OPTIMAL MANAGEMENT OF AN INTEGRATED ELECTRIC VEHICLE CHARGING STATION UNDER WEATHER IMPACTS

A Dissertation

by

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ABSTRACT

The focus of this Dissertation is on developing an optimal management of what is called the “Integrated Electric Vehicle Charging Station” (IEVCS) comprising the charging stations for the Plug-in Electric Vehicles (PEVs), renewable (solar) power generation resources, and fixed battery energy storage in the buildings. The reliability and availability of the electricity supply caused by severe weather elements are affecting utility customers with such integrated facilities. The proposed management approach allows such a facility to be coordinated to mitigate the potential impact of weather condition on customers electricity supply, and to provide warnings for the customers and utilities to prepare for the potential electricity supply loss. The risk assessment framework can be used to estimate and mitigate such impacts.

With proper control of photovoltaic (PV) generation, PEVs with mobile battery storage and fixed energy storage, customers’ electricity demand could be potentially more flexible, since they can choose to charge the vehicles when the grid load demand is light, and stop charging or even supply energy back to the grid or buildings when the grid load demand is high. The PV generation capacity can be used to charge the PEVs, fixed battery energy storage system (BESS) or supply power to the grid. Such increased demand flexibility can enable the demand response providers with more options to respond to electricity price changes. The charging stations integration and interfacing can be optimized to minimize the operational cost or support several utility applications.

DEDICATION

To my beloved family, for their love, support, encouragement and trust during my Ph.D. life. I love you all.

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NOMENCLATURE

Variables	**Description**
t (Chapter IV, V);	Index for time
i (Chapter VI, VII)	
i (Chapter IV, V)	PEV index
Chapter IV	
PDF	Probability density function
$f(d)$	PDF of miles driven value d
k	Shaping parameter of a Weibull distribution
λ	Scaling parameter of a Weibull distribution
$f_{ST}(\tau)$	PDF of start time of charging value τ
α	Shaping parameter of a log-logistic distribution
β	Scaling parameter of a log-logistic distribution
γ	Location parameter of a log-logistic distribution
SOC	State of Charge, percentage left in the PEV battery
μ	Percentage of distance driven in electric mode
AER	All-electric range
s	Index of SOC
r	Percentage of battery can be charged per hour
η	PEV charging efficiency

$P_{EV}^{i,t,s}$	PEV charging power demand for PEV *i*, with remaining SOC *s*, at time *t*
$SOC^{i,t,s}$	Initial SOC before charging
SOC^{f}	Final SOC after charging
C_{cap}	Usable battery capacity
$P_{EV}^{t,s}$	PEV charging power demand for one charging station at time *t*
$N_{EV}^{t,s}$	Total number of PEVs in the target area
ρ^{l}	Percentage of each type of vehicles *l*
ψ	Population in the target area
δ	Average people amount per resident
ε	Average number of PEVs per resident
θ	PEV penetration ratio
n	Charger number

Chapter V

T	Total number of time slots
T_i^0, T_i	Time when PEV *i* starts to connect and total connection time
$e_i^{t+}, e_i^{t-}, e_i^{t}, e_i^{\max}$	Amount of *i*-th PEV's power that is charged (+) or discharged (-), $e_i^t = e_i^{t+} - e_i^{t-}$, and the battery capacity of PEV *i*
E_i	Pre-determined target of battery energy level when disconnected
SOC_i^{in}, SOC_i^{fn}	Initial and pre-determined target SOC for PEV *i*
σ	Electricity price, unit cost of the power supplied by grid

$P_G^{t+}, P_G^{t-}, P_G^t$	Power transaction from (+) or to main grid (-), and $P_G^t = P_G^{t+} - P_G^{t-}$
σ_G / σ_{EV}	Unit bonus for supplying power back to grid/ discharging of the participating PEVs
$\theta_{EV} / \theta_{PV} / \theta_{BS}$	Unit cost for charging PEVs/ operating PVs/ operating battery storages
$p_{PV}^{\max}$	Capacity of PV
D_b^t / b_b^t	Load demand/ actual load supplied for building *b*
c_b^{EENS}	Unit cost for energy not supplied (EENS) for building *b*, with different load types
$s_{BS}^{\max}$	Capacity of battery storage
$s_{BS}^{\max,\mathrm{d}} / s_{BS}^{\max,\mathrm{c}}$	Maximum allowable discharging/ charging rate for battery storage
b_b^t	Electricity consumption of building *b* connected to the charging station
$b_b^{\max}$	Maximum allowable demand of building *b*
$e_i^{\max,d} / e_i^{\max,c}$	Maximum allowable discharging/ charging rate for PEV *i*
p_{PV}^t	Power that the PV generation can provide
$s_{BS}^{t+}, s_{BS}^{t-}, s_{BS}^t$	Amount of battery storage power that is charged (+) or discharged (-), $s_{BS}^t = s_{BS}^{t+} - s_{BS}^{t-}$
$P_{cs}^{\max}$	Power flow limit for the integrated charging station (IEVCS)

