.3 Sample charging and discharging profile of PHEV-40 battery under Scenario II



3.5.2. Arbitrage profits

The five-year total arbitrage profit is shown below. Under all three scenarios, price arbitrage can't bring any profit to PHEV owner. PHEV with a larger battery loses more. For a PHEV-10 with a 4-kWh battery, the median value of the net loss is -74, -99, and -45 dollars under Scenario I, II, and III, respectively. For a PHEV-40 with a 16-kWh capacity, the loss is -253, -371, and -139 dollars under Scenario I, II and III, respectively. Figures 3.4 to 3.6 show the simulation results of each scenario.

Figure 3.4 Arbitrage profit under Scenario I (discount rate=0.21)

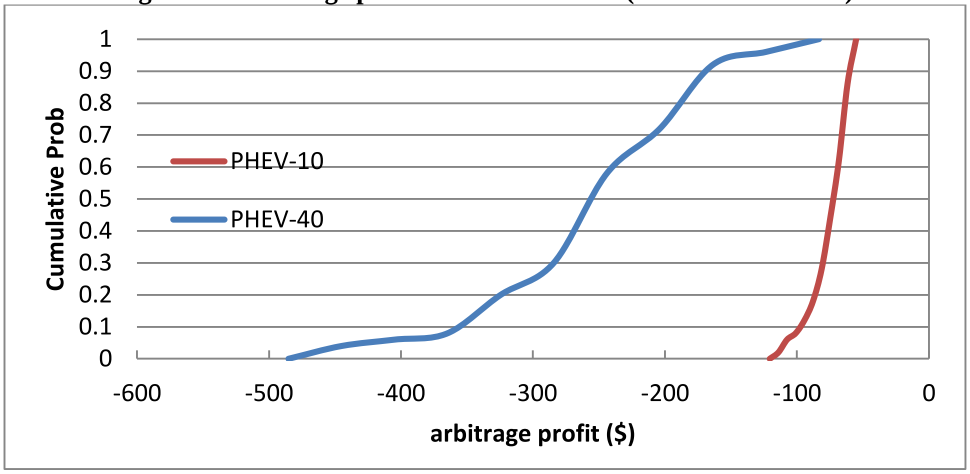


Figure 3.5 Arbitrage profit under Scenario II (discount rate =0.21)

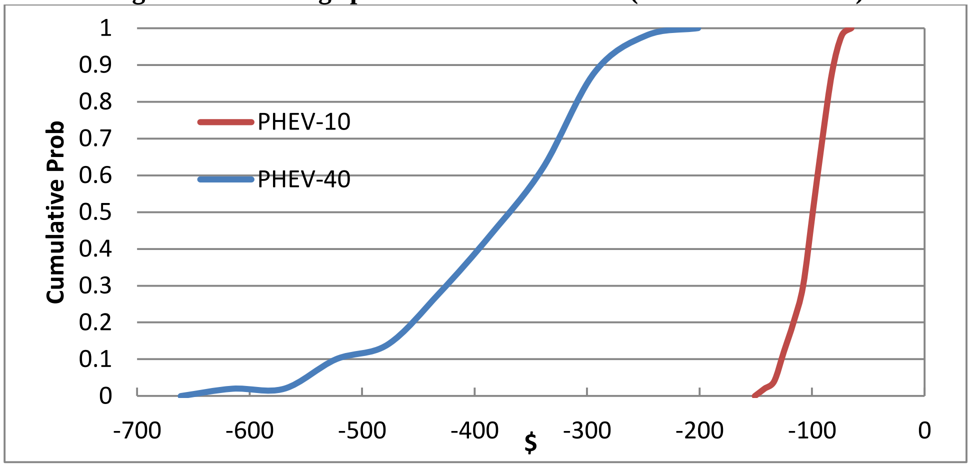
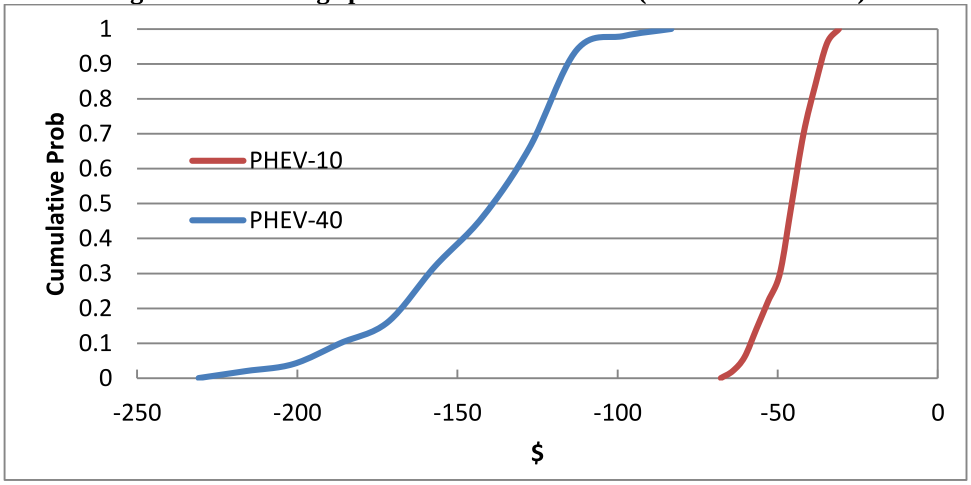


Figure 3.6 Arbitrage profit under Scenario III (discount rate=0.49)



3.5.3. Arbitrage profits and the impact of degradation cost

The simulation results indicate that the degradation costs have significant impacts on the arbitrage profits. Table 3.7 shows the arbitrage profits with degradation cost included and excluded cases. When excluding degradation costs, electricity price arbitrage can generate profits to the owner.

The gains from price arbitrage for PHEV-10, however, are negligible even excluding degradation costs under three scenarios. Under Scenario I, PHEV-10 doesn't participate in arbitrage for two reasons: (1) with a small battery, there is no electricity left after driving events, and hence no capacity for further V2G arbitrage; and (2) a time-of-use tariff provides little financial incentive to recharge the battery for later V2G arbitrage. Even with real time pricing mechanism (Scenario II, and III), price arbitrage brings to owners a gain of $1-2 over 5 years. For PHEV-40, when excluding degradation cost, PHEV arbitrage can gain financial profits as $62, $88, and $58 per vehicle per year under Scenarios I, II, and III, respectively.

Price arbitrage brings PHEV owners more profits as the battery capacity increases. Yet, once degradation costs are included, they offset all the gains. As results shown in Table 3.7, the impact of degradation is much more significant than the gains from price arbitrage, and hence negative profits.

Table 3.7 Arbitrage profits with and without degradation costs

	Scenario I (r=0.21)		Scenario II (r=0.21)		Scenario III (r= 0.49)	
	No Degradation	Degradation	No Degradation	Degradation	No Degradation	Degradation
PHEV-10	0	-74	1.2	-99	2.2	-45
PHEV-40	62	-253	88	-370	58	-139

3.5.4. Electricity tariff and arbitrage profits

The only difference between Scenario I and II is the electricity tariff. Table 3.8 compares the arbitrage profits under Scenario I and Scenario II. With a TOU tariff, price arbitrage causes a loss to PHEV owner, which is -$74, -$253 over 5 years for PHEV-10, and 40, respectively. When a RTP mechanism is used, losses are -$99 and -$370 for PHEV-10, and 40, respectively.

The PHEV owners under Scenario II (RTP) lose more than those under Scenario I (TOU), which contradicts with previous studies that RTP tariff can enable owners to save more than the other price tariff system (Doostizadeh et al., 2011; Mohsenian-Rad & Leon-Garcia, 2010). The primary reason that RTP leads to more losses is that RTP provides PHEV owners more opportunities (i.e., electricity price varies more frequently) to conduct arbitrage. Figure 3.7 demonstrates the charging and discharging events in a typical day. There is only one V2G discharging under TOU scheme, but two discharging events under RTP scheme. More discharging causes more battery degradation, and hence higher degradation cost.

Figure 3.7 PHEV-40 Operates at TOU vs. RTP at day=64

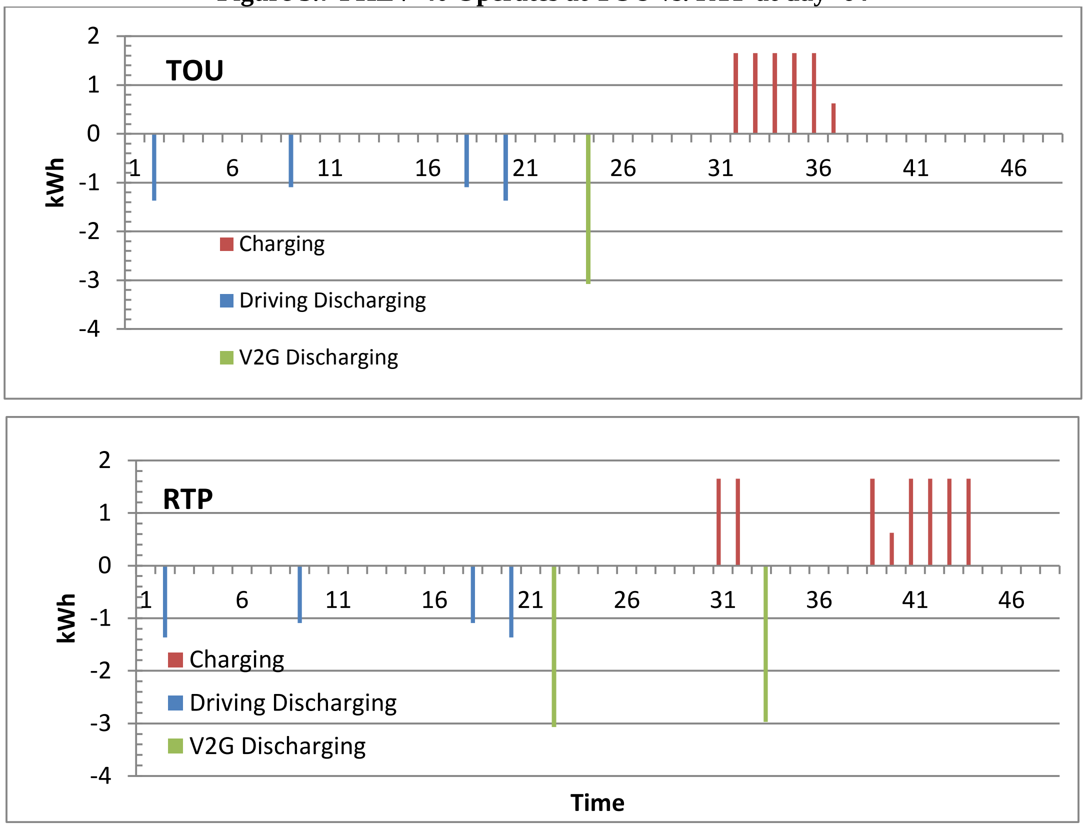


Table 3.8 Arbitrage profits comparison between scenarios I and II (discount rate = 0.21)

Vehicle (battery capacity)	Scenario I (TOU)	Scenario II (RTP)
PHEV-10 (4 kWh)	-$74	-$99
PHEV-40 (16 kWh)	-$253	-$370

3.5.5. Technology progress and arbitrage profit

There are two differences between Scenarios II and III, which are the battery technology performance and PHEV owners' discount rate. This study assumes that battery in Scenario III is more advanced than that in Scenario II. First, the round-trip efficiency has increased from 90% to 95%. Second, the cost of PHEV-10 battery drops from $825/kWh-capacity in Scenario II to $475/kWh-capacity in Scenario III; and cost of PHEV-40 battery drops from $875/kWh-capacity in Scenario II to $500/kWh-capacity in Scenario III.

Another difference is the type of PHEV buyers and hence their discount rates. The buyers in Scenario III are assumed to be a late adopter and have a higher discount rate. The discount rate is 0.49 in Scenario III, and 0.21 in other Scenarios.

The degradation cost in Scenario III is much lower than in Scenario II (see Table 3.9). With the same electricity prices, Table 3.9 shows the median values of the arbitrage profit of the two scenarios. The loss in Scenario III is about half of those in Scenario II. Yet, the arbitrage profits are still negative. This finding suggests that even with a much better battery technology, the degradation cost is still so high that PHEV owner can't make a profit from price arbitrage.

Table 3.9 Arbitrage profit under Scenario II and III

	Scenario II **(discount rate= 0.21)**	Scenario III **(discount rate= 0.49)**
PHEV-10	-99	-45
PHEV-40	-370	-139

3.5.6. Sensitivity analysis

A set of sensitivity analyses are conducted to examine the impact of discount rate on arbitrage profits. Economic literature on consumer behavior suggests that the discount rate for consumers with higher income tends to be lower. This study assumes the discount rate equals to 0.21 when early adopters are the major buyers (i.e., market penetration is very low), and 0.49 when market share is high. Additional discount rates are examined. Under Scenarios I and II, when PHEV is still an emerging technology and is at early stage of market penetration, potential buyers are innovators or early adopters who have financial resources to pay a premium. Two more discount rate cases (0.12 and 0.16) are tested to examine the impact of more types of customers.

This study also examines the impact of a very high discount rate (0.7) on arbitrage profit under Scenario III. Buyers with very high discount rate are assumed to be conservative buyers who are sensitive to the vehicle price and concern heavily on future savings. To demonstrate the impacts of discount rate on the arbitrage profit, Figures 3.8 and 3.9 show the cases of PHEV-10 under Scenario I, and PHEV-40 under Scenario III, respectively.

Figure 3.8 Impacts of discount rate on arbitrage profit (PHEV-10 under Scenario I)

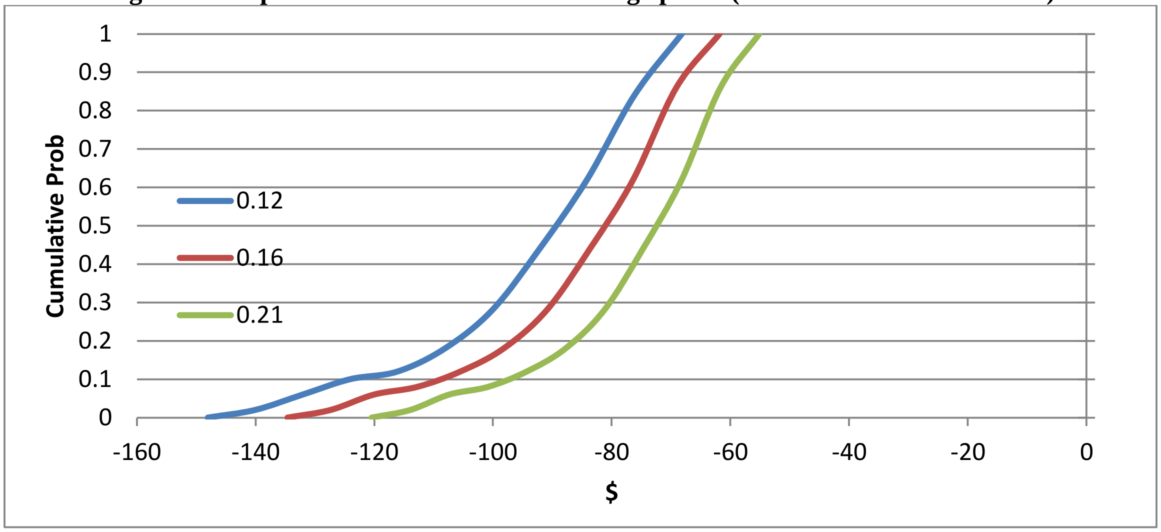
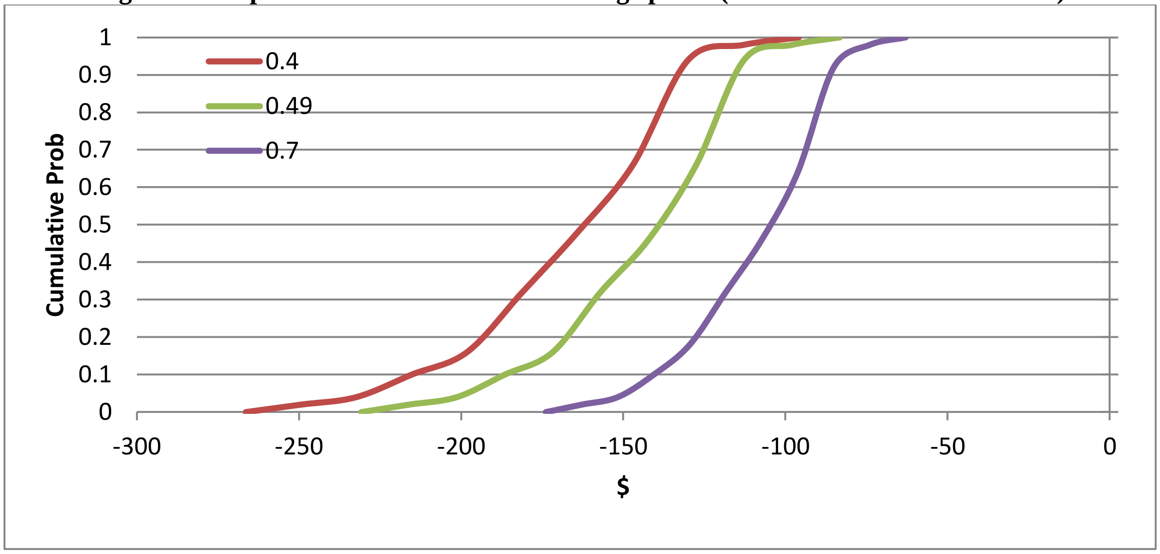


Figure 3.9 Impacts of discount rate on arbitrage profit (PHEV-40 under Scenario III)



When arbitrage profit is negative, the owners (who don't know the final outcome ahead) with high expectation of PHEV technology will lose more money through the price arbitrage. Under Scenario II, the arbitrage profit for aggressive early adopters with a discount rate of 0.12 lose $30 more than the group of consumers with standard discount rate (r = 0.21). Under Scenario III, in figure 3.9, the expected value of arbitrage profit for a conservative customer (discount rate=0.7) loses less than a typical late adopter (discount rate=0.49).

3.6. Conclusion

This study develops a method to estimate the potential profit of using PHEV in electricity-price arbitrage. The simulation is conducted under three scenarios of electricity tariff and PHEV buyer.