Chapter VII

DSM	Demand Side Management
OM	Outage Management
w, w_0, w_i	Index for weather scenarios: w_0 refers to deterministic scenario, w_i refers to probabilistic scenarios
pr_w	Probability of weather scenario w_0 or w_i
$pr_{CL/w}$/ $pr_{CL/w,k}$	Probability of customer impact (CL) under weather scenario w_0 or w_i / for feeder area *k*
$Loss_w$	Worth of loss (in risk assessment) under weather scenario w_0 or w_i
W_i	Set for all probabilistic weather scenarios
x	Index for customer
$ct(x)$	Customer type for customer *x*
$p(\cdot)$	Percentage of demand change that are not supplied for each customer type
$q(\cdot)$	Percentage of interrupted energy not supplied for each customer type
FA	Feeder area
$CT(k)$	Total number of customer type for feeder area *k*
$lp;\ L$	Load point; Total number of load points in certain *FA*

$Loss_{i,w}^{k}$/ $Loss_{j,i}^{k}$	Worth of loss at time *i* for feeder area *FA=k*, under scenario *w*/ for customer type $ct = j$
$CDF_{i,w}^{FA=k}$	Customer damage function at time *i*, under scenario *w*, for feeder area *FA=k*
$EL_{i,w}^{FA=k}$	Function of additional loss caused by environment elements, at time *i*, under scenario *w*, for feeder area *FA=k*
$HL_{i,w}^{FA=k}$	Function of health loss, at time *i*, under scenario *w*, for feeder area *FA=k*
T_1, T_2	Sets of deterministic and probabilistic time steps
$r_{G,i}^{w}$	Electricity price at time *i* under scenario *w*
$p_{G,i}$/ $p_{G,i}^{FA=k}$	Power to be purchased at time *i* / for feeder area *FA=k*
$\sigma_{EV,i}^{w}$	Unit bonus for participating PEVs discharging at time *i* under scenario *w*
$f_{EV,i}^{w}$	PEV participation factor for discharging at time *i* under scenario *w*
$S_{EV,i}$	PEVs' power to serve as reserve at time *i* under scenario *s*
$r_{EV,i}^{w}$	Charging price for PEVs at time *i* under scenario *w*
$p_{EV,i}$/ $p_{EV,i}^{w}$	PEVs' charging power at time *i* / under scenario *w*
$r_{R,i}^{w}$	Reserve price at time *i* under scenario *w*
θ_{PV}	Unit benefit of selling PV generation energy

$p_{PV,i}^{g,w}$	PV generation energy to be sold to grid side at time *i* under scenario *w*
$\tau, \lambda_1, \lambda_2$	Penalty coefficient for: customer loss, PEV discharge, and battery storage discharge
$\Delta Loss_w$	Customer loss difference after demand response support
$p_{BS,i}$/ $p_{BS,i}^{w}$/ $p_{BS,i}^{k}$	Battery storages' charging or discharging power at time *i* / under scenario *w* / for feeder area *k* (+ means charging, - means discharging)
$p_{BS+,i}^{\max}$/ $p_{BS-,i}^{\max}$	Battery storages' maximum charging/ discharging power at time *i*
Ld_i^w/ Ld_i^k	Load prediction at time *i* under scenario *w* / for feeder area *k*
$P_{PV,i}$/ $P_{PV,i}^{k}$	PV generation prediction at time *i* / for feeder area *k*
$p_{PV,i}^{l}$/ $p_{PV,i}^{l,w}$/ $p_{PV,i}^{k,l}$	PV generation energy to be used for local load at time *i* / under scenario *w* / for feeder area *k*
$p_{EV+,i}^{\max}$/ $p_{EV-,i}^{\max}$	PEVs' maximum charging/ discharging power at time *i* respectively
$p_{EV+,i}^{k,max}$/ $p_{EV-,i}^{k,max}$/ $p_{EV,i}^{k,max}$	PEVs' maximum charging/ discharging/ total power at time *i* for feeder area *k*
$p_{BS+,i}^{k,\max}$/ $p_{BS-,i}^{k,\max}$	Battery storages' maximum charging/ discharging power at time *i* for feeder area *k*
$n_{R,EV}$	Percentage of allowed participation of PEV discharge