The simulation results show that when degradation is excluded, PHEV in market with RTP scheme gains more benefit than it does that with TOU scheme. When degradation cost is included, PHEV owner will have a net loss in both current market and future market. PHEV owner loses money in all cases and the value of arbitrage in RTP loses more than those in TOU. Technology progress will reduce the loss. Yet, they can't make the price-arbitrage profitable. The impact of degradation cost is more significant than the benefit earned by the corresponded arbitrage benefit.

This finding confirms that customers will lose money in the arbitrage practice. The significant impact of degradation cost is the primary reason contributed to the negative result, and limited benefit of arbitrage can't offset the cost to make profit. By comparing with previous literature, the differences of the outcome are resulted from the parameters with different settings. For example, the scale of electricity price tariff (both TOU and RTP) is much smaller than the ones quoted by other literature.

Overall, this finding implies that expected profits from arbitrage are not a viable option to engage PHEVs in dispatching and in providing ancillary services. Subsidy or change electricity tariff or both are needed from external resources.

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Chapter 4 Pricing Emergency Service of Dynamic Microgrid as a Measure to Increase Distribution Resilience

4.1. Introduction

Customers, utilities, and society can gain many benefits from the applications of DERs (Corey, Iannucci, & Eyer, 2004; I. KEMA, February 2012; Mohd, Ortjohann, Schmelter, Hamsic, & Morton, 2008; Zogg, Lawrence, Ofer, & Brodrick, 2007). It can: (1) increase energy efficiency, reduce energy costs and pollutant emissions; (2) when integrated with the grid, improve power quality and reliability of the grid; (3) relieve transmission and distribution congestion and avoid or defer investment in the upgrade of transmission and distribution system; and (4) improve system resilience, especially to critical loads and vital services; and (5) increase generation diversity. Although there have been discussions of DERs as a promising supplement to the current centralized grid, the extent of those benefits hasn't been fully understood (Lasseter et al., 2002). Since current distribution configuration is not designed to accommodate much DER integration (Zhenhua, 2006), DERs' implementation to the current distribution grid system will be a critical issue to the system operator. Previous assessment methodology in the grid distribution will not be adequate to assess DER value, and new assessment should be conducted under the emerging power industry.

Large grid integration of DERs will increase system resilience to weather resistance. In the aftermath of extreme weathers, power grid may suffer outage or blackout. DERs can supply continuous electricity to customers who are temporally losing power either from a major unanticipated surge in demand or from a substantial breakdown on the supply side in the main feed line of the distribution network (Vickrey, 1971). By integrating primary power sources and supplemental DERs in a grid islanding paradigm, end-users will be able to pay these continuous electricity services at a fair rate to avoid power loss.

The pricing issue, however, hasn't drawn much attention in previous studies. Theoretically, the pricing process distinguishes with that in a normal distribution operation since the resources of power generation are different. Zeineldin considered a pricing model to formulate a single auction market, and assumed a real-time forecast of the load demand before the pricing activity(Zeineldin, Bhattacharya, El-Saadany, & Salama, 2006). The service rate of DERs in his model depended on the cost of DG portfolio and the unserved energy cost resulted from power shortage. The result showed that the electricity price was different between the two sides of island, and the electricity price within the island was directly affected by the distribution status. Zeineldin's research, however, was limited by the state-of-the-art islanding technology, and the unserved energy costs as index of economic evaluation were given judiciously.

My research will address both technical and economic issues to assessing DERs as supplemental power resources enhancing distribution resilience. It's different with previous studies in the following aspects. First, the study will be conducted by implementing an emerging power distribution system (the dynamic microgrid scheme) to estimate the electricity market clearing prices of islanding regions at various circumstances. In addition, unserved energy costs will be given in a set of well-founded economical schemes, and the pricing scheme will be tested at various scenarios to reduce uncertainty. In order to maximize social benefits, i.e. total revenue of electricity off the operational cost, an optimal planning model is conducted by complying with associated distribution physical constrains.

The remaining study has the following sections. Section 4.2 introduced the innovative dynamic microgrid islanding scheme with current pricing practices of grid and off-grid islanding cases. Section 4.3 described an optimization methodology to estimate the market clearing price in a single-bid auction market. The overall benefit in the dynamic islanding region shall be maximized. Section 4.4 designed a hypothetical community with various type of building types in different load sectors. Four scenarios are proposed to comprehensively assess the impact of DER enhancing grid resilience. Section 4.5 explained the data sources and described the data structure, followed by a group of analyses in terms of the simulation result in section 4.6. Section 4.7 concluded the study.

4.2. Dynamic microgrid and pricing DG services at normal and islanding situations

4.2.1. Power islanding schemes and dynamic microgrid

One promising implication of deploying DERs is to enhance the power distribution reliability. Current practices in distribution systems, however, disconnect all distributed generations and don't permit islanded operation during outages (IEEE, 2000). Therefore, partial capacity of DGs is wasted(Mahat, Chen, & Bak-Jensen, 2010). To address this issue, IEEE released the standard 1547.4, which allows intentional islanding by using available DG sources for continuous power supply [2]. Since DG technology will have significant improvement and cost of operation will be reduced in the coming future, it's foreseeable to implement DG as back-up resource in intentional islanding schemes to enhance distribution system resilience (Chowdhury, Agarwal, & Koval, 2003; Zeineldin et al., 2006).

A few islanding schemes have been discussed in the previous studies (Fuangfoo, Lee, & Kuo, 2007; Londero, Affonso, Nunes, & Freitas, 2010; Tortós & Terzija, 2012; You, Vittal, & Wang, 2004). The scale of intentional islanding depends on the aim of design, ranging from solar panel and battery storage combined system at individual homes (Hales, 2014), to a microgrid providing continuous power supply to critical load under extreme cases. An innovative islanding scheme -- dynamic microgrid, is an ad hoc micro-grid that is created through dynamic islanding. Dynamic microgrid has a great potential as a way enhancing system resilience. Traditional microgrid has a fixed boundary, in which all the DGs and loads are affiliated to the microgrid. Dynamic microgrid, however, has a dynamic boundary which is established in accordance with status of distribution (e.g. generation capacity and load demand, voltage and frequency, etc.). Under such circumstances, DERs, which were independently operated by end-users or utilities, will be controlled by distribution operators. Loads and DERs in distribution are sectioned by intelligent controls and devices to minimize the number of household who would otherwise lose power. Smart switches are the key technologies to establish boundaries of each islanded section. They are displaced either on the routes extended from a single feeder, or deployed between feeders closed to each other.

4.2.2. Pricing DG services at normal and islanding situations

Previous literature lacks of study on pricing power supplies in a dynamic islanding paradigm. This study focuses on the issues of pricing the dynamic microgrid service.

Pricing electricity in normal operation depends on the bids of each generator participant. In a wholesale electricity market, independent system operator (ISO) and regional transmission organizer (RTO) of the grid use auctions to set wholesale electricity market clearing prices. Each generator offers bid(s) to an independent administrator with the amount of electricity and the associated schedule when it plans to dispatch. The independent administrator then dispatches powers from generators with the lowest to highest bid prices until all power demands are matched.

In order to keep total cost of operation at minimum, an economic load dispatch (ELD) activity or its extension form --Optimal Power Flow (OPF), which regulates the optimization process following the physical laws of electricity and network (Bhattacharya, Bollen, & Daalder, 2001), is implemented. The market clearing price of electricity is determined by the types of auction. If market clearing price is set as the bid price offered by the generator who meets the last increment of demand regardless the rest less expensive bid offers, this type of auction is a single/uniformed auction.

The pricing scheme may not be applicable at islanding cases, where imbalanced supply and demand status and costly small scale power resources impact regional electricity rates. Zeineldin examined the impact of intentional islanding on electricity market price(Zeineldin et al., 2006). The system cost consists of DG generation costs and unserved energy cost. DG generation cost is the sum of fuel cost and the maintenance cost. Unserved energy cost is defined in terms of the value (in $ per kWh) of electricity not supplied due to an unplanned outage (S. DOE, 2010). The Electricity price in island is set as the generation cost of DGs which satisfies the last piece of demand of the island (S. DOE, 2010) When unit cost of unserved energy is less than unit cost of DG, customers will choose losing power instead.

Previous literature assumes distribution system operators "judiciously" assigning unserved energy costs for customers(S. DOE, 2010). In real practices, however, reflecting a true value of unserved energy is difficult. It depends on the extent and duration of interruptions and other factors which are complex to acquire. Bose's study identifies several types of methods estimating the cost of unserved energy (Bose, Shukla, Srivastava, & Yaron, 2006). "Direct assessment" intuitively perceives the cost as an economic loss in production due to the loss of certain electricity power.

Such losses are perceived from questionnaires completed by electricity consumers. This method requires further classification of each outage duration and type. In this method, unserved energy cost is represented as the "interrupted energy assessment rate (IEAR)" in \$/kWh being the ratio of the expected customer interruption cost (ECOST) and the expected energy not supplied (EENS) (Wangdee & Billinton, 2005). The survey result depends on the classification of customers and accuracy of power loss estimation. The second method, the "indirect assessment", uses operation cost of alternative power generations as unserved energy cost in order to avoid unfinished load demands. This assessment, however, is only applicable when sufficient alternative power generation capacity is guaranteed. Otherwise, there is not applicable to estimate the rest unserved load demand that hasn't been supplied by generators(Bose et al., 2006). Other literature proposed a price elasticity demand model to analyze the demand responsiveness of customer, which correlates energy price with the extent of power that customers are willing to pay at that price (Bompard, Carpaneto, Chicco, & Gross, 2000). The elasticity, as an intrinsic attribute of customer, greatly affects the demand prices, but is limited by the availability of data sources.

4.3. Methodology of electric market clear pricing

4.3.1. Objective function and constrains

The purpose of this study is to implement a pricing scheme in a dynamic microgrid case in terms of enhancing distribution resilience. This research adopts a single-auction market settlement model that prices electricity based on generation bids only. Bids are visible to market operators and spot prices of electricity are obtained every five minutes by maximizing the social welfare (Zeineldin et al., 2006). The social welfare is defined as the total revenue less the total generation cost submitted to the market.

Since maximizing the social welfare is implicitly related to minimizing the total generation cost, the objective function of this model is defined as:

$$\min \mathrm{J} = \sum_{i=1}^{NG} C_i P_i + \sum_{j=1}^{N} C_{un} P_{un}(j)$$

where

1. J is the total generation cost
2. $C_i(P_i)$ is the bid price of the i^{th} DG associated with P_i , the i^{th} generator power output capacity. DG portfolio includes installed generators in dynamic microgrid (CHP, PVs, etc.) and may have parked PHEVs which are controlled by a dynamic islanding control center through Vehicle-to-Grid technology;
3. NG is the number of distributed generators within the dynamic microgrid boundary;
4. Unserved power P_{un} and the unit cost of unserved energy C_{un} are also included in the second part.

The objective function is minimized subject to the following constraints:

1. Generator capacity limits

$$P_i^{Min} \leq P_i \leq P_i^{Max}$$

Where

P^{min}, P^{Max} are the lower and upper thresholds on real power output of the i^{th} DG;

2. PHEV Battery SOC minimum threshold

$$SOC_t \geq SOC_{min} * C$$

Where

SOC_t is battery SOC at time t (kWh);

SOC_{min} is the minimum electricity SOC (assumed as 30% in this case) of modeled battery;

C is a constant equaling to the maximum capacity of battery (kWh).

3. Stored gasoline in PHEV should be nonnegative at any time t,

$$GS_t \geq 0$$

Where

GS_t is the remaining gasoline at time t (gallon);

4. Demand and supply balance

$$\sum_{k=1}^{NL} D_k = \sum_{i=1}^{NG} P_i + \sum_{j=1}^{N} P_{un}(j)$$

Where

D_k is the load demand of the k^{th} bus, and NL is the total number of load buses.

5. Uniform market price formulation

$$\rho \geq \lambda_i, \forall i \in NI$$

Where

ρ is the market clearing price for customers in the dynamic microgrid;

λ_i is the incremental cost at the i^{th} bus within the island;

NI is total buses of the islanded system.

4.3.2. Unit cost of electricity model

4.3.2.1. Combined heat and power (CHP) model

A CHP plant is installed in a microgrid. During normal times, the CHP fulfills the power needs of microgrid. When an outage happens, the microgrid disconnects from its connected grid. The CHP must continuously supply electricity to maintain vital facilities working as usual. The cost of generating one more unit of electricity in CHP is termed as the unit cost of electricity (COE). COE is a short-term marginal cost, which is combined by the capital, fuel, and operations and maintenance (O&M) costs of plant. COE can be interpreted as the price at which electricity must be sold in order to cover all expenses and to match the return on power plant's equity(Gulen, 2011). The formula is shown below:

$$COE = \frac{\beta \cdot C}{P \cdot H} + \frac{f}{\eta} + OM$$

Where

β = Levelized carrying charge factor or cost of money (assumed as 0.15/year in this model);

C = Total plant cost ($) = $45M;

H = Annual operating hours = 8670 h;

P = Net rated output (MW) = 40 * load capacity factor;

f = fuel cost ($/MWh);

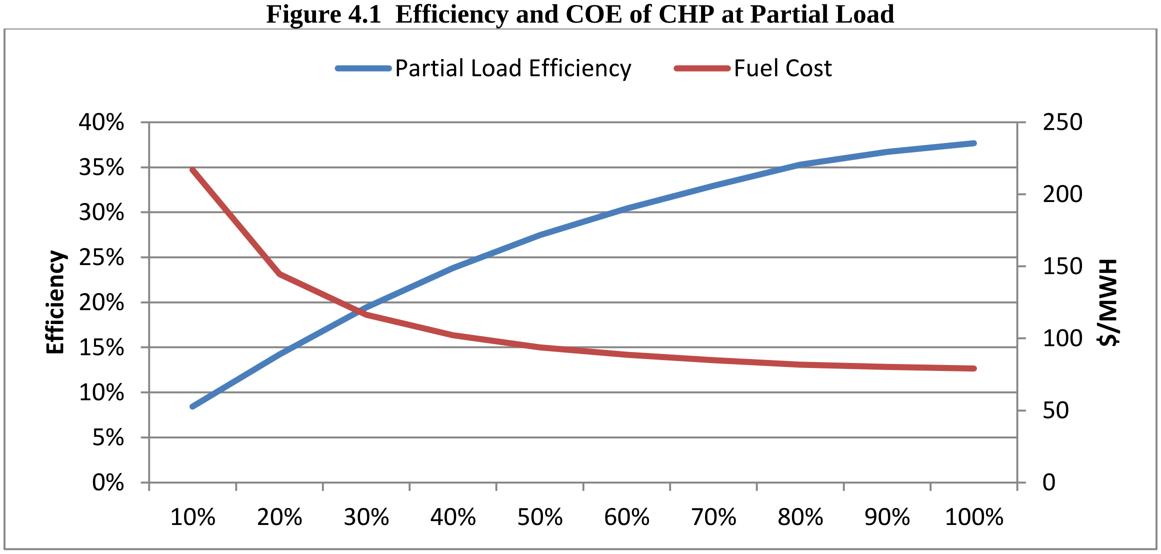
η= Net rated efficiency of the combined-cycle plant;

OM = fixed O&M cost ($/MWh) =$ 4.2/MWh.

By assuming a targeted CHP with constant load capacity factor (KEMA), the average power output, equaling to the load capacity factor times the rated output power capacity, is constant. Hence, the capital cost is constant for each year. Assuming the O&M cost is constant, the fuel cost is the only variable in the COE formula.

The formula of COE shows that the electricity generation efficiency at partial loads impacts the fuel cost, and further the COE. A simulation of partial load efficiency has been run by a third party company. The extent of power plant efficiency at each partial load is listed in the figure 4.1, which shows an upward but decreasing tendency when picking up more load. Assuming the fuel of CHP will always be satisfied and the fuel price doesn't change in short term, the fuel cost curve at each partial load has an inverse relationship with the efficiency curve (see figure below). The curve of fuel cost indicates that the COE of CHP is less expensive if CHP supplies more power to its served region.

Figure 4.1 Efficiency and COE of CHP at Partial Load



4.3.2.2. PHEV model

When parking at home, PHEVs can provide emergent power. The fuel sources of electricity differentiate PHEV discharging operation, which can be classified in two modes. PHEV can directly discharge electricity from battery if there is adequate energy stored. PHEV discharging electricity in this situation is termed as the “pure electric” mode. After the SOC of battery decreasing to its minimum threshold, the battery SOC becomes invariant. PHEV discharging in this situation is termed as the “hybrid mode”. In this mode, chemical energy instead of battery electricity becomes the primary power source. PHEV as a stationary emergency generator consumes gasoline from its battery packs to generate electricity.

In the “pure electric” mode, the unit cost of electricity consists of the electricity price in $/kWh and the degradation cost of battery per kWh discharged. To simplify the calculation, the electricity price in normal hours uses a flat price, which is quoted from the average rate of electricity proposed by long island power authority (LIPA). The degradation rate, which is inferred as independent with the battery depth of discharge, is derived from the previous PHEV arbitrage research (Peterson, Apt, & Whitacre, 2010).

In the “hybrid” mode, PHEV generator consumes gasoline to generate electricity. It’s assumed that the efficiency of gasoline consumption and its corresponding electricity generated is constant. The unit costs of electricity equals to the petroleum unit price in $/gallon divided by the transformation efficiency, represented in kWh/gallon.