$E_{EV,i}^{w}$/ $E_{BS,i}^{w}$	PEVs'/ battery storages' aggregated energy at time *i* under scenario *w*
η^{+}/ η^{-}	PEVs' and battery storages' charging/ discharging efficiency
ΔT	Scheduling interval
$E_{EV,req}$/ $E_{BS,req}$	PEVs'/ battery storages' minimum energy requirement
$E_{EV,max}$/ $E_{BS,max}$	PEVs'/ battery storages' maximum energy capacity
$w_D(k)$/ $w_d(j)$/ $w_c(j)$	Weight based on load in feeder area *k*/ load demand for customer type *j*/ reversed load demand for customer type *j*
$w(pr_{CL/w,k})$	Weight based on the probability of customer impact (CL) under weather scenario w_0 or w_i for feeder area *k*
$E_{EV,i}^{FA=k}$	Energy provided by PEV battery at time *i* for feeder area *k*
N_{FA}	Total number of feeder areas
$p_{EVc,i}^{k}$/ $p_{EVd,i}^{k}$	PEVs' charging/ discharging power at time *i* for feeder area *k*
$D^{i}(j)$	Load demand for customer type *j* at time *i*
$p_{ct=j,i}^{FA=k}$	Total power exchange for customer type *j* at time *i* for feeder area *k*
$DC^{i}(j)$	Load demand change for customer type *j* at time *i*

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I. INTRODUCTION

1.1 Introduction

In this chapter, the problem statement, motivation, and challenges of the dissertation topic are described. To be more specific, the motivation to integrate PEVs, renewable (solar) energy resources and BESS in the proposed IEVCS, and develop energy management algorithms to mitigate weather impact on electricity customers are discussed. The challenges of the work are also discussed, which proposes the problems that the following chapters intend to solve. Then the organization of the dissertation is presented, followed by the conclusion of this chapter.

1.2 Problem Statement

The proposed "Integrated Electric Vehicle Charging Station" (IEVCS) includes the charging stations for the PEVs with mobile battery storage, renewable energy resources (PV panels), and fixed battery energy storage (BESS), and the building load connected to the same bus.

- Renewable energy resources, such as PV generation, are important sources to provide clean energy. PEVs with mobile battery storage and BESS can help store the extra energy supply and serve to balance the fluctuations caused by PV generation [1]. In our study, PEV charging stations integrated with PV generation and BESS can help lower the operation cost as well as reduce the carbon footprint [2-5].

- In order to address the random nature of renewable power generation resources, avoid peak load caused by PEV charging, and make use of the energy stored in PEVs with mobile and fixed battery storage to mitigate the variability of renewables, intelligent energy management system, mainly focusing on optimal scheduling and control is developed for the overall IEVCS.
- The reliability and availability of the electricity supply caused by severe weather elements are also affecting utility customers with such integrated facilities. A risk assessment framework can be used to estimate such impacts and provide warnings for the customers and utilities to prepare for the potential electricity supply loss [6-8].
- The development of an optimal energy management of the proposed IEVCS based on the risk assessment results of the weather impact allows such facilities to be coordinated to mitigate the potential impact of weather condition on customers electricity supply.

1.3 Motivation

Outcomes of climate change are becoming more and more challenging in many countries in the 21st century. Environmental issues are given higher priority in the electric energy industry. The largest contributing source of greenhouse gases is the burning of fossil fuels leading to the emission of carbon dioxide [9]. Also, low thermal efficiency of internal combustion engines and its associated air pollution have led to transportation electrification becoming an attractive trend [10].

PEVs with mobile battery storage have gained significant attention in recent years due to their prospects in reducing greenhouse gas emissions benefitting both the transportation sector and the electricity sector. PEV batteries can be utilized as mobile energy storage, with the flexibility of charging via grid-to-vehicle (G2V) acting as a "load" or discharging via vehicle-to-grid (V2G) or vehicle-to-building (V2B), acting as a "generator" or a "back-up energy storage" [11]. Statistically, more than 90% of the time on average passenger vehicles are parked and their idle time is much longer than the required time to fully recharge the batteries [12]. PEVs equipped with mobile battery storage are estimated to be idle the same length of time as a utility generator is used for an online operation [12-13]. Thus, as an environmentally and economically friendly choice for transportation, PEVs can be used both as a mobile energy storage and as an emergency generator if aggregated to support buildings' energy demand [14].