This model uses a 2011/13 Chevrolet Volt as an example(U. DOE, 2014), whose battery capacity is 16kWh with 12.4kW power output, and the fuel tank can contain a maximum of 9.3 gallons of gasoline. The PHEV gasoline to electric conservation rate is quoted from a study in University of

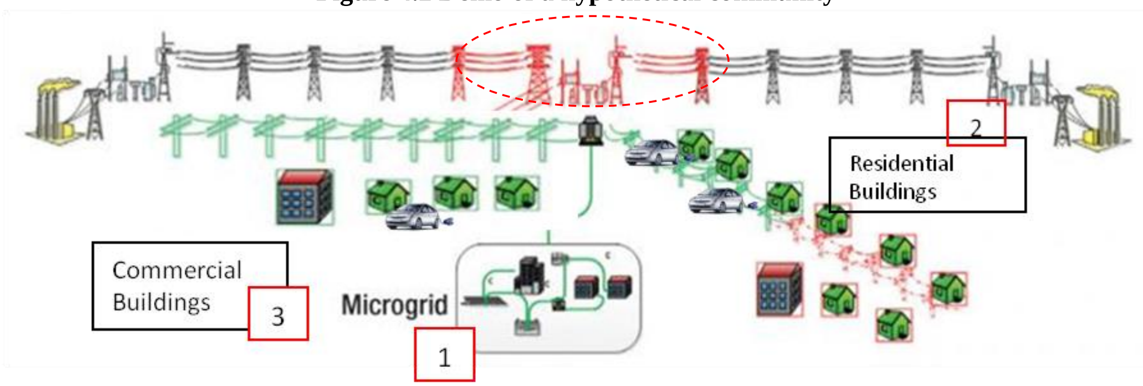
Texas at Austin(Tuttle, Fares, Baldick, & Webber, 2013), which is 8.4kWh/gallon. The model complies with the physical constrains of vehicle and battery which has been stated in the PHEV arbitrage section, and no other operation cost (e.g. vehicle-to-grid connection cost, congestion cost, etc.) is considered in the model. The cost of discharging one extra unit of electricity depends on at which mode the vehicle is operating.

4.4. A hypothetical community and model scenario design

4.4.1. A hypothetical community

The figure 4.2 shows a hypothetical community on which a dynamic microgrid system is established. A combined heat and power (CHP) plant associated with the loads of critical infrastructures (hospital, policy station, and colleges) consists of the "traditional" microgrid, which is the No.1 sector in the hypothetical community. When an outage happens due to substation or transmission failure (shown in a dashed circle), all loads connected to this substation lose power immediately, except the ones in No.1 sector (the original microgrid). When dynamic microgrid scheme is enacted, excess power from CHP can supply power to the neighborhood areas. The power dispatched from microgrid is transmitted to the connected distribution substation, where multiple feeders connect with loads of closed sectors. No.2 sector is the next sector to have power restored. It consists of loads of residential buildings with identical daily load profile per household. PHEVs are deployed and assumed only deployed in this building sector. The electricity stored in PHEV battery is the second power source in the dynamic microgrid. Were there excess power after supplying the first two sectors, dynamic microgrid will expand to the No.3 sector, the commercial building sector. In the commercial sector, the buildings function differently with a wide range of commercial building types. Therefore, an average load profile representing all of the commercial building types is not adequate to state commercial building characteristics. Further specified classification of building types is required, and the average hourly load profiles of each building type requires to be identified. The load profiles per building type and DG portfolio in this hypothetical community will be stated explicitly in the next section.

Figure 4.2 Demo of a hypothetical community



Building sectors other than the first building sector will be affected by the power outage. These buildings won't be powered until the dynamic microgrid is able to pick up the loads from a new load sector. Assuming only facilities in the dashed circle were damaged by the outage events and no other technical issues are in the hypothetical community. It's assumed that load demand within a same sector shall have power restored at the same time. When dynamic microgrid expands to a new building sector, it takes time for the new formulated dynamic microgrid to reach its reliability standard. The waiting time is assumed identical and is given arbitrarily due to lack of data sources. The impact of assigning different waiting times by system operator will further be tested in its sensitivity analysis section.

This study only examines the concept of dynamic microgrid in a hypothetical community, and the electricity market clearing prices on the island estimated in this study don't represent a real case.

4.4.2. Scenario Design

Previous studies examined that electricity price in islanded operation directly affected by the status of distribution. The status of distribution is determined by generation and load demand profiles. To further examine the impact of these factors on electricity price, four scenarios are tested in the designed hypothetical community.

The first two scenarios are in terms of dynamic microgrid restoring all load demand in the hypothetical community. Facilities are either powered by a solely CHP plant or by a combination of CHP and PHEVs.

The second two scenarios are in terms of dynamic microgrid restoring only significant load demand in the hypothetical community. The “significant load” differs from critical load, and is defined as a minimum cluster of load demand that satisfies people’s living or staying need without enduring apparent discomfort feelings. It not only satisfies critical needs for evacuation and life safety tasks, but fulfills fundamental needs that a facility is designed for. For example, cooking and refrigeration are the significant loads in restaurants, and refrigeration is the significant loads in refrigerated warehouse, etc. Significant instead of critical load is selected because the scale of CHP power capacity is large enough to supply more load than only the critical fractions.

The four scenarios are summarized in a 2x2 matrix in the table 4.1 below.

Table 4.1 Dynamic microgrid pricing scenarios

Dynamic microgrid status \ **With PHEV?**	No (CHP is the primary source)	Yes (CHP and PHEV are the primary sources)
All Load Demand	Scenario I	Scenario II
Significant Load Demand	Scenario III	Scenario IV

a) Scenario I and II are the scenarios in which dynamic microgrid restores **all load demands** of facilities in the islanding boundary. The maximum number of facilities restored in the first two scenarios is N_1. Whether PHEV being allowed is the only factor that distinguishes the Scenarios between I and II.

Scenario I: Under generation capacity limits, only CHP supplies load demand of end-users. The electricity market clearing price only applies to end-uses who involve in the dynamic islanding service.

***Scenario II*:** The combined generation sources supply all load demands of dynamic microgrid.

CHP and PHEVs provide continuous electricity to fulfill all load demands of dynamic microgrid. With extra energy capacity, dynamic microgrid will have excess generation capacity supplying all facilities.

b) Dynamic microgrid only restores **significant load demand** of involved facilities. "Significant load" satisfies more than critical needs for evacuation and life safety tasks. The identification process is introduced in the following section. In Scenario III and IV, DG(s) supplies only the significant portion of load demand. The insignificant load will be shed by operation, but their unserved cost will not account for the system operation cost since it is mandatorily excluded by system operators.

Since load demands per facility are reduced in the “significant load” scenario, according to the dynamic microgrid definition, the dynamic microgrid boundary will expand. Hence, more facilities will be involved in the dynamic microgrid, and their associated load demand will be restored. Assuming the maximum number of facilities restored in the second two scenarios is N_2, N2 should be larger than N1. In this section, whether or not PHEV being deployed before the outage is the only factor that distinguishes the Scenarios between III and IV.

Scenario III: Under generation capacity constraints, CHP only supplies significant loads of end-users.

Scenario IV: The combined sources of CHP and PHEVs supply only significant loads of facilities in the dynamic microgrid

4.4.3. Sensitivity analysis design

Three sensitivity analyses will be conducted to examine factors that may impact electricity market clearing price results.

1) Penetration rate of PHEV

The penetration rate of PHEVs directly impacts the aggregated PHEV power capacity and further the total power capacity of DG portfolio. The rate is 5% as a default to simulate an emerging PHEV market case. The result in the 20% penetration rate case as a future market prediction will be compared.

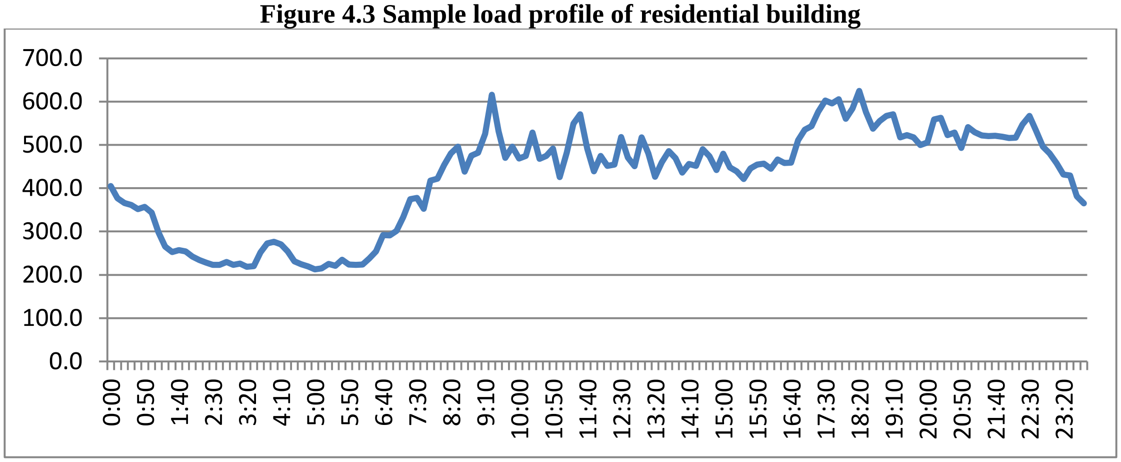
2) Time selection of outage cases

Load demand impacts distribution status and it varies with time. In this study, starting times and seasons in which outages happen impact the load demand profile and further the outcome of electricity market clearing price.

a. Start time of the power outage

Electricity load demand varies with time. The figure 4.3 shows a sample load profile of residential building within a day (Zimmermann et al., 2012). Different starting time of power outage will have different extent of load demand.

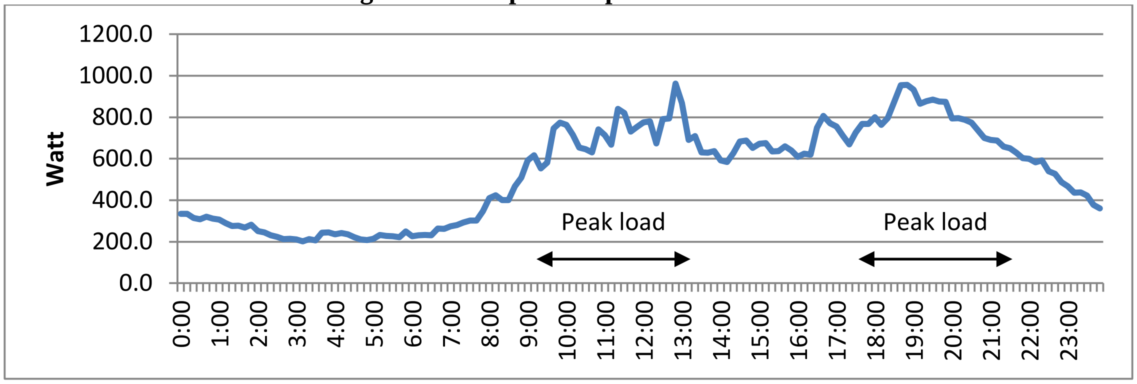
Figure 4.3 Sample load profile of residential building



b. Date/Season

Electricity load profile varies with seasons. For example, residential peak loads in summer and winter are different. Peak load in summer starts from late afternoon till early night; by comparison, there are two peak load periods in winter which are at early morning and evening (seen figure 4.4. below) (Zimmermann et al., 2012).

Figure 4.4 Sample load profiles in winter



To address these two factors, three outage cases resulted from extreme weather are implemented. Detailed information of outage is stated in the data description section.

3) Waiting time between sectors with different restoration priorities

Waiting time is manually controlled and defaults as 20 minutes in this model. Earlier or later restoration of new load sectors may induce significant load profile changes in dynamic microgrid. To address this issue, 10 and 30 minute cases of waiting time are compared in this sensitivity analysis.

4.5. Data description

4.5.1. Outage case description

Outage duration and intensity (i.e. number of loads affected) determine the impact of outage damages.

Two cases of outage duration are considered: 1) one-hour outage, and 2) four-hours outage. Since CHP fuel is unlimited by assumption, outage duration may affect PHEV operation if its energy is required to make cost-effective power supplies. Stored electricity and reserved gasoline are more likely drained away in longer outage durations.

The two duration cases will be repeated in three major outages, whose starting times and seasonal indexes are different. Specifically, hurricane Sandy brought strong winds and significant storm surge to the Long Island Sound and New York harbor in the early morning of Oct. 28, 2012 (Macmath, 2013). Hurricane Irene, in the summer of 2011, made landfall along the coast of New Jersey at 5:35 am, and condition was at the strongest between 5am to 10am (Dover, 2011). Nor'easter Storm has appeared in winter in multiple years. The starting times in this research are set as: 7am (Irene, fall), 9am (Sandy, summer), and 4pm (Nor’easter, winter).

In terms of the coverage of outage damage, we assume only transmission and lines shown in red are failed to work. All loads connected to this substation and lines lose power immediately, except the ones in No.1 sector (the original microgrid). Dynamic microgrid can only power facilities connected on the green lines in the hypothetical community.

4.5.2. Load profile of residential sector

The residential load profile data is quoted from a household electricity survey conducted by the department of energy and climate change in U.K. The preliminary report (Zimmermann et al., 2012) was first published in 2012, and presented the results of a survey of 251 households in England whose energy demand and consumptions were recorded over a year started from May 2010.

To better understand the survey result, the data from each household were compiled in a database, and shown by a simple, user-friendly tool. The tool shows how much electricity, broken down into eight end-use types, is used for each 10-minute, either in aggregated or in average single household(s) form. The outcome layout demonstrates the result in tables and graphics. The hourly load curves represent all types of dwellings on each type of days (weekday and weekend, month of the day average, the hottest and coldest day of a month). A sample hourly load profile for a single household in January workdays is shown in the figure 4.5 below. It's assumed that the load of electric heating is excluded in the residential sector. Appliances in each type of end-use are described in the appendix A (Zimmermann et al., 2012).

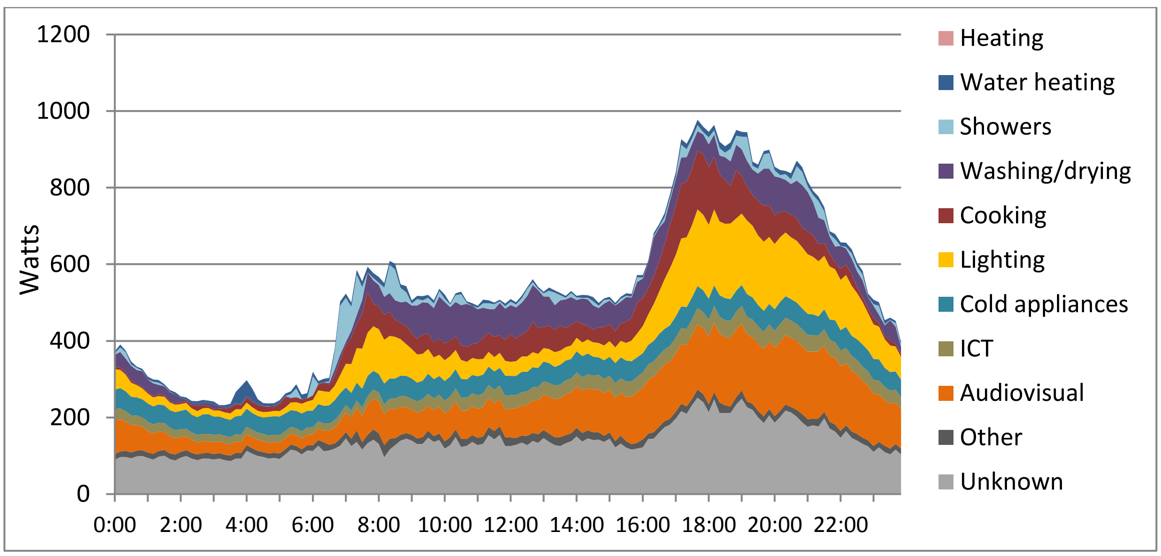
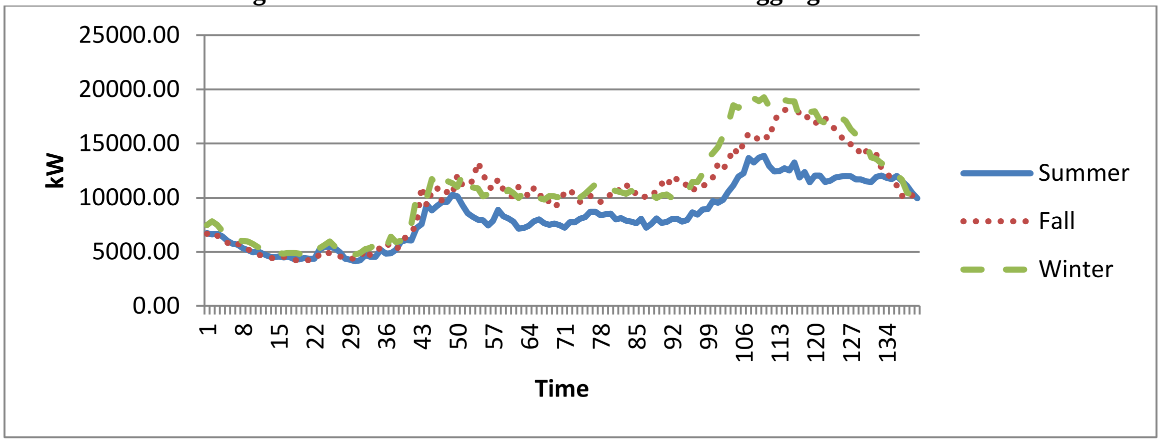


Figure 4.5 A sample hourly load profile for a single household in January workdays

There are assumed 20,000 residential households with identical load profile in the No.2 sector. The No.2 sector load profiles of three seasons are shown below.

Figure 4.6 Residential sector load demand in aggregated form



In figure 4.6, the periods of peak demands are between 5pm and 9pm. There're semi-peak demand periods from 6am till 10am.