Renewable generation and the utilization of electrified transportation are emerging as the most promising strategies to meet the increasing environmental concerns and energy scarcity, and this trend is expected to grow in the future [13]. The PV generation has attracted attention, especially in the "Solar Belt" countries where the annual mean of global solar radiation is large. The PV panels can be easily installed on the roof of buildings or as the cover for outdoor parking areas. The ample roof space on large residential and commercial buildings and the ability of the PV panels to serve as a cover to protect vehicles from the sun exposure makes the use of PV generation a natural choice. The amount of electricity that PV generation produces varies from peak sunshine hours to cloudy days to night time. The load demand requires a continuous supply of energy regardless of the sunshine, hence a reliable battery storage device, such as BESS is needed [15].

The reliability and availability of electricity supply are essential for utility customers. If the customers own buildings equipped with PV power generation, charging stations for PEVs with mobile battery storage, and local BESS, the impact can be mitigated through the optimized energy management of such facilities. The technology of distributed generation has been studied and deployed intensively in the last decade. The intermittent renewable energy coming from natural resources is difficult to use due to its variability. PEVs can be considered as mobile energy storage that can together with BESS be potentially used to mitigate the impact of power fluctuation from renewable energy.

Therefore, with proper control of the IEVCS including PV generation, mobile (PEVs with mobile battery storage) and fixed energy storage, customers' electricity demand could be potentially more flexible. They can choose to charge the vehicles when the grid load demand is light, and stop charging or even supply energy back to the grid or buildings when the grid load demand is high. The PV power can be used to charge the PEVs (with mobile battery storage), fixed BESS or supply power to the grid. Such increased demand flexibility can enable the demand response providers with more options to respond to electricity price changes or shortage of electricity supply. Operation of such IEVCS comprising the PEV (with mobile battery storage) charger, fixed energy storage, and PV panels can be optimized aiming at maximally reducing operation cost.

Severe weather conditions can cause damage to or deterioration of electricity delivery system and power infrastructure leading to power interruptions to a large number of customers. Studies indicate that estimated annual financial loss from storm-related outages to the American economy is between $20-55 billion and the trend is still growing [3]. The historical blackout data from 2012 to 2014 in Texas shows 33% of the historical outage events are caused by weather/ falling trees [16]. The Vermont study [17] analyzed 933 outage events for over 20 years and stated that about 44% of the events were related to different weather conditions. It also pointed out that some of the events are triggered by "multiple factors". Thus, it is useful to relate the weather condition with power interruptions and analyze the risk of the weather impact on customers.

Different weather conditions can cause potential power supply interruptions to the built environment [18] where the IEVCS facilities are located, hence potentially affecting customers' everyday activities, health, and economic loss. It is useful to utilize risk assessment methodology to estimate the potential impact of weather condition change on customers' electricity supply lifeline and demonstrate the effect of the feasible actions in mitigating the negative impact. The IEVCSs in the targeted distribution network can be coordinated to alleviate the impact of weather-related power supply intermittency and outages. The charging stations integration and interfacing can be optimized to support several utility applications, such as Demand Side Management (DSM) and Outage Management (OM) [19-21].

1.4 Challenges

PEVs with mobile battery storage pose challenges and introduce complexity in the analysis of the impact, mainly because of the randomness of charging and driving behavior of PEV owners. Due to the relatively large amount of electricity that PEVs consume, the charging of PEVs can cause undesirable large peak demand, and therefore, may have a tremendous impact on the distribution system with uncontrolled and centralized charging [22].

The sun offers the most abundant, reliable and pollution-free power. The availability of solar power is considerably dependent on the real-time weather condition and the movement of clouds, which makes it extremely variable. While large energy storage systems can be installed to help consume variable PV power, and provide a constant and reliable power output, it is fairly costly. The consideration of integrating mobile (PEVs with mobile battery storage) and fixed battery energy storage with PV power generation can reduce the need for the large energy storage systems since the existing PEVs with mobile battery storage can help mitigate the effect of PV generation variation.

Since the PEVs (with mobile battery storage), fixed battery energy storage, and rooftop PVs may be owned by customers, how to effectively integrate these elements into the grid operation and markets to benefit such customers remains a challenge. Moreover, after the integrated system is modeled, a comprehensive strategy to optimally schedule and control each element in the integrated system to realize more objectives, such as maximally reducing the operational cost while guarantee the continuity of power supply, needs to be established.

In addition, quantifying the impact of weather elements on customers' worth of loss in the risk assessment is rather complex. How to intelligently manage the integrated system to mitigate the weather-related impact is an issue to be solved. When estimating the potential impact of weather change on reliability of customers' electricity supply, one of the components in the risk assessment formulation is the worth of loss. Power supply interruption can bring extensive cost to commercial, residential and industrial customers in the way of spoiling the perishable materials/food, damaging equipment, causing production loss, income loss, health impact, and extra mitigation expenses [23]. Some of the effects are quite dependent on the weather conditions, but this impact has not been discussed before. Among the possible cost, some of the impact elements are somewhat hard to quantify. While it is difficult to evaluate the health impact on the customers, it cannot be neglected. Thus, the worth of loss formulation needs to be improved to consider additional financial loss and health effect caused by outages resulting from the weather elements.

1.5 Organization of Dissertation

This dissertation is organized as follows. Chapter II describes the problem formulation and hypothesis of the study. Chapter III discusses the state of art of the related topics, followed by simulation models established and utilized to illustrate some important model features in Chapter IV. In Chapter V, the fundamentals of the proposed algorithm in optimal scheduling & control are presented, and some experimental results are included. Weather-related risk assessment and the proposed approach in supporting utility applications are formulated in Chapter VI and VII. The expected contribution and conclusions of the dissertation are discussed in Chapter VIII. References and author's own published papers related to this work are listed in the end.

1.6 Conclusion

The dissertation is focusing on a timely issue of integration of renewable source and energy storage located at the customer site into the electricity grid. We narrowed down the problem of optimizing such interfacing by assuming a very specific IEVCS architecture, and yet we broadened the fundamental problem to solving a multi-objective optimization that will benefit both the IEVCS owner (customer) and the grid owner. The objectives are to minimize the interruption of the electricity supply to the customer while at the same time serving the objective of utilizing such resources in reaching the customer and grid needs for the benefit of both.

II. RESEARCH OBJECTIVES

2.1 Introduction

This chapter provides an overview of the proposed Intelligent Management System for the IEVCS to benefit both IEVCS owner and grid owner and the research objectives of the management system, describes in detail the proposed four hypothesis scenarios that the dissertation aims to evaluate, and draws a conclusion for the chapter. The targets of the following chapters are to analyze different use cases to validate the proposed hypothesis scenarios in sequence.

2.2 Problem Formulation

This dissertation proposes an Intelligent Management System (IMS) for the Integrated Electric Vehicle Charging Station (IEVCS), including PEVs with mobile battery storage connected via the PEV chargers, PV panels, fixed BESS, and the building load connected to the same bus.

Figure 1 shows the tree diagram of the research in this dissertation. For a single IEVCS, a four-stage intelligent optimization and control algorithm is proposed to minimize the overall operational cost of the IEVCS and maximally guarantee the power supply. For multiple IEVCS in a targeted distribution network, weather impact is considered because the impact varies depending on different locations and different customer distribution. Several utility applications are supported for optimally scheduling the IEVCS in different areas.

Figure 2 shows in detail the integrated system and research objectives. PEVs with mobile battery storage, PV generation, and local BESS are integrated and interfaced to a building, which is then connected to the power grid.

For single IEVCS, two objectives are considered. Objective 1 is to maximally guarantee the power supply, resulting in the minimum potential customer loss. While achieving Objective 1, the optimal scheduling is also developed to maximally reduce the overall operational cost considering all the components in the IEVCS, which is Objective 2. The electricity supply interruptions caused by severe weather elements are affecting customers and may cause customers' health and economic loss. When considering the IEVCSs in a distribution network, weather-impact risk assessment is implemented to estimate and mitigate such impact through the proposed management approaches. Thus, the Objective 3 in this case is to maximally mitigate the potential weather impact on customers.