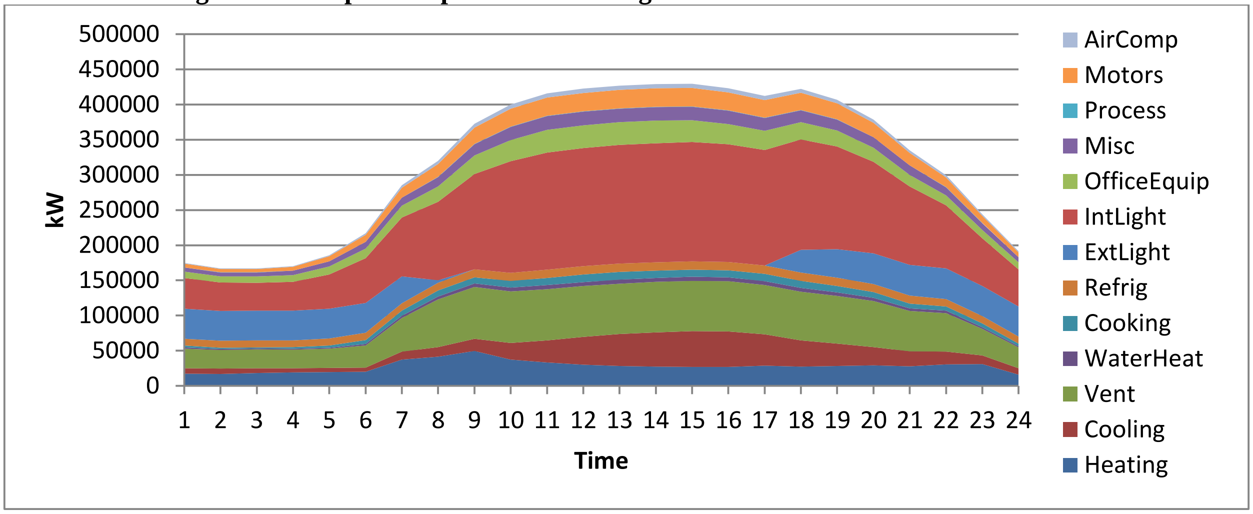
4.5.3. Load profile of commercial sector

Commercial buildings are buildings that devoted to commercial purposes. In the commercial sector, buildings function differently with a wide range of commercial types. Therefore, an average load profile of all commercial types can't represent a single commercial building designated to different commercial purposes. Further specified classification of building types is required, and the average hourly load profile of each building type will be implemented as the commercial load data.

A comprehensive study of commercial building sector end-use energy use, the California Commercial End-Use Survey (CEUS), is conducted by the Itron Inc. and other companies. This survey records detailed building system data, including electricity and gas usage, operating schedules, and other elements reflecting commercial building characteristics (Commission & Commission, 2006). A random sample of 2,790 commercial facilities has been completed representing the total 574,273 Commercial buildings in the State. Specified software developed for the CEUS project automatically transfers the on-site survey data to the end-use load profiles for user-defined commercial market segments. The commercial segments in the report (Commission & Commission, 2006) include Small (<30KSqFt) and Large Office (≥30KSqFt), Restaurant, Retail, Grocery, Refrigerated and Unrefrigerated Warehouse, School, College, Hospital, Lodging, and Miscellaneous (including fire department and police station). Three out of twelve segments are marked as critical commercial infrastructures, which include college, hospital, police and fire station. The end-use load types of commercial facility include Space Heating, Space Cooling, Ventilation, Indoor and Outdoor Lighting, Office, Cooking, Refrigeration, Water Heating, Motors (non-HVAC), Air Compressors, Process, and Miscellaneous (for equipment that is not covered by one of the pre-defined end uses). End use mappings on building appliances are described in the appendix.

The result of CEUS is shown in a 16-day hourly end-use load profile diagrams for each commercial segment. The 16-day graph presents a set of stacked end-use hourly curves on the selected 16 days of a year: 4 day types (Typical, Hottest/Coldest day, Weekdays and Weekend) in 4 seasons (winter, spring, summer, and fall). The results show the aggregated forms of electricity consumptions for each commercial sector in the California State. A sample hourly load profile of all colleges in California on a Winter Typical Day is presented below:

Figure 4.7 Sample load profile of all colleges in California State in winter season



The load demands for each commercial building type are further transformed to the demands in per unit floor area. It's assumed that the energy consumption per unit floor area data in the survey is identical to the ones in the hypothetical community buildings. The total load demand in the hypothetical community equals to the multiplication of per unit floor area load profile data and the extent of floor areas of each commercial building type.

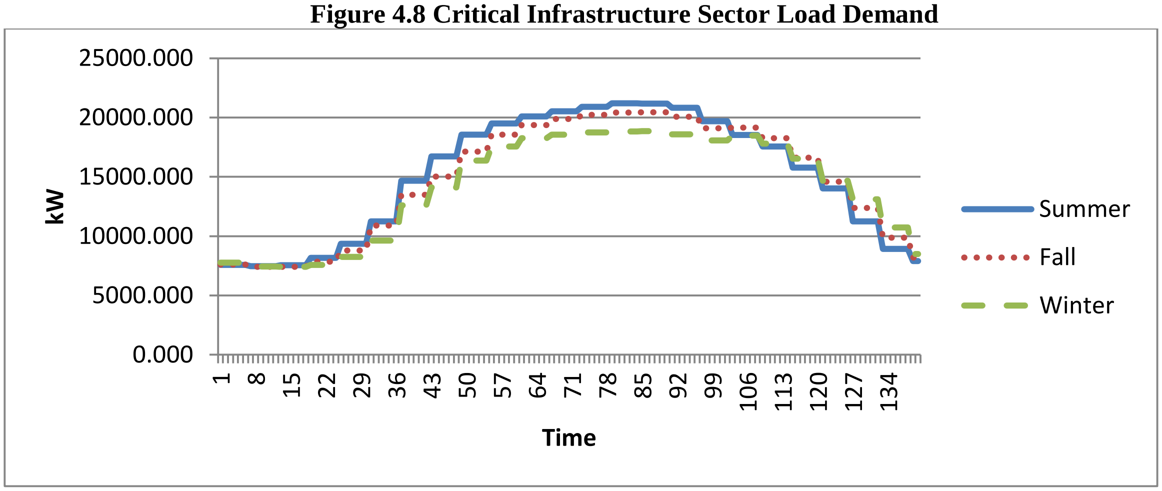
Table 4.2 No.1 sector building type and building numbers, and average floor areas

Building Type	**Data Source**	**Average floor areas (kSqFt)**	**# of building(s)**
College	Stony Brook Campus	8561.369 (Main Campus) + 85.561 (R&D park)	1
Hospital	Stony Brook Hospital	202	1
Police station	Suffolk County Police Station	25.8	1
Fire station	East Setauket Fire District	22.99	1

Buildings in the No.1 sector (college campus, hospital, police station and fire station) are assumed having the same floor areas as the ones around the Stony Brook region. The average floor areas and assumed number of buildings in No.1 sector are listed in the table 4.2.

The three-season hourly load profiles for buildings in No.1 sector are shown in figure 4.8 below. The curves of each season are similar to each other, and the peak demands happen in the middle of the day. This shows a daily electricity consumption pattern in critical infrastructures, e.g. college, hospital and enforcement departments, where people's working hours are commonly during that time.

Figure 4.8 Critical Infrastructure Sector Load Demand



It's also assumed that the floor area spaces of other commercial building types (i.e. buildings in the No.3 sector) are quoted from the result of average commercial building floor space in the 2012 Commercial Buildings Energy Consumption Survey (EIA, 2014). The result is listed in the table 4.3 below.

Table 4.3 No.3 sector building type and building numbers, and average floor areas

Building Type	Average floor areas(kSqFt)	Number of building(s) assumed
Small office	15.8	100
Large office	50	10
Lodging	37.4	5
Restaurant	4.8	10
School	31.6	1
Non-refrigerated warehouse	16.4	1
Refrigerated warehouse	16.4	1
Retail store	19	6
Grocery	7.4	10

Figure 4.9 No.3 sector load demand in aggregated form

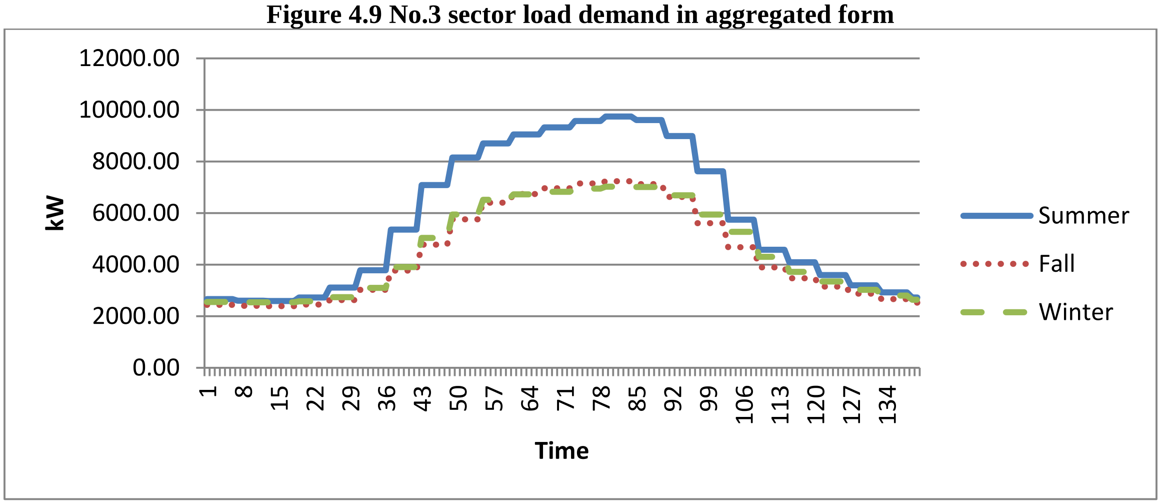
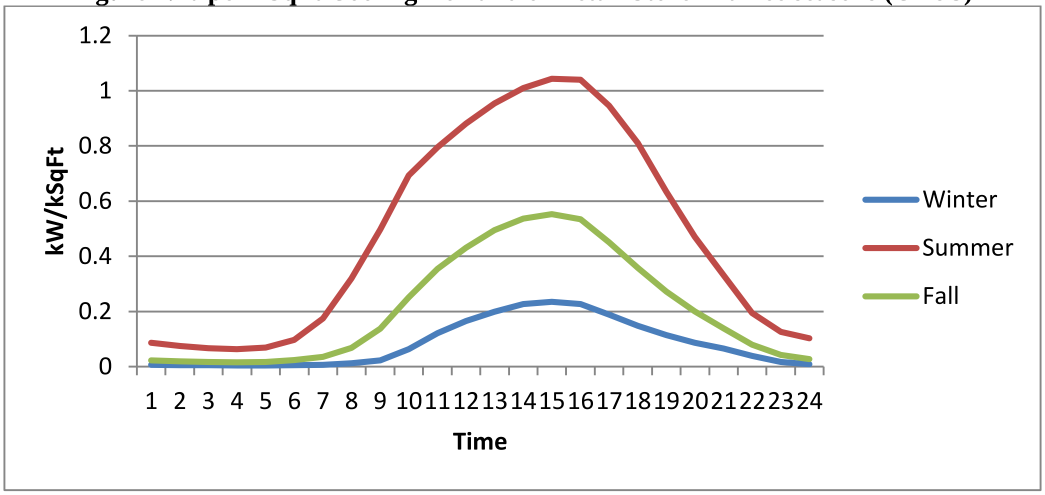


Figure 4.9 demonstrates the aggregated load demand in No.3 sector. The curves follow the same load characteristics as the one in No.1 sector, on which loads tend to pile up around noon times. The extent of load demand in summer has an apparent rise over the other two seasons. This is due to the gigantic commercial AC consumptions in summer. The figure 4.10 shows the per thousand

square feet cooling demand of retail stores in three different seasons (Commission & Commission, 2006). Load demand in summer has an apparent increase on the cooling needs.

Figure 4.10 per kSqFt Cooling Demand of Retail Store in three seasons (CEUS)



4.5.4. Identifying significant load in each sector

The definition of significant load has been described in the Scenario section. Significant load refers to the load of appliances which are "significant" to building operation otherwise users in facility will experience apparent discomforts. In the CEUS data, the minimum unit of load demand is "end-use type", not load of appliances in each end-use (i.e. end-use mapping). The definition of significant load in this section can extend to the load of end-use types which include significant load appliances.

Identifying significant load is a key factor determining the extent of a facility's backup power capacity (Bachman, Bliss, & Caldwell, 2014). The process of identification is determined by which equipment or appliances must be operated to avoid apparent discomforts during a power outage. For example, heating and cooking are required in a shelter facility in aftermath, but may have minor effect on retail or storage facilities. Therefore, identifying significant load requires classification of each facility.

The classification of facility is determined by its occupancy type and risk code. The 2012 International Building Code (IBC) made a detailed classification(IBC, 2006). In the occupancy classification table, the left column lists the categories of occupancy types relevant to this study. The facilities belonging to the respective occupancy categories are enumerated in the right column.

Table 4.4 Building occupancy classification by IBC

Occupancy Classification	**Facility**
Assembly	Restaurant
Business	Policy/Fire Station, Office, College
Educational	School (K-12)
Institutional	Hospital
Mercantile	Grocery, Retail
Residential	House, Hotel/Lodging
Storage	Warehouse/ Refridged Warehouse

In the Risk Category table, each facility is assigned to a risk code. Risk-I indicates the lowest risk, and Risk-IV tags for the most critical facilities. FEMA’s study (Bachman et al., 2014) identifies four levels of operation for facilities of each risk code. In NFPA 99, the Health Care Facilities Code (NFPA, 2012) provides additional requirements for critical health care facilities beyond the basic requirements of the 2012 International Building Code (IBC, 2006). The additional code specifies the equipment(s) that must have continuous electricity supplies at emergency.

Table 4.5 Risk category by FEMA and IBC

Risk Category	Facility
I: low hazard	Storage
II: Except those listed in the other three category	
III: Substantial hazard to human life in the event of failure	School, College, Office, Lodging , Residential house, Restaurant, Grocery, Retail
IV: Essential facilities	Hospital, fire/police

It's assumed that facilities with same occupancy classification and risk category having same significant load types. Since the CEUS data only focuses at end-use level, based on the assumption and essential functionality of facilities, the end uses of significant load in each facility are identified in the table 4.6:

Table 4.6 Identified significant end-use in each facility type

Facility	**Significant End-use**
Hospital	Vent, Interior Light, Office Equipment, Misc, Motors, Air Compressor
Residential/Lodging (Pipattanasomporn, Feroze, & Rahman, 2012)	Refrigeration, freezer, cooking, and interior lighting
Warehouse	Interior Light and Ventilation
Refridged Warehouse	Refrigeration and Interior Light
Fire/Police	Interior lighting, Outside Lighting, Miscellaneous, Office Equipment, Motors, Ventilation
School (K-12)	Interior lighting, office Equipment, Cooking, Refrigeration, Motors, Miscellaneous, Ventilation
College	Outside lighting, Interior lighting, office Equipment, Cooking, Refrigeration, Motors, Miscellaneous, Ventilation
Small Office	Interior lighting, office Equipment, Miscellaneous, Ventilation
Large Office	Interior lighting, office Equipment, Miscellaneous, Ventilation, Motors
Restaurant	Interior lighting, Cooking, Refrigeration, Miscellaneous, Ventilation
Retail	Interior lighting, Miscellaneous, Ventilation
Grocery	Interior lighting, Refrigeration, Miscellaneous, Ventilation

Identifying significant end-use instead of significant load of appliances, however, may induce inaccurate estimation. Load appliances in each significant end-use category may not be of same significant. For example, in “motors” end-use mappings, loads of passenger elevator is much more significant than loads of swimming pool in large population gathered facilities (e.g. hospital). Hence, only loads of the passenger elevators are significant by definition. Since the residential and commercial load demands are only broken into various end-uses, the estimation of significant load demand could be inaccurate.

A sub-scenario under the “supplying significant load” scenario is designed. In the sub-scenario, it’s assumed that only half appliances in the identified significant end-uses are significant. The sub-scenario is termed as “50% Significant End-use”. The load demand in the “50% Significant End-use” scenario accounts for the fewest significant load cases in the “significant load” scenarios. The impact of different merits of significant load identification will be tested in a sensitive analysis.

In dynamic microgrid, with fewer loads per facility in the “significant load” scenarios, more facilities in the hypothetical community shall be involved. The numbers of facilities in residential and commercial sectors are assumingly doubled in the significant end-uses scenario and tripled in the “50% significant end-use” sub-scenario. The number of facilities in No.1 sector doesn’t change in both scenarios because the number of facilities served by the original microgrid is fixed.

The aggregated significant load profiles in each sector of hypothetical community are listed from figure 4.11 to 4.13. When AC load is removed from significant end-use, the significant load profiles of each sector are closer to each other among different seasons.