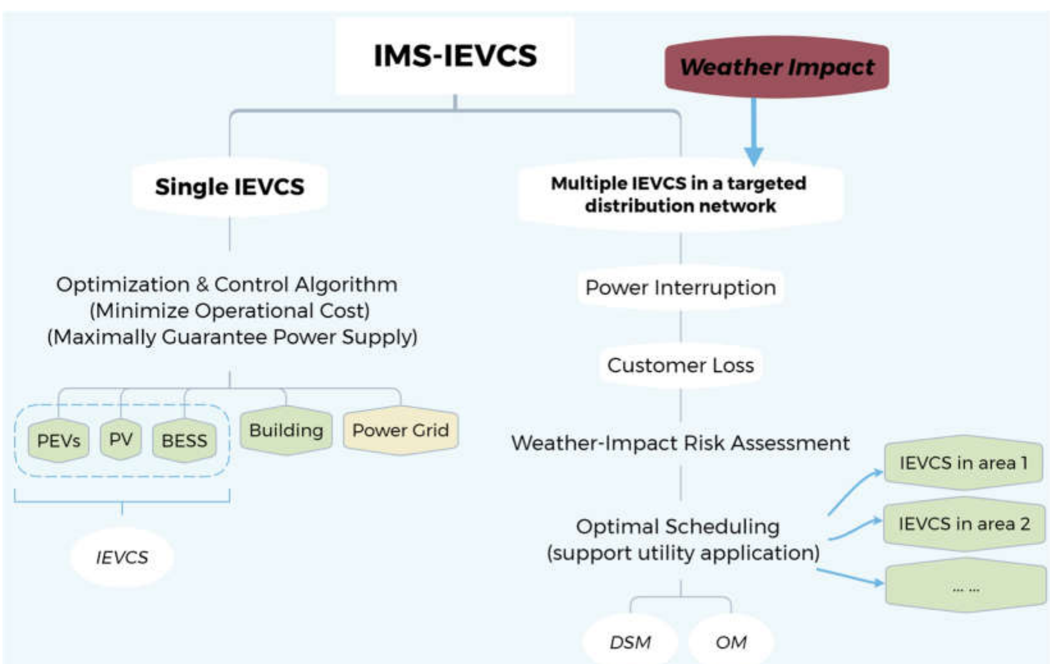


Figure 1: Tree Diagram of the Research

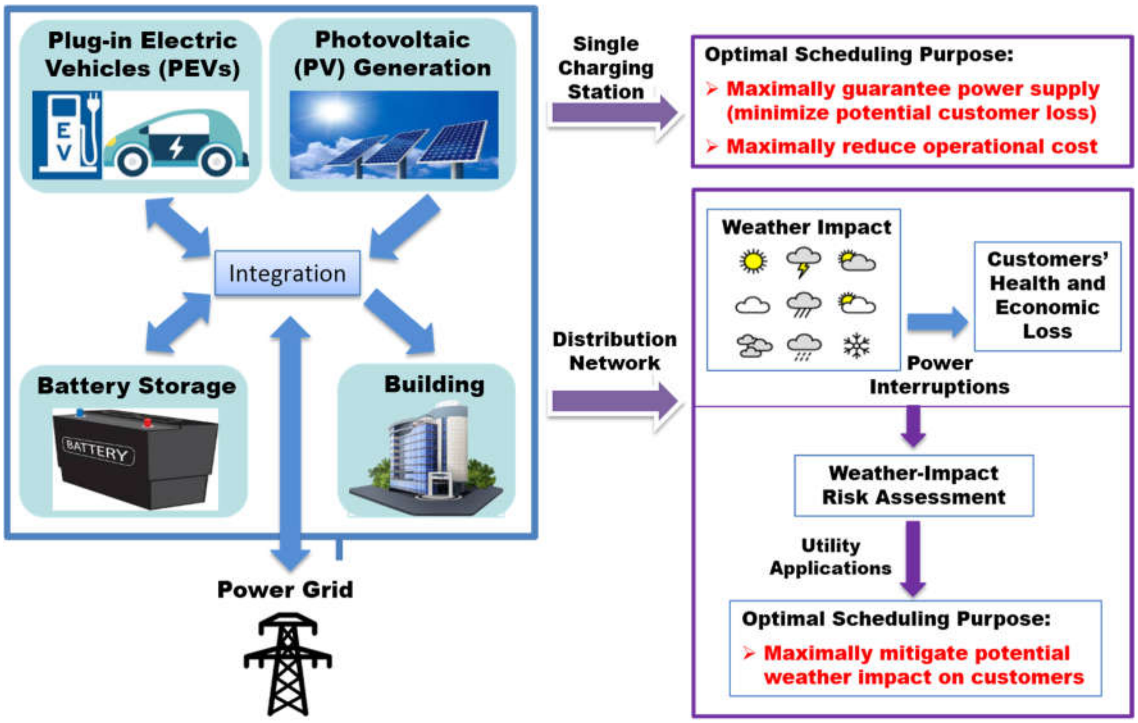


Figure 2: Research Focus Scheme

2.3 Hypothesis

We make hypotheses that with intelligent energy management, the IEVCS is able to maximally reduce the operational cost and provide high tolerability for unpredictable circumstance and interruptions in the power supply. Such IEVCS is also able to help alleviate the detrimental weather impact on the reliability of customers' electricity supply taking into account the risk prediction and stochastic nature of PEV and PV participation.

We evaluate the hypothesis through various studies aimed at demonstrating that:

1) The estimated electricity consumption of PEV charging can be used for centralized feedback control in order to be prepared to reduce the potential charging impact on power distribution systems. The multi-tiered pricing

schemes can also provide incentives for PEV users to help reduce the charging impact and flatten the load profile. This aspect of the hypothesis is elaborated in Chapter IV. The higher utilization of the supply from the power grid can be achieved utilizing IEVCS by decreasing the possibility of creating peak load caused by PEV charging.