Figure 4.11 Critical infrastructure sector significant load demand

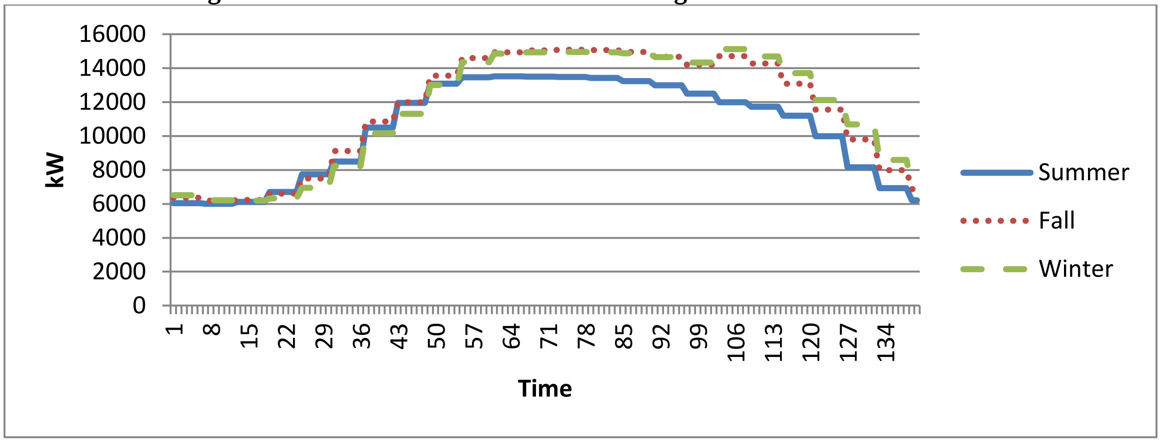


Figure 4.12 Residential sector significant load demand

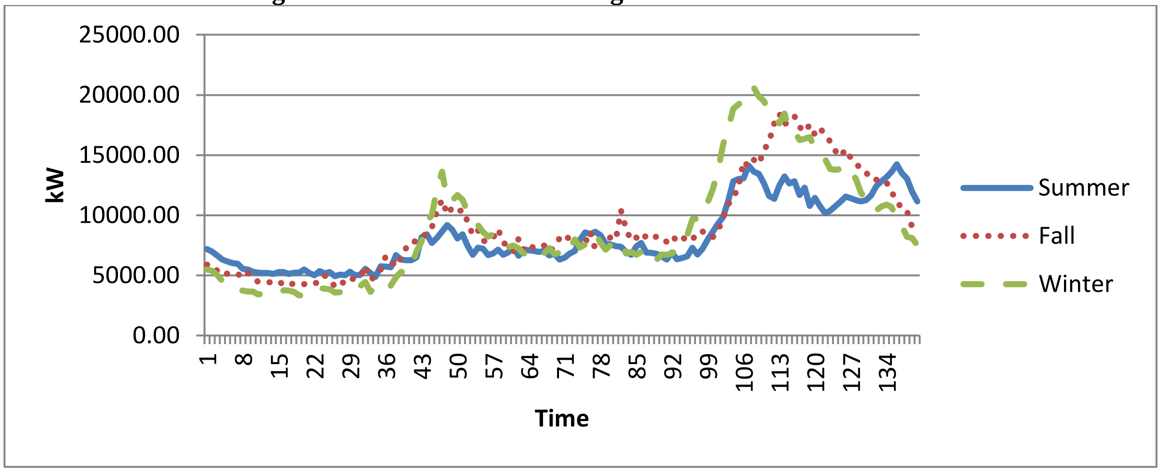
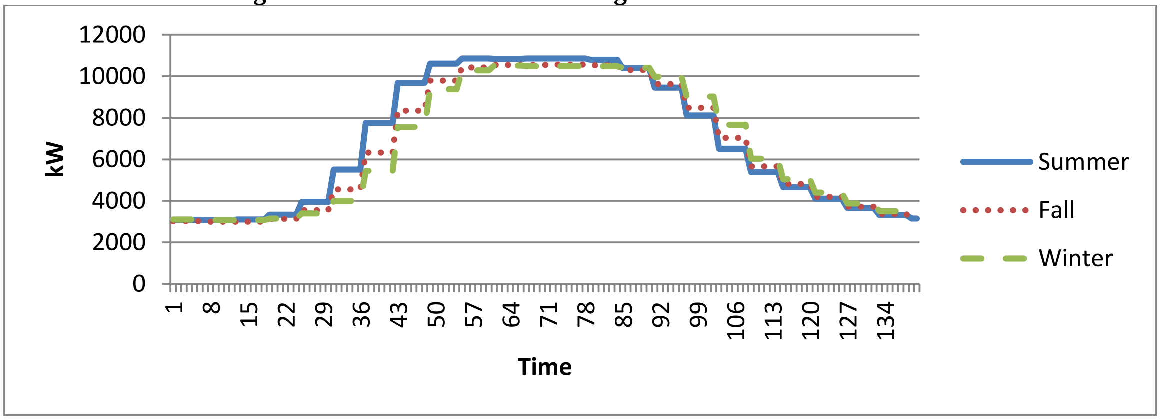


Figure 4.13 Commercial Sector Significant Load Demand



4.5.5. Unserved energy cost

In the model, the unserved energy costs are assumingly equivalent to the load interruption costs, which are impacted by outage duration and load characteristics (Balducci, Roop, Schienbein, DeSteese, & Weimar, 2002). The interruption costs are interpreted as the cost of interruption per unit load of annual peak demand ($/kW). Balducci and their colleagues conducted a couple of customer surveys interpreting the interruption costs in Canada in 1992 and 1996(Balducci et al., 2002). The 1992 and 1996 surveys asked Canadian energy consumers from residential, industrial, and commercial sectors submitting their willingness to pay in several cases of outage disruptions. The 1996 survey exclusively focused on some specific commercial industries (e.g. government, banking, insurance, health, etc.) (Balducci et al., 2002). The interruption costs were then converted to the U.S. dollars based on the 1992 and 1996 Canadian–U.S. currency exchange rates (Balducci et al., 2002).

The interruption costs of energy customer in three sectors are summarized in the table 4.7 below:

Table 4.7 Interruption costs of energy customer

Sector ($/kW)	Duration of Interruption	
	1 Hour	**4 Hours**
Commercial	12.87	44.37
Residential	0.15	1.64
Transportation	16.42	45.95

The interruption costs of commercial sector are further broken down into different commercial groups. The group interruption costs are termed as the group customer damage functions (GCDFs) in US $/kW. Table 4.8 only listed the commercial sector groups which are relevant to this research.

Table 4.8 The interruption costs of commercial sector broken down by commercial groups

Industry ($/kW)	Duration of Interruption	
	1 Hour	**4 Hours**
Food Stores/Restaurant	28.41	147.93
General Merchandise	21.14	228.15
Miscellaneous retail	11.32	33.19
Health Service	3.02	4.38
State Government	8.36	19.84
Lodging	1.13	3.05
Amusement and Recreation	63.83	78.01
Education service	1.13	4.27

4.6. Result and analysis

A 40-MW CHP power plant is simulated as the power source within the traditional microgrid boundary. The partial load efficiency associated with other parameters follows the data description in the previous section, since the 40-MW CHP equivalents to a combination of two 20-MW scaled power plants of the same type. It's also assumed that 5% of residential households (20,000 household numbers) have PHEV deployed. A further sensitivity analysis on a higher penetration rate (20%) of PHEV will be conducted in the respect section.

The simulation results are presented for the problem formulated in this research. A 24-hour time frame, dived into 144 10-minute intervals, is used for the simulation. CHP supplies power demand of hospital and campus at normal situations, and picks up all the demands of critical infrastructures when outage happens. After waiting for a constant time (defaults as 20 minutes), the dynamic microgrid expands to include the neighborhood residential load demands, and last, buildings of the commercial sector. The dynamic expansion process is referred as the two increasing segments of generation profile after the outage begins. The market electricity prices within the dynamic microgrid are obtained every 10 minutes. The uniform market prices are determined by calculating the incremental cost at each power buses and setting the highest bus incremental cost as the market price. Results in each subsections represents the outcomes in each designed scenarios.

4.6.1. Scenario I: CHP as the only source covering all loads within the boundary

The figures below show the market-clearing price ($/kWh) of electricity within the dynamic microgrid for 1 hour and 4 hours outage durations. Since CHP is the only power source, the fuel and O&M costs of CHP for each extra unit of electricity generated equals to the maximum incremental costs which is the market clearing price. The electricity market clearing prices among different seasons (figure 4.14 to 4.16) depends on the power output (figure 4.17) of CHP at each time interval.

Figure 4.14 Electricity Market Price at 1-hour/No-PHEV Scenario/Summer Case

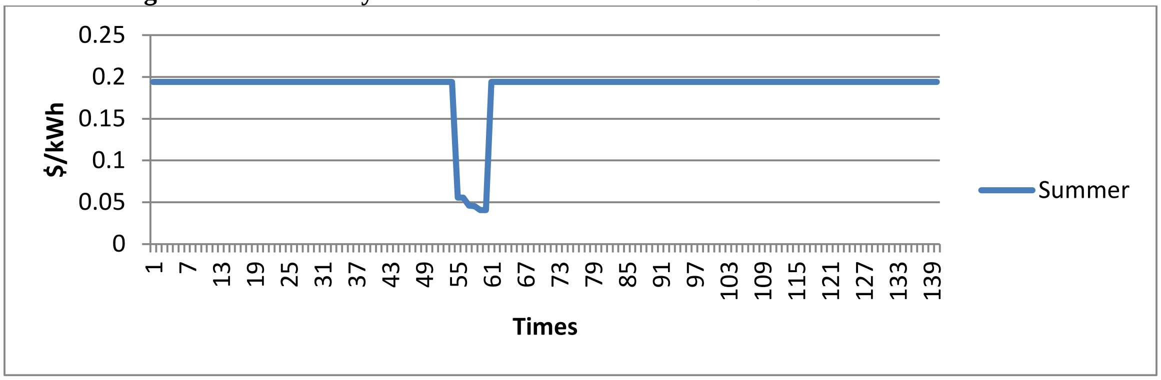


Figure 4.15 Electricity Market Price at 1-hour/No-PHEV Scenario/Fall Case

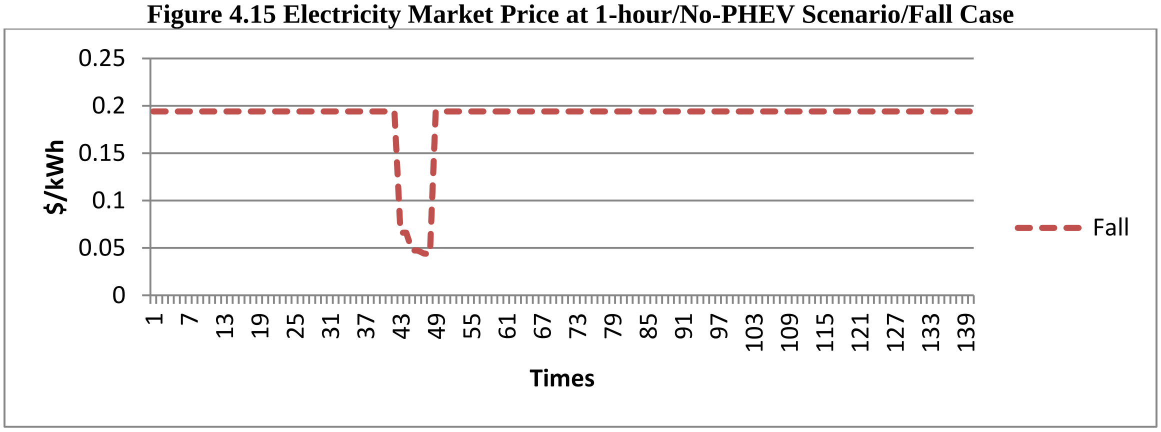
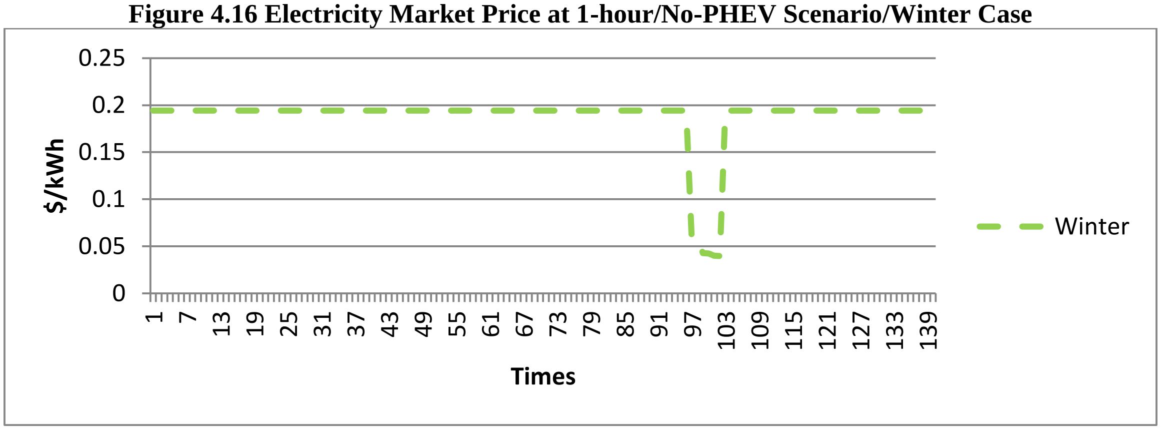
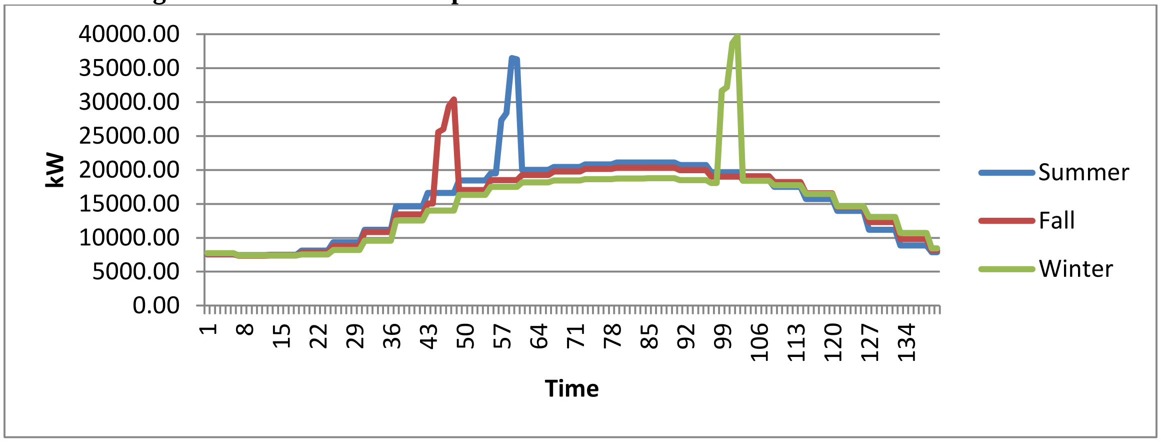


Figure 4.16 Electricity Market Price at 1-hour/No-PHEV Scenario/Winter Case



CHP is the only power source in the dynamic microgrid. The figure 4.17 demonstrates the CHP power output during the three outage events.

Figure 4.17 CHP Power Output at 1-hour/No-PHEV Scenario/All-Season Cases



In the 4-hour/no-PHEV cases, there is unserved energy in winter season. When CHP is the only source within the dynamic microgrid, electricity demand over the generation capacity (i.e. 40MW) has to be unserved. The supply and demand imbalance only increases the total system cost, but has no impact on the electricity price since the market clearing price only matters with the incremental cost of buses. The electricity rate and CHP power output during three outage events in 4-hour/no-PHEV case are listed in the figures 4.18-21 below.

Figure 4.18Electricity Market Price at 4-hour/No-PHEV Scenario/Summer Case

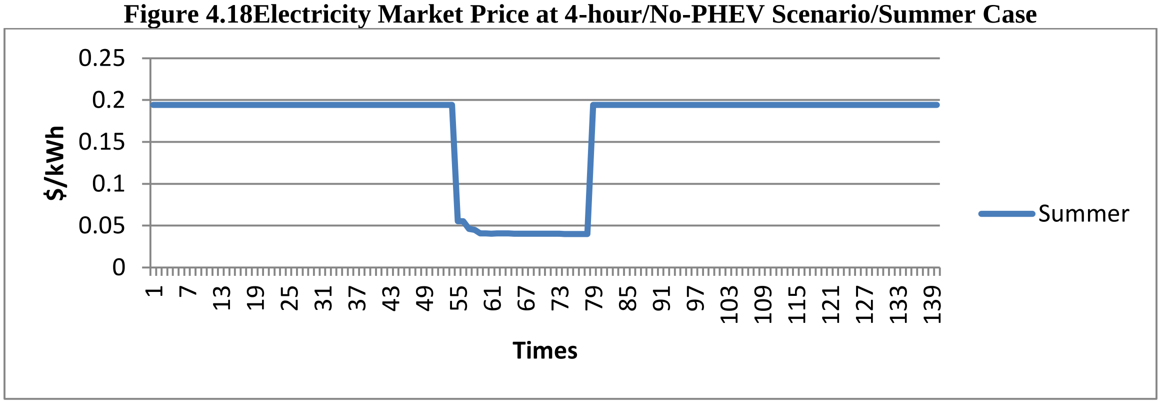


Figure 4.19 Electricity Market Price at 4-hour/No-PHEV Scenario/Fall Case

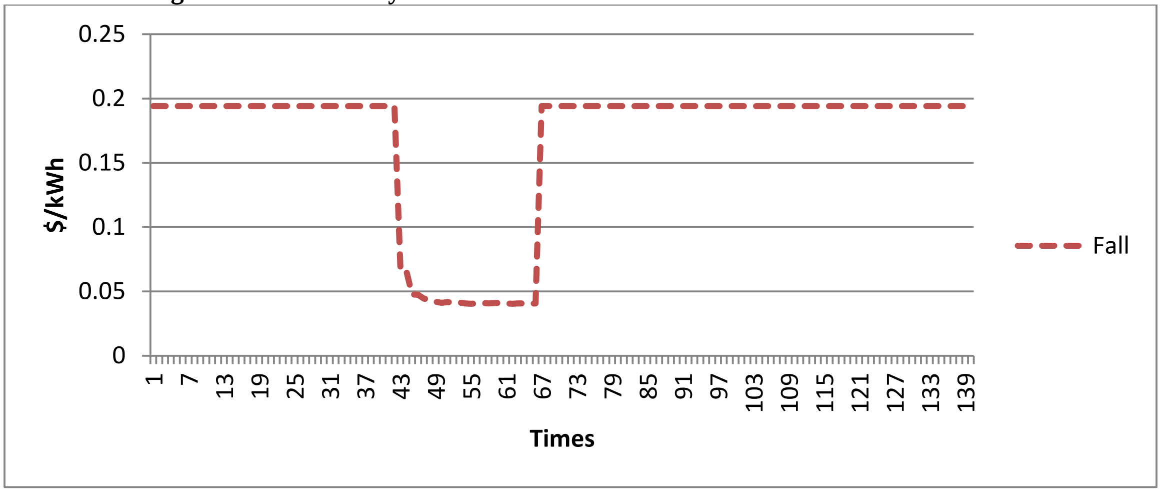


Figure 4.20 Electricity Market Price at 4-hour/No-PHEV Scenario/Summer Case

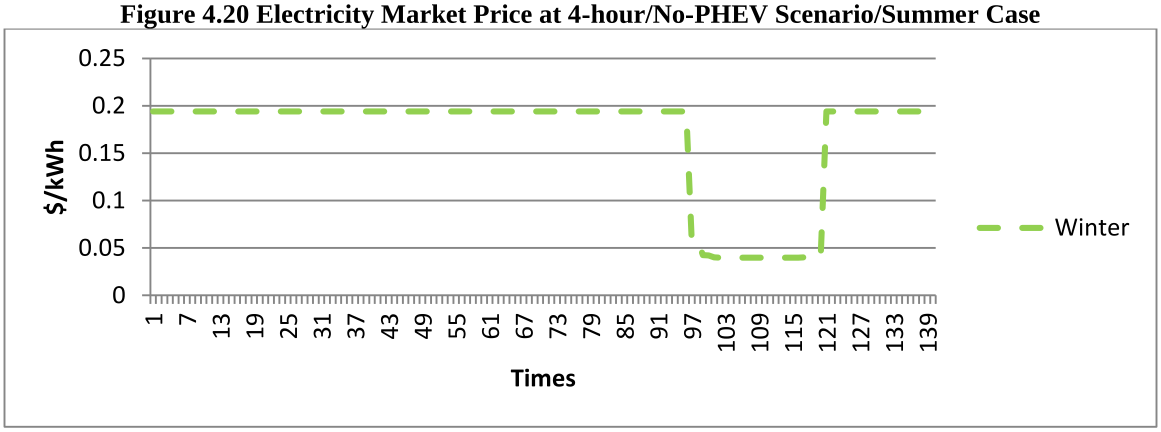
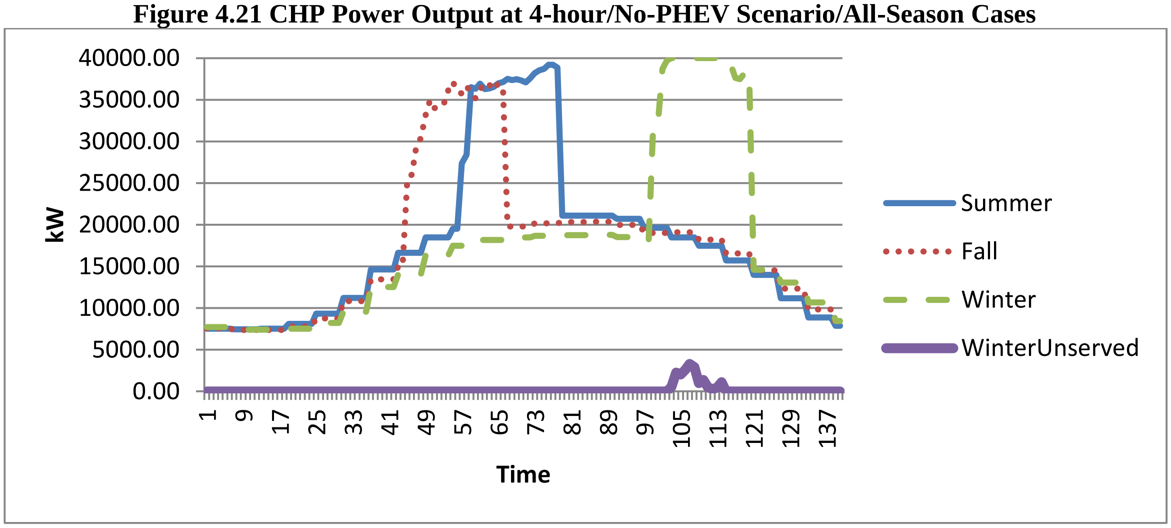


Figure 4.21 CHP Power Output at 4-hour/No-PHEV Scenario/All-Season Cases



4.6.2. Scenario II: CHP pluses PHEVs to cover all load demands

For all the 1-hour outage cases in this scenario, there is no difference of electricity rates between the first two scenarios. Since CHP has a huge economic advantage over PHEVs, it still works as the only active power source despite whether or not PHEV were deployed.

For the 4-hour outage cases in this scenario, the electricity rates in "summer" and "fall" cases are similar to the counterparts in scenario I. Electricity demands are still below the CHP power capacity. In the "winter" case, however, when demand exceeds the CHP power capacity, PHEV has to be activated to fill the extent of demand unserved. Nevertheless, under the low penetration settings (i.e. 5% residential houses has PHEV stand by), the power capacity of PHEV is not adequate to fill up the remaining unserved power at peak intervals. There is still unserved energy that neither CHP nor PHEV could cover.

The figure 4.22 shows the electricity rate at 4-hour/PHEV scenario in winter case. When outage happens, the first rise of electricity rate is resulted from the activation of standby PHEVs in the residential sector. The SOC of aggregated PHEV batteries reduced to the minimum SOC threshold after four 10-minute intervals. PHEV then switched to the battery charging sustaining mode at 107^{th} time interval, in which the engines (consuming gasoline) started working to supply electricity. Figure 4.23 demonstrates the electricity output of PHEV in winter seasons.

Figure 4.22 Electricity Market Price at 4-hour/PHEV Scenario/Winter Case

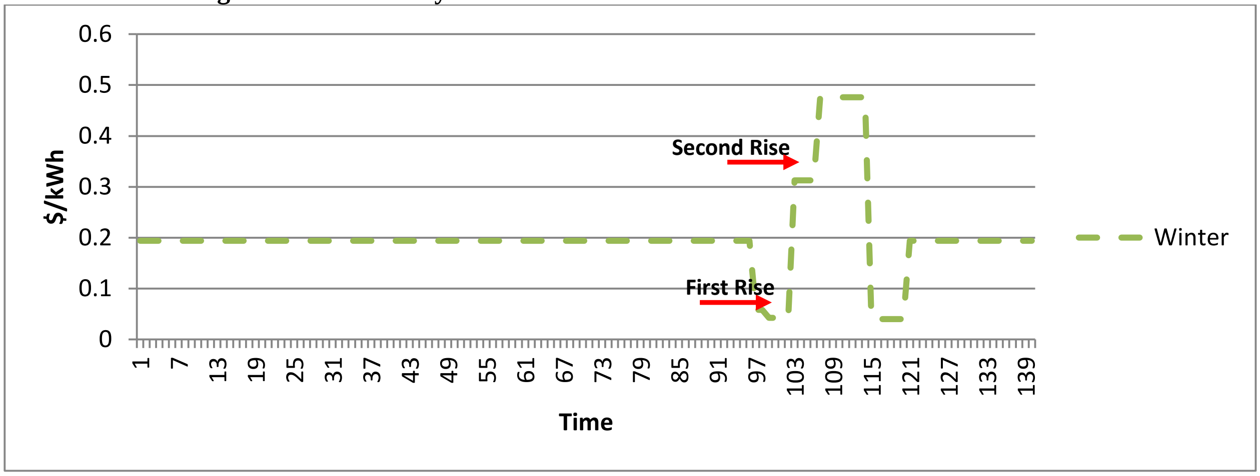
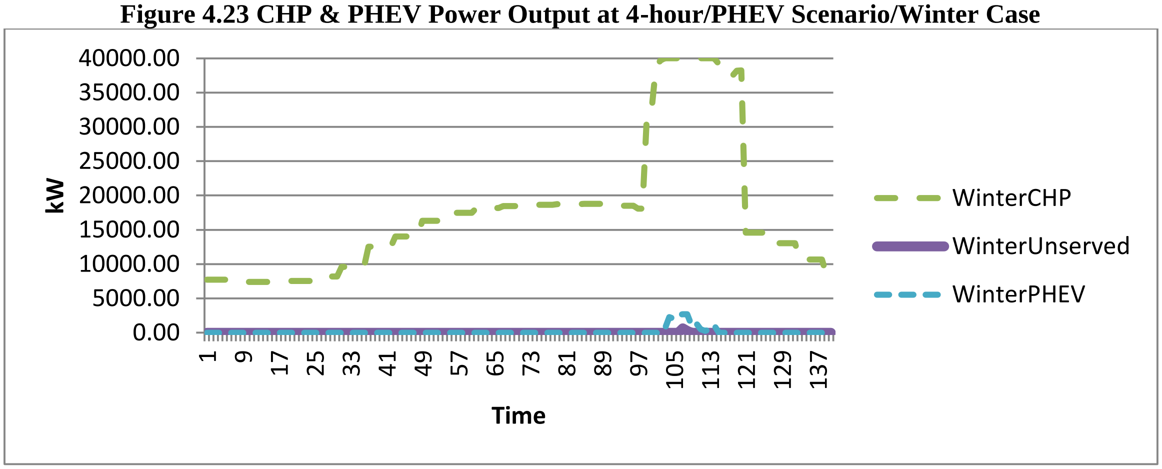


Figure 4.23 CHP & PHEV Power Output at 4-hour/PHEV Scenario/Winter Case



4.6.3. Scenario III: CHP covers only significant load demand

In this scenario, electricity market clearing prices in the one-hour outage case is demonstrated from figure 4.24 to 4.27. By comparison, the narrow lines show the respective market clearing prices in the counterpart cases in Scenario I. Electricity prices in scenario III cases are higher than the Scenario I cases at the beginning of the outages, but reduce sharply after load demands of new sectors are restored.

Figure 4.24 Electricity Market Price at 1-hour/NoPHEV/Significant Load/Summer Case

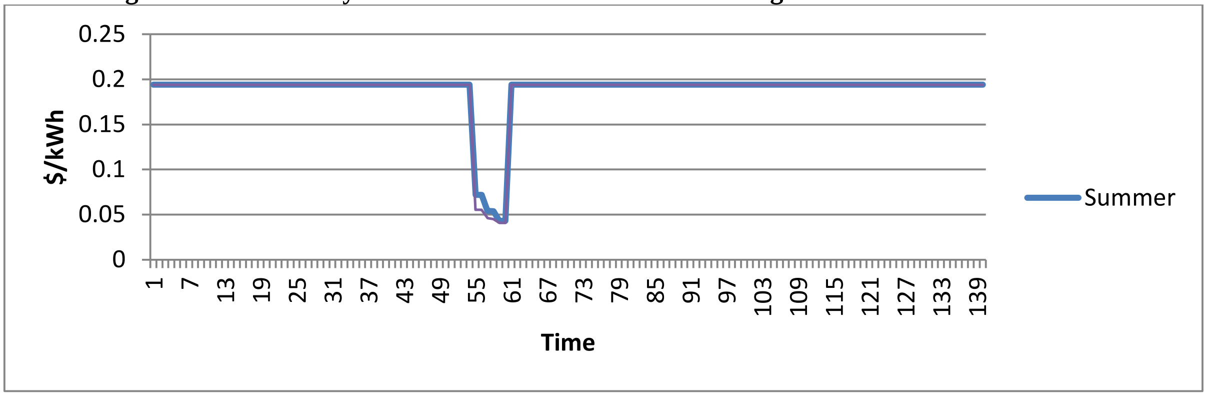


Figure 4.25 Electricity Market Price at 1-hour/NoPHEV/Significant Load/Fall Case

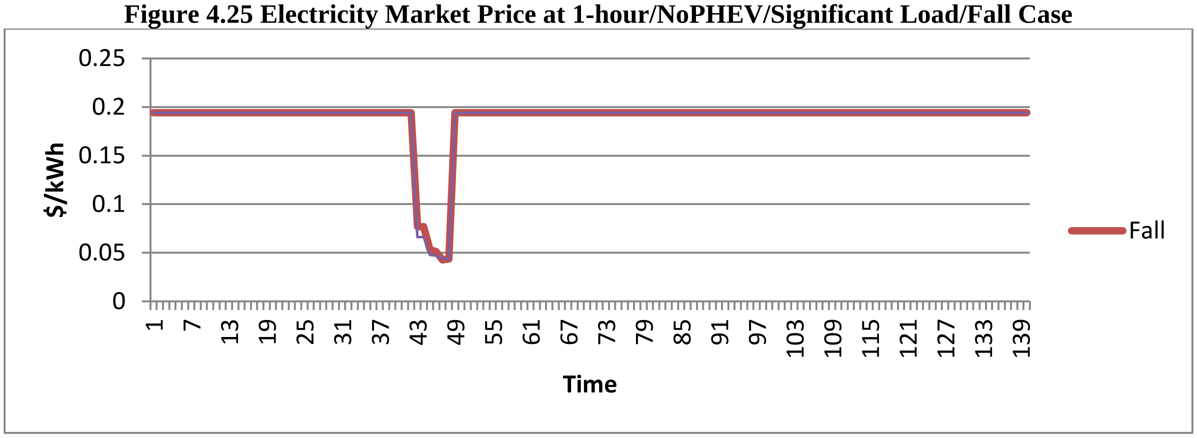
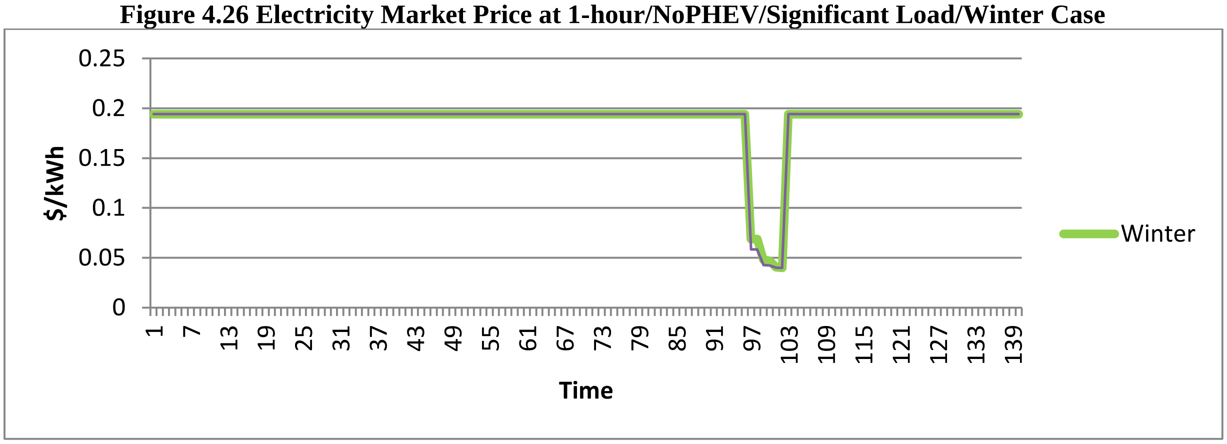
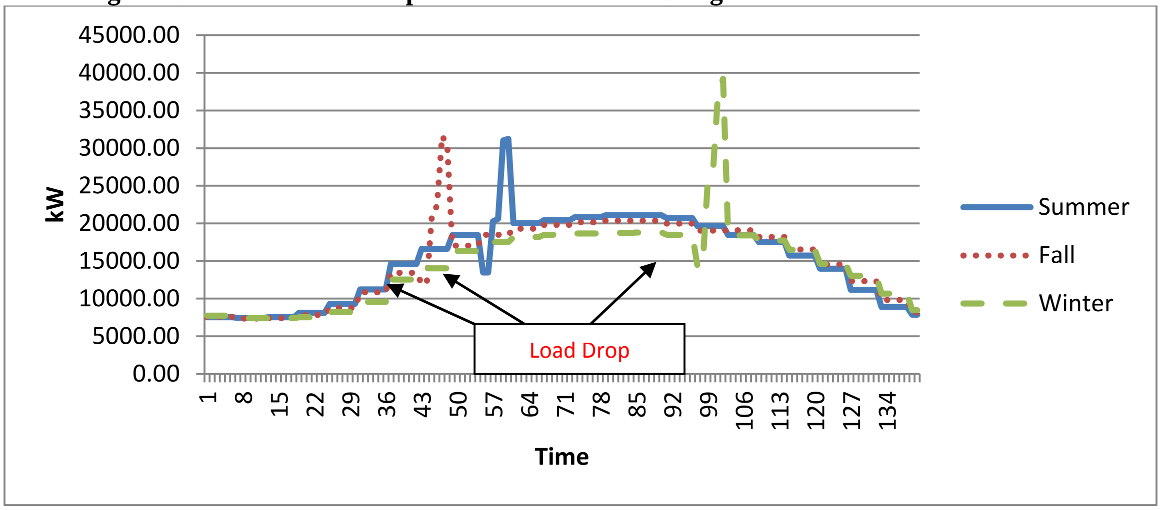


Figure 4.26 Electricity Market Price at 1-hour/NoPHEV/Significant Load/Winter Case



The CHP power output time-variant profiles in figure 4.27 show three load drops happen at the beginnings of each outage. This is because only the significant load demands in critical facility sector were restored during these time periods.

Figure 4.27 CHP Power Output at 1-hour/No-PHEV/Significant Load/All-Season Cases

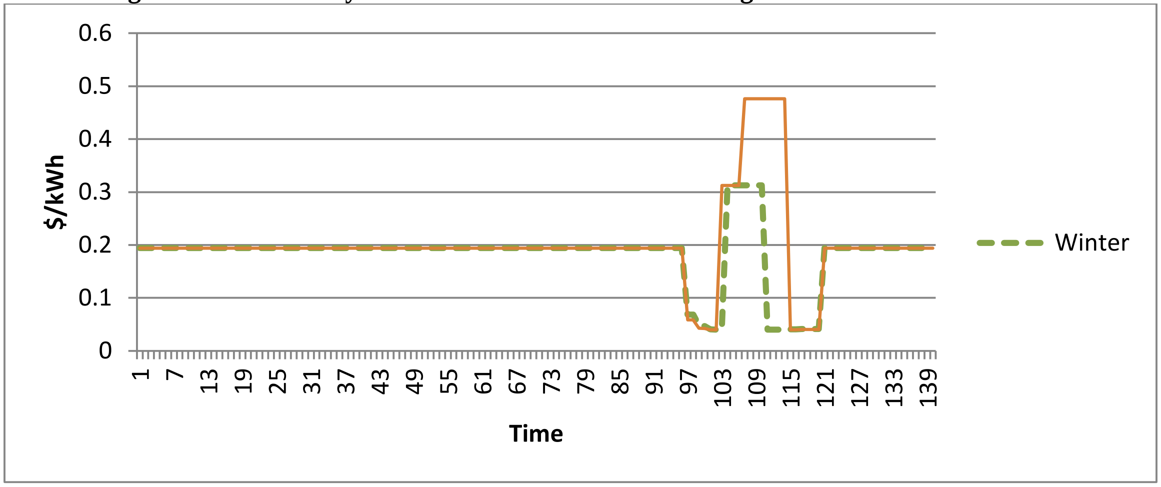


The electricity market clearing prices in 4-hour/No-PHEV/Significant-load cases have little differences with the counterpart cases in scenario I.

4.6.4. Scenario IV: CHP and PHEV to cover only significant load demand

In the 1-hour outage cases and 4-hour outage summer and fall cases of this scenario, the CHP has excess capacity to cover the significant demands of new formed hypothetical community. PHEVs don’t need to supply emergent electricity to customers in the 1-hour or 4-hour outage cases. The electricity market clearing prices of the 1-hour outage cases and 4-hour outage summer and fall cases are similar with the counterpart cases in Scenario II.