2) Using IEVCS more incentives for PEV users to participate can be provided resulting in more resilience for unpredictable conditions allowing the building load to be more flexibly coordinated to reliably serve the customers while lessening the operation cost. This aspect of the hypothesis is elaborated in Chapter V.
3) Distribution system operators and utility customers can benefit from the assessment of weather impacts on the risk of the loss of electricity supply by allowing them to be aware of the impending risk and take preventive countermeasures to mitigate the potential customer financial losses. This aspect of the hypothesis is elaborated in Chapter VI.
4) The IEVCS can contribute as preventive countermeasures to help mitigate negative weather impacts on the power supply with the purpose of supporting DSM and OM, according to the risk results in different locations. This aspect of the hypothesis is elaborated in Chapter VII.

2.4 Conclusion

We made a hypothesis that for utilizing IEVCS for the mentioned benefits to the IEVCS owner (customer) and the grid owner, the proposed architecture and system functionalities need to operate in multiple modes allowing optimization of resources for different purposes. We are aiming at validating the hypothesis through detailed analysis of different IEVCS operating scenarios (Use Cases) and applying different optimization objectives and constraints to reach the proposed goals.

III. PRIOR RESEARCH

3.1 Introduction

This chapter discusses the literature survey of the related topics: PEV models, optimization and control algorithms, weather impact and risk assessment, and electricity grid support. The issues that have not been addressed and this dissertation intends to solve are stated at the end of each subsection, which will be discussed in Chapters IV-VII respectively. Conclusion is made at the end of the chapter.

3.2 Electric Vehicles Models for the Electricity Grid Related Studies

The impact of PEV penetration on distribution network is discussed at length in the literature [24-31]. To evaluate the impact of PEVs and optimally coordinate their energy consumption, it is necessary to explore the PEV characteristics, analyze charging/discharging profiles and establish typical models [32-33].

Battery characteristics, typical driving behavior, and drivers' preferences are essential elements to be considered [34]. Thus, stochastic models need to be built to take into consideration the uncertainties in regard to the charging demand profiles, including charging locations, charging start time, the capacity of battery, charging level, and battery SOC while charging [22, 34-35]. Such studies allow for not only an estimation of the PEV (with mobile battery storage) charging demand under different scenarios of PEV market penetration, but also the potential to support the power grid as a mobile energy storage [14, 35].

Deterministic models are developed based on average and worst-case peak load in some studies, but the required information for system operation is often not available. In addition, a substantial difference between deterministic and stochastic analysis is observed in [34]. Among stochastic modeling methods, most studies use Monte Carlo approach to simulate the randomness [36-38]. Paper [39] assume probability models to predict the PEV charging load under different charging scenarios. In some papers [22, 33-34, 40], the PEV parameters such as vehicle trips and drivers' behaviors are derived from actual survey data and measurements, such as National Household Travel Survey (NHTS) and Electric Power Research Institute (EPRI) report [41]. The mentioned data source provides abundant real information including vehicle types, daily trip departure times, last trip arrival time, miles driven per day, driving behavior on weekdays and weekends, and etc. Paper [33] describes the type of data from NHTS 2009 in detail.

The previous papers either did not use the actual data to build statistical model, or did not comprehensively consider different parameters in their model, such as vehicle types, battery capacities, penetration level, etc. In our work, the survey data from NHTS [42] is utilized to simulate the PEV characteristics. The charging locations are assumed to be close by customers' workplace. In order to build the statistical model for the studies of interest, different types of vehicles, battery capacities, percentages of market shares for each type, and levels of PEV penetration are considered. In addition, the established PEV interfacing models can be utilized in the utility applications of interest, as well as the related optimization and control methodology.

3.3 Optimization of Operational Cost and Related Control Algorithms

It is estimated that around 30% of the end-use energy-related carbon emission is from load consumption of buildings including commercial and residential ones, which consume about 39% of the total global energy use [43-44]. In this context, PEVs with mobile battery storage are considered to help increase the reliability of power supply and reduce energy cost and carbon emissions with DSM via vehicle-to-building (V2B) operation mode [45, 46-49]. Roof-top PV generation is also considered as an efficient way to meet the buildings energy demand, and at the same time reduce carbon emissions [50-51]. Many researches integrated PEV charging stations with PV generation to help further lower the cost as well as reduce the carbon footprint [5-8]. To mitigate the random nature of renewable energy and improve the performance, additional energy storage or spinning reserve are often utilized [4, 15, 52-54]. Energy storage system is often included when the implementation of microgrids are investigated [52-54].