Figure 4.28 Electricity Market Price at 4-hour/PHEV/Significant Load/Winter Case



In figure 4.29, the electricity price in the winter case (shown in green dashed line), however, differs with its counterpart result (shown with the orange narrow line) in Scenario II. First, there is no unserved energy in this case. Second, the electricity price in winter has only one apparent rise at the 104th time interval when energy from PHEV battery is required to restore excess demand. In comparison with the 4-hour outage winter case in Scenario II, there is no second rise of market clearing price. Third, the high electricity prices resulted from PHEV discharging last shorter in the 4-hour winter case in Scenario IV than its counterpart in Scenario II. This can be interpreted as the excess demand over the CHP limit last shorter than the ones in the counterpart case in Scenario II. PHEVs, therefore, have less energy required to discharge in this case. In figure 4.30, PHEVs have adequate energy stored in battery after discharging. The second rise of electricity market clearing price is avoided because PHEV doesn't consume gasoline in this case.

Figure 4.29 CHP & PHEV Power Output at 4-hour/PHEV/Significant Load/Winter Case

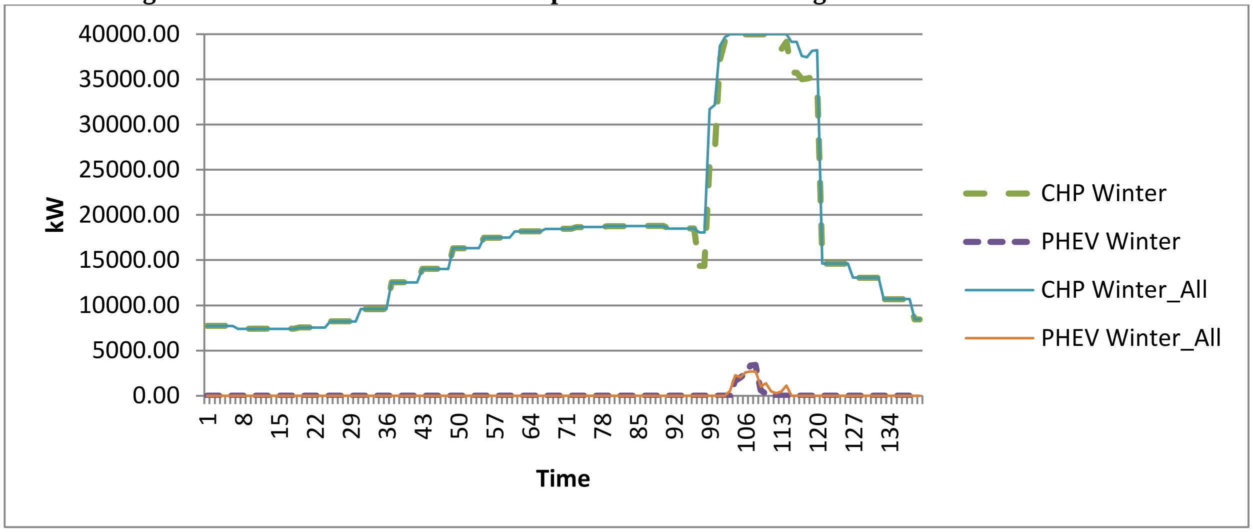
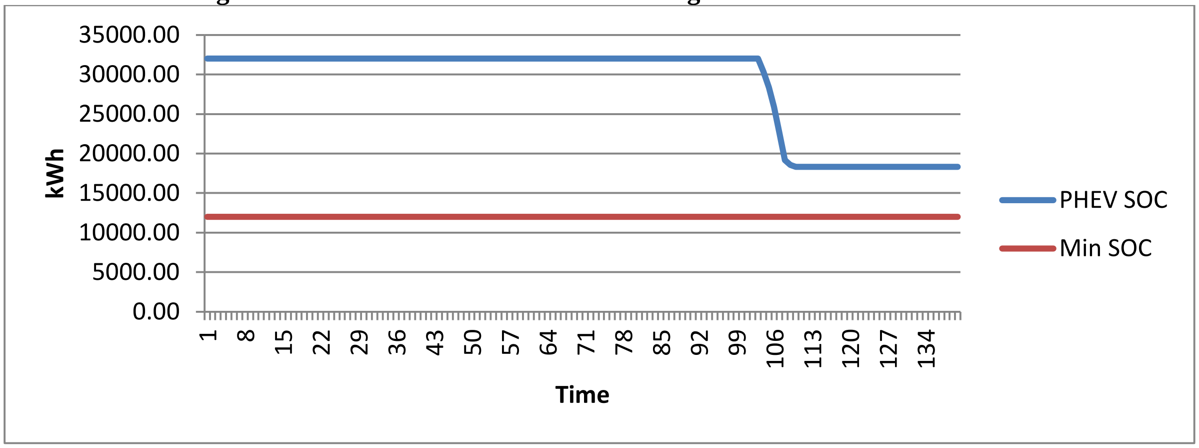


Figure 4.30 PHEV SOC at 4-hour/PHEV/Significant Load/Winter Case

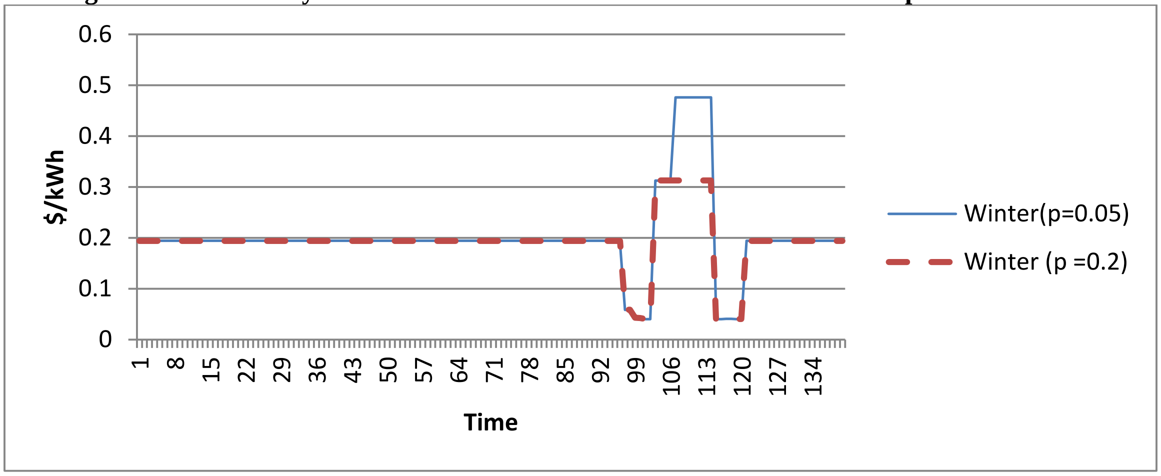


4.7. Sensitivity analyses

4.7.1. PHEV Penetration Rate

Sensitivity analysis on PHEV penetration rate duplicates the simulation of 4-hour outage with PHEV deployed in winter outage case in Scenario II but with a higher penetration rate (20%) of PHEV in the residential sector. The figure below stated that, when demand profile unchanged, more PHEV energy capacity will induce more power output from pure electric mode. Therefore, at a higher penetration rate, PHEV consumes electricity from battery solely without using gasoline as a secondary source.

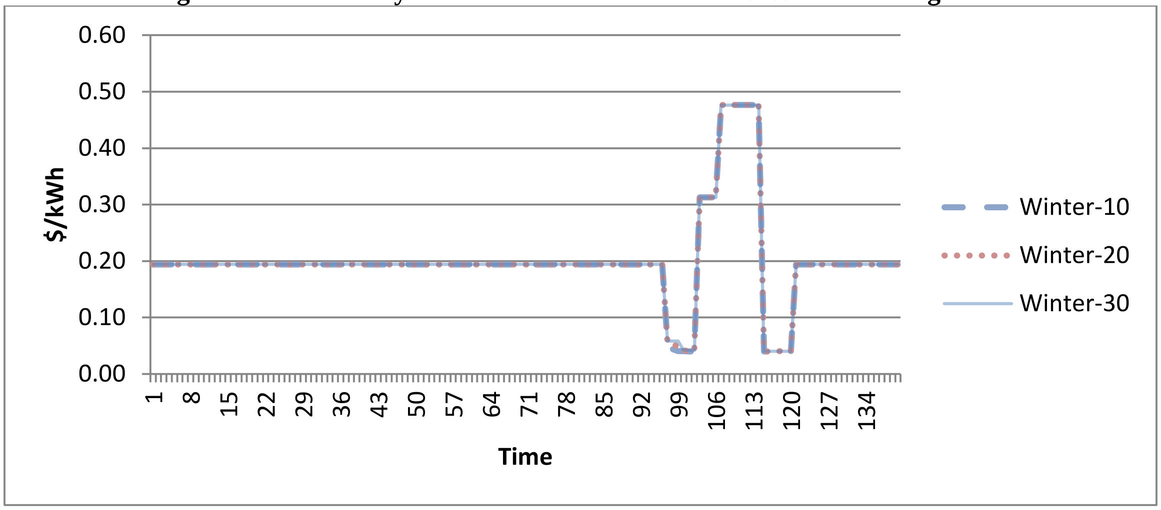
Figure 4.31 Electricity Market Price at 4-hour/PHEV/Winter Case PHEV penetration rates



4.7.2. Waiting time between sectors

The waiting time of dynamic microgrid before expanding to the next load demand sector impacts the aggregated load profile. Sensitivity analyses were conducted on all 8 cases (1-hour and 4-hour; with PHEV and without; All-load and significant load). There is no obvious difference among electricity market clearing prices at different waiting time cases. An example of electricity market clearing prices at different waiting time cases is listed below. The demonstration shows electricity market clearing prices at 4-hour outage case in Scenario IV.

Figure 4.32 Electricity Market Price at 4-hour/PHEV/Winter/waiting times

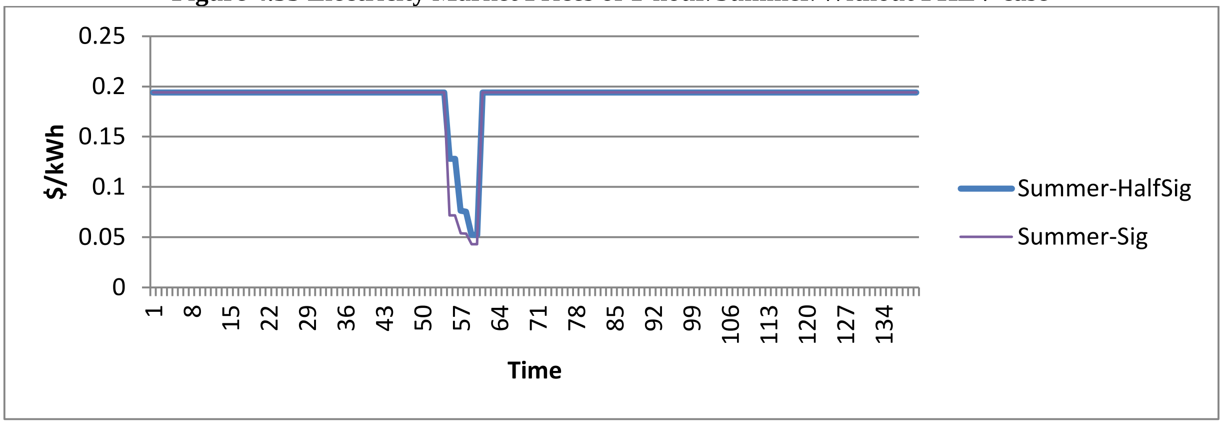


4.7.3. Sub-scenario of Significant end-use

In the "50% significant end-use" sub-scenarios, load demand per facility is only half of the counterparts in the "Significant load-demand" scenario. The sensitive analyses are tested in each season and outage–duration case and repeated in both sub-scenarios (with and without PHEV).

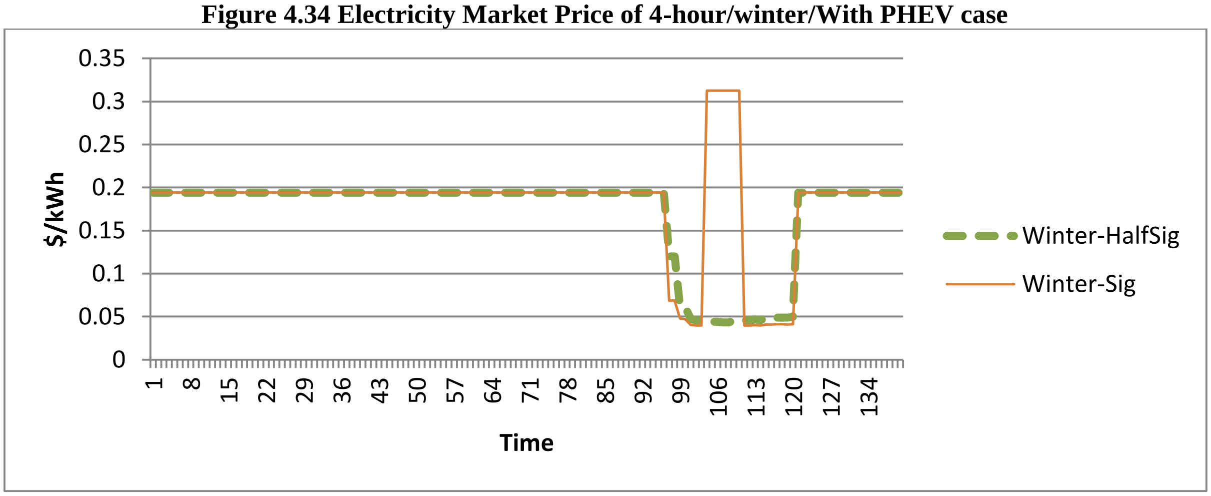
The electricity market clearing prices in sub-scenarios are then compared with the counterparts in the significant end-use scenarios. Except for the "4-hour winter" case in the "with PHEV" sub-scenario, the electricity prices in other cases of sub-scenarios are similar to the counterparts in the "significant-load" scenarios. The figure 4.33 exemplifies a comparison between scenarios in the 1-hour/summer/Without PHEV case. The electricity price of sub-scenario is "embraced" by the counterparts of the "Significant end-use" scenario. The figure shows that the highest price differences exist at the beginning of the outage case. The gap then reduces as the dynamic islanding expands. The price differences are resulted from the design of each scenario, since the extent of demand in sub-scenario is only half of the ones in the "Significant-load" scenario. Although, the number of facilities in the first facility sector has been unchanged as always. As the restoration process of dynamic islanding starting proceeded, the extent of load demand in the sub-scenario gradually increases until it reaches to the generation capacity of dynamic microgrid.

Figure 4.33 Electricity Market Prices of 1-hour/Summer/Without PHEV case



At the 4-hour/winter/with PHEV case, shown in figure 4.34, the electricity market clearing price in the sub-scenario doesn't' have an upward spike during the outage case, which is different with the price curve in the "Significant Load" scenario. This is due to the configuration of total load demands in the sub-scenario where the design of half-load of significant end-use per facility and tripled facility numbers resulted in an excessive supply of CHP in the sub-scenario. Therefore, the electricity market clearing price is only determined by the CHP operation cost.

Figure 4.34 Electricity Market Price of 4-hour/winter/With PHEV case



4.8. Conclusion

This research uses the ELD model to calculate the electricity market clearing prices in a hypothetical community with single bid auction electricity market. According to the generation and load demand status, the research developed four scenarios to assess the impact of these factors on the electricity prices. Each scenario is further dived into six cases, which include three extreme weather cases and two outage duration types in each extreme weather case.

The simulation result indicates that the electricity market clearing price in this designed dynamic microgrid is predominantly decided by the power output and cost of electricity of each DGs. When CHP has surplus capacity over demand, no matter whether or not PHEVs are deployed, electricity price is only impacted by the CHP operation cost which owns a huge economic advantage over other DERs. When CHP is deficient to power the designated loads, energy from PHEV will be consumed. The expensive operation cost of PHEV raises electricity price within the dynamic microgrid. When PHEV stored electricity reached to its minimum threshold, PHEV needs to stop discharging from the battery, and gasoline, a more expensive resource, will be consumed after that. Therefore, two price hikes are expected if PHEV uses both gasoline and stored electricity to generate emergent power. When the total capacity of CHP and PHEV are deficient, there will be unserved energy. Some facilities in the dynamic microgrid have to lose power again and suffer the outage. The deficiency of power supply won't impact the electricity prices for facilities who already have power restored, but the overall system cost will be increased.

To further examine the impact of designed factors, three sensitivity analyses were conducted. The first sensitivity analysis states that the penetration rate will increase the power capacity of PHEV and enhance PHEV output in pure electric mode. After increasing the penetration rate from 5% to

20%, the previous two hikes of electricity price appeared only once. The waiting time of dynamic microgrid expansion has trivial impact on the electricity price and therefore could be neglected from policy implication concerns. The last sensitivity analysis examined the impact of significant load demand identification on the electricity price. A 50% of significant load demand case is selected. The simulation results indicated that, with less extent of load demands per facility but more numbers of facilities involved, there is little impact on the electricity price. At extreme cases where the change of load demand profile impacted the power output of each DG, the electricity market clearing price shall appear an apparent difference.

This research implicates that dynamic microgrid offers an option that end-users can gain access to emergency power supply without paying high prices. Dynamic microgrid is, therefore, an economically viable alternative to enhance grid resilience.

4.9. Reference

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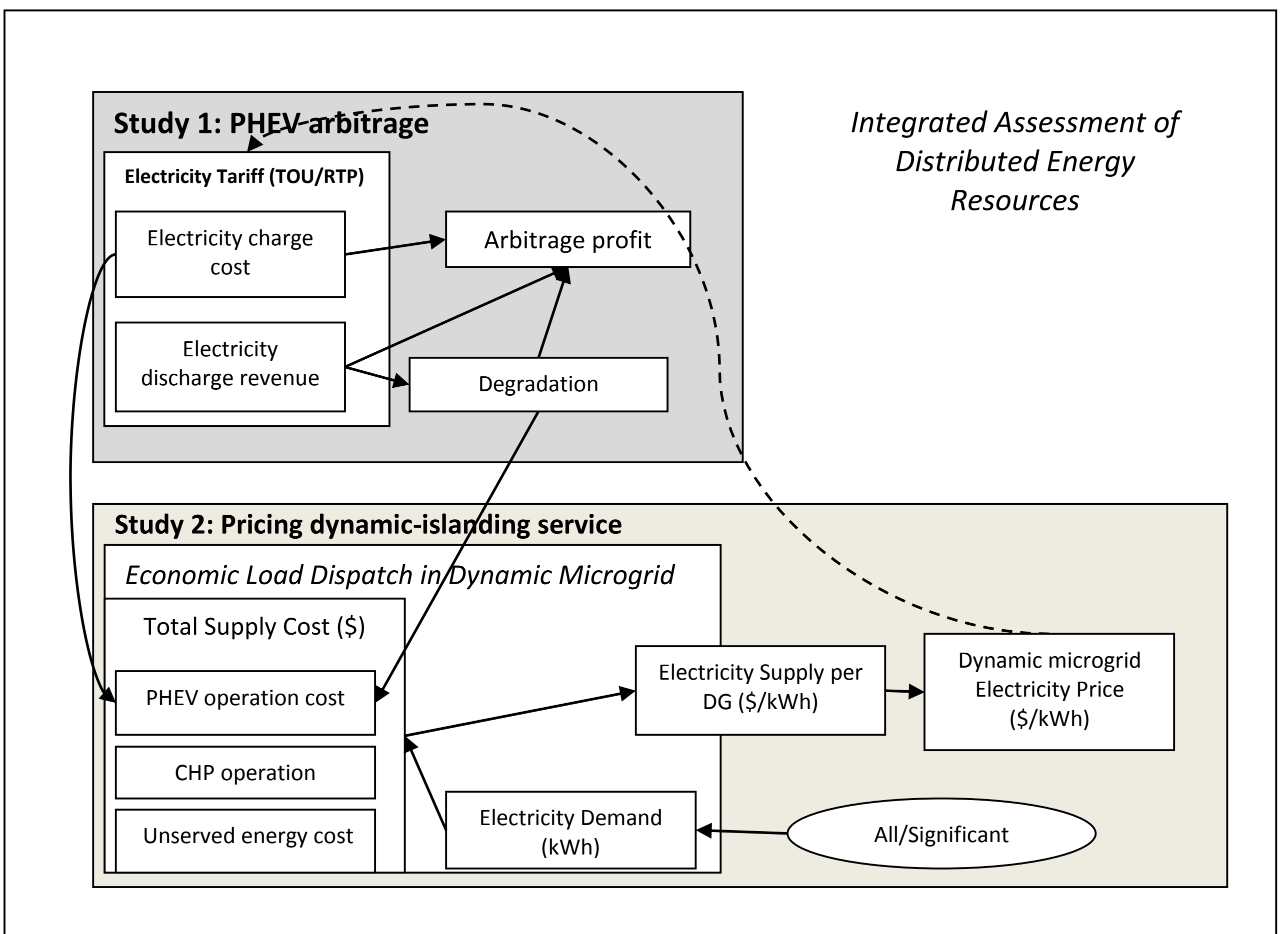
Chapter 5 Summary of Major Findings, Policy Implications, and Future Researches

5.1. Result summary of primary researches

Figure 5.1 summarized the primary elements in the two major studies. In figure 5.1, the PHEV charging cost and its associated degradation cost in Study 1 are the PHEV operation cost in Study 2. The electricity market clearing price in dynamic microgrid, as a possible electricity rate scenario in an emergent condition, could further influence PHEV arbitrage value (not considered in this dissertation). The benefit will provide PHEV owners financial incentives to offset partial operation cost in normal times.

Figure 5.1 Structure of major researches and relationship between major researches



5.1.1. Summary of PHEV arbitrage research

In the PHEV arbitrage research, the simulation results show that when degradation is excluded, electricity price scheme in RTP helps PHEV owners gaining more benefit than the TOU scheme. When degradation cost is included, PHEV owner will have a net loss in both current market and future market. Technology progress will reduce the loss. Yet, they can’t make the price-arbitrage profitable. The impact of degradation cost is more significant than the benefit earned by the corresponded arbitrage benefit.

This finding confirms that, unless having significant improvement on battery degradation rate, customers will lose money in the arbitrage practice. The significant impact of degradation cost is the primary reason contributed to the negative result, and limited benefit of arbitrage can’t offset the cost to make profit.

5.1.2. Summary of pricing dynamic microgrid research

In the pricing dynamic microgrid research, it uses the ELD model to calculate the electricity market clearing prices in a hypothetical community with single bid auction electricity market at emergency.

The simulation result indicates that the electricity market clearing price in this designed dynamic microgrid is only impacted by the status of generation and demand. The simulation result indicates that the electricity market clearing price in this designed dynamic microgrid is predominantly decided by the power output and cost of electricity of each DGs. When CHP is deficient to power the designated loads, energy from PHEV will be consumed. The expensive operation cost of PHEV raises electricity price within the dynamic microgrid. PHEV consumes electricity either from battery or gasoline, which causes different operation costs. Unserved energy may exist at extreme cases, though it won't influence the electricity price but increasing overall system cost by the amount of unserved energy cost.

5.2. Policy implications from primary studies

The findings in PHEV arbitrage research implies that expected profits from arbitrage are not a viable option to engage PHEVs in dispatching and in providing ancillary services under the current and predicted power industry and PHEV battery technology. Subsidy or change electricity tariff or both from government are needed. The source of charged electricity from almost zero-marginal cost of power sources (e.g. renewable energy) will be another promising way of reducing PHEV charging cost.

In the dynamic microgrid pricing research, the result estimates the electricity market clearing prices in a hypothetical community where a dynamic microgrid paradigm is enacted. At circumstances where CHP as the only source restoring facility power within the dynamic microgrid, the electricity market clearing price is even cheaper than the on-grid electricity price at normal times. Hence, dynamic microgrid offers an option that end-users can gain access to emergency power supply without paying high prices. Dynamic microgrid is therefore an economically viable alternative to enhance grid resilience.

5.3. Future researches of DERs assessment

The value of DER integration is impacted by technology performance, electricity market design, and customers' attitude and behavior of adopting emerging technologies. Some factors whose uncertainties haven't been discussed in this thesis will be my future research aims.

A change of load demand in long-term will be a primary uncertainty factor influencing the future value of DERs integration. When more people adjust their behavior in response to differentiated electricity rates, the aggregated adjustment in electricity use behavior will lead to a demand curve with smaller difference between peak and off-peak. The rate difference between peak and off-peak will be reduced or even disappeared. Some researchers(Exarchakos, Leach, & Exarchakos, 2009) analyzed the impact of the demand-side management (DSM) on arbitrage profit. When load demand curve becomes flatter, the arbitrage profit drops, and consumers are less likely to participate in arbitrage. Vytelingum (Vytelingum, Voice, Ramchurn, Rogers, & Jennings, 2010) used game theory to analyze the relationship between the arbitrage profit and the fraction of population involving in arbitrage using stationary battery. They found that the Nash equilibrium is at 38% of the population at which the social welfare is at maximum. A flat load curve implies the sunk cost of storage facility will be larger than the benefit from arbitrage. At the equilibrium, any variation of strategy on opt-in or opt-out of the technology participation will hurt the general benefit, and the average saving on electricity bill will decrease. In a quick response, a new equilibrium associated with the same proportion of participants will be reached when some customers opt-out or in the program. Therefore, from a longer term perspective, the equilibrium of market participation stands for the lowest value from arbitrage behavior, where the benefit of wide technology adoptions equals to the avoided cost from not participating into the program (Vytelingum et al., 2010). The distribution system, however, benefits the most since it's the most cost-effective operation when power generation powers in an invariant manner.

More types of DERs, other than PHEV or BEV installed battery, will be deployed in the grid integration paradigms, and the intermittency essential of these DERs will bring more uncertainties in the assessment. In a long term view, with development of manufacturing and performance of

DER technique, capital costs of DER manufacturing and handling will be much cheaper to be affordable by individuals or families. The development of internet of the thing (IOT) makes end-users easier to get access to grid integrated DERs, and the negligible short term marginal cost of renewable energy will become a great advantage for enhancing DERs' value and facilitating more DER integrations (Rifkin, 2014).

5.4 Reference

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Appendix A: Residential End-use Mapping of Appliances to End Use

Cold appliances	**Other**	**Audiovisual Site**
Fridge-freezer	Sockets	Television
Refrigerator	Vacuum Cleaner	Set Top Box
Upright Freezer	Hair Dryer	DVD
Chest Freezer	Iron	Audiovisual Site
Wine Cooler	Garage	Nintendo Wii
	Hair Straightener	VCR
Computer site	Fan	Sky set Top Box
Laptop	Aquarium	Hi-Fi
Router	Alarm	Sony PS3
Printer	Other	DVD recorder
Desktop	Sewing Machine	Microsoft Xbox 360
Monitor	Electric Blanket	Sony PS2
Computer Site	Pond Pump	Home Cinema Sound
Speakers	Door Bell	Audiovisual Equipment
Multifunction Printer	Sterilizer	Radio
Modem	Paper Shredder	Microsoft Xbox
Computer Equipment	Smoke Detector	Blue-ray Player
Fax/Printer	Vivarium	CD player
Scanner	Clock Radio	Aerial
Hard drive	Cordless Phone	Game Console
	Dehumidifier	TV booster
Cooking	Fire	Video Sender
Kettle	Organ	
Microwave	Trouser Press	**Water Heating**
Cooker	Charger	Shower
Toaster	Massage Bed	Water Heater
Oven	Baby Monitor	Immersion Heater
Extractor Hood	Electric Chair	
Bread Maker	Jacuzzi	**Washing/Drying**
Coffee Maker	Motor home	Washing machine
Hob	Digital Picture Frame	Clothes Dryer
Food Mixer	Sun-bed	Dishwasher
Grill		Washing/Drying machine
Fryer	**Heating/Cooling**	
Food Steamer	Heater	
Bottle Warmer	Central Heating	**Lighting**
Hot Tub	Circulation Pump	Lighting
Yogurt Maker	Air Conditioning	Light Distribution

Appendix B: Commercial End-use Mapping of Equipment to End Use

DRCEUS utilizes seven electric-only end uses and six end uses that can be either electric or natural gas. There are three HVAC end uses (1 – 3) and 10 non-HVAC end uses (4-13).

1. Space Heating (Electric & Gas)

Heating source equipment
Hot water circulation pumps
Supplemental heat pump heating

2. Space Cooling (Electric & Gas)

Cooling source equipment
Chilled water circulation pumps
Heat rejection equipment

3. Ventilation

AHU Supply & Return fans
Exhaust fans
Make-up air fans

4. Water Heating (Electric & Gas)

Water Heater (boiler, standard, instantaneous)
Swimming Pool/Spa Heater

5. Outdoor Lighting

Parking Lot Lighting
Parking Garage Lighting
Building Façade Lighting
Advertising Lighting

6. Indoor Lighting

Area Lighting
Task Lighting
Exit Signs
Track Lighting
Display/Advertising Lighting

7. Office Equipment

Personal Computer-- Desktop	Workstation
Personal Computer-- Laptop	Servers
Printer -- Ink Jet	Switching Equipment

Printer-- Laser	FAX machine
Uninterruptible Power Supply	Telephone System
Small Copier	Point-of-sale terminals
Medium Copier	Cash Registers
Large Copier	Typewriter
Blueprint Machine	Hole Punch
Monitor/Terminal	Shredder
Computer-- Mainframe	Other office equipment
Printer-- Mainframe	

8. Cooking (Electric & Gas)

Broiler, Conventional	Oven (in Range or standalone)
Broiler, Infrared	Oven, Convection
Charbroiler (32" X 36" reference)	Oven, Finishing/Toaster
Coffee Maker	Oven, FlashBake
Cold Food Table	Oven, Microwave
Dishwasher	Oven, Pizza, Counter-top
Dishwasher Booster Heater	Oven, Pizza, Large
Drink Dispenser (Refrigerated)	Popcorn Maker
Food Steamer	Proofers/Holding Cabinet
Food Warmer/Well	Range, Large (6 burners)
Fryer, Counter-type	Range, Medium (4 burners)
Fryer, Floor-type	Range, Small (2 burners)
Fryer, Induction (1 vat reference)	Rotisserie (3 spits reference)
Garbage Disposal	Slicer (Meat, Cheese, etc)
Griddle	Soup Pots
Hot Food Table (4 holes reference)	Steam Kettle
Hot Plates (2 burners reference)	Toaster, Conveyor-type
Ice Cream Dispenser	Toaster, Slotted-type
Induction Cooktop (2 burner ref)	Trash Compacter
Mixer, Large	Other (describe)

9. Refrigeration

Non-Commercial Refrigerators/Freezers
Single-door
Two-door
Three-door
Under counter/compact
Chest
Other (describe)____________
Commercial Refrigeration Equipment (Self-Contained)
Glass door beverage cases (e.g. vendor supplied) from 2 to 4 doors
Open upright display cases (pizza, juice, etc.) usually 4,5,6 ft lengths
Island cases (cheese, sometimes produce or juice) from 8 to 16 ft long
Service cases (bakery, sometimes deli) from 4 to 8 ft long
Closed door storage cases, one to three doors
Upright glass door freezer cases from one to three doors
Coffin type glass top freezer cases (usually ice cream) typically 6 or 8 ft
Ice storage boxes
Other: self-contained refrigeration not listed above
Ice vending machines (hotel-sized icemaker)
Remote Refrigeration
Display Cases (and all peripherals like fans, lights, etc.)
Walk-Ins/Prep Areas (and all peripherals like fans, lights, etc.)
Compressors
Condensers

10. Motors

Pumps
Fan/Blower
Material Handling/conveyor
Machine Tool
Grinding/milling
Escalator
Passenger Elevator
Freight Elevator
Separation
Other ______________
Hot Water Circulation Pumps
Swimming Pool/Spa Pump
Swimming Pool/Spa Circulation Pump

11. Process (Electric & Gas)

Heat Processing:	Pulping:	Drying/Curing/Baking:
Direct Fired Gas Heating	Batch Digesters	Ovens
Direct Fired Oil Heating	Stock Refiners	Microwave
Blanchers	Paper Preparation	Infrared

Microwave	Pulpers	Electric Resistance
Sterilizers	Refiners	Steam from Process Boiler
Pasteurizers	Stock Mixers	Ultraviolet
Induction Heating		Kiln
Induction Melting	**Separation and Distillation**	Radio Frequency
Radio Frequency	Thermal Distillation Column	Electron Beam
Indirect Resistance	Freeze Concentration	
Direct Resistance	Vacuum Condensation	**Refrigeration/Freezing:**
Encased Resistance	Membrane Separation	Forced Air Cooling
Plasma Processing	Pressure Swing Absorption	Blast Freezing
Electric Arc Furnace	Vacuum Concentration	Hydro cooling
Ion Nitriding	Ultra Filtration	Belt Freezing
Laser Hardening	Reverse Osmosis	Plate Freezing
Cupola	Evaporators	Vacuum Cooling
		Immersion Freezing
Dehydration:	**Solid-Liquid Extraction**:	
Convection Dryer	Single Stage Extractors	**Mixing and Emulsification**:
Infrared Dryer	Multi-Stage, Static Bed Extractors	Pressure Homogenizers
Electric Resistance Drying	Continuous Moving-Bed Extractors	Ultrasonic Emulsification Devices
Microwave Dryer		
	Plastic Molding:	**Fiber Preparation**
Material Preparation:	Injection Molding	Dye Tanks
Arc Welding	Extrusion Molding	
Laser Cutting	Blow Molding	**Crystallization:**
Water Jet Cutting	Rotational Molding	Oil Winterization
Electron Beam Welding	Compression Molding	Freeze Concentration
Laser Welding	Thermoforming	Ice Crystallization
Plasma Cutting		Lactose Crystallization
	Washing and Drying:	Fat Crystallization
Filtration:	Rotary Kilns	
Pressure Filters	Cascade Dryer	**Screening and Separation**
Vacuum Filters	Fluidized Bed Dryer	Froth Floatation Baths
	Suspension Dryer	
Finishing:		**Exploration and Drilling:**
Ovens Standard	**Other**	Engine Driven Boring Equipment
Electroplating		
Hot Dip Galvanizing		**Emission Reduction Equipment:**
		Standard Thermal Oxidizer
		Recuperative Thermal Oxidizer

12. Miscellaneous (Electric & Gas)

Building Equipment	**Electronics**	**Laundry**
Air Hand Dryers	Broadcasting Equipment	Clothes Dryer, Residl.
Alarm System	Stereo System	Clothes Washer, Residl.
Automatic Door	Television	Clothes Dryer, Commcl.
Battery Charger	Video Recorder (VCR)	Clother Washer, Commcl
Janitorial Equipment		Dry Cleaning Unit
Vacuum Cleaner	**Shop Equipment**	Sewing Machine
	Forklifts	
Medical/Hospital	Hand Truck/Pallet Lifts	**Service/Retail**
Autoclave	Non-Forklift Elec. Vehicles	ATM Machine Portable Shop Tools
CAT Scan Machine	Other Electric Transport	Change Machine Shop Equipment
Centrifuge	Battery Chargers	Conveyor (check-out) Soldering Gun or Iron
Chromatograph, analyzer	Electric Crane	Film Processing Welder
Cytometer, blood analyzer	Portable Shop Tools	Photo Equipment
Dentist Chair	Shop Equipment	Pinball or Video Game
EKG Machine	Soldering Gun or Iron	Hair Dryers
Hot Plate, Lab Equipment	Welder	Exercise Equipment
Incubator		Industrial Compactor
Laboratory Oven	**Space Comfort**	Vending Machine, Hot Food
Laboratory, other equip.	Air Cleaner	Vending Machine, Refrig.
Sterilizer	Ceiling or Portable Fan	Vending Machine, Non-Refr.
X-Ray Machine	Dehumidifier	Water Vending Machine
	Humidifier	
Other	Portable Heater	
Describe		

13. Air Compressors

Cleaning
Drive Tools
HVAC Pneumatic
Other