To deal with the intermittent and variable properties of the renewable energy resources, many optimization or control algorithms are proposed [55-59], including ordinal optimization [55], genetic algorithm [56], and model-predictive control approach [7, 12, 59]. But, not all the factors such as operational cost, customer satisfaction, load loss, and profit for charging station owners are considered in one objective function. For example, only PEV charging cost as a convex function of load demand is considered to be minimized in [56]. Some papers classified PEVs by the owners' preference [5], but none of the papers classifies PEVs based on real-time state and charging demand.

Although a lot of work aimed at reducing the complexity of the optimization algorithm to coordinate the PEV (with mobile battery storage) charging, i.e. by sacrificing minimum performance gap, still substantial time is required to compute and obtain the optimal results. The recent work reported in [59] indicates that the computational complexity is $O(T^3)$ where T is the total number of time stages and the computational time for each stage has the range of 1-10 seconds for each PEV. The computational time needs to be reduced to realize the real-time coordination.

In this Dissertation, several factors, i.e. operational cost, customer satisfaction, load loss, and profit for charging station owners are considered in one objective function. PEVs are classified based on real-time state and charging demand. The computational time is saved to implement the real-time coordination.

3.4 Weather Impact and Risk Assessment

To reduce the storm-related outages, possible methods are: improved tree-trimming schedules, reliability-centered maintenance practices, distributed generation support, grid redundancy improvement, underground cables construction, and mutual assistance agreement [3]. All these methods are for long-term approaches. In a short-term view, if the utilities are aware of an upcoming severe weather scenario and the estimated severity of the related customer impact, preventive measures can be deployed to mitigate the customer vulnerabilities few hours ahead.

There are two types of indices to measure reliability, load point reliability indices and system reliability indices which sum up all the load points [60]. The most commonly used indices are SAIDI, CAIDI, SAIFI, and EENS [61-62]. Such indices consider the outage parameters (restoration time, affected number of people, event frequency) and unsupplied energy which is the only customer parameter involved, and they calculate average values for a given time period, normally on either monthly or yearly basis. For the purpose of evaluating impact from a single event, Customer Interruption Cost (CIC) can be used.

The CIC is essential for assessing the investments and quantifying the risk associated with operating and planning strategies. Brief summaries of the CIC estimation methods are provided in [23]. Different methods to estimate CIC during power outages were proposed in the literature. The following evaluation methods are commonly used by engineers [63]: 1) Ratio of Economic Output to Energy Consumption, 2) Customer Survey (CS), 3) Amalgamated Customer Surveys, 4) Mapped Customer Survey, and 5) Blackout Case Study. The most common assessment is through Customer Surveys (CS), which are the most proper tools for individual customers [64]. Literature [64-68] used surveys from industrial, commercial, residential and agricultural consumers to determine the interruption cost from the perspective of the individual consumer. Indices for different outage durations are summarized. When the surveys are designed and implemented appropriately, the method can produce very reliable estimation due to the directly obtained data from customers. In most cases, customers cannot comprehensively estimate their loss, and it takes a long time and requires a prohibitively high cost to do that. Economists prefer the Ratio of Economic Output to Energy Consumption (EO/C) in terms of the national economy impacted by electricity interruption [69-71]. They used the ratio of a gross economic measure and electricity consumption measure by industry.

The assumptions used create many strict constraints that are often invalid. The amalgamated CS and mapped CS methods are used to save expense and time by utilizing the existing survey results [72-74]. References [72-73] integrated multiple CSs from various regions of a country into a big dataset for the whole country, while [74] used another variation of CS, which is to modify the CS from one country to suit the context of another country, so as to avoid high expense and time for another CS effort. Post-event analysis of specific blackout impact is used in [75], e.g. the 1977 New York City blackout, the US Northeast blackout of 2003. The issue with this is the limitation of the geographic area, duration and characteristics of the analyzed outages, which were usually in an urban area with high population density.

Among the existing CIC estimation methods, most of the results give the loss indices reflecting unsupplied energy, which are classified by types of customers (residential, small/large industrial & commercial, agricultural, etc.). Some methods provide indices based on different outage duration [74]. Some of the customer filling surveys differentiated the questions for winter days and summer days, but the statistical final indices only show the average values since they are evaluating the reliability on a yearly basis [64, 76-77].

In terms of reliability and power-quality issues, customers' economic losses can be expressed by Customer Damage Function (CDF). It was first proposed in [78] and improved in [79]. Expected Interruption Cost Index, one of the reliability indices described in [60], requires the output from CDF. Nowadays, the most proper methods to estimate CIC in CDF for residential customers are mainly based on customer surveys statistics or analytical methods. But the problem with the customer filled surveys is that in most cases the customers cannot estimate their loss comprehensively. In addition, this method requires long period of time to complete and cost associated with the survey may be prohibitively high.

On the whole, CIC indices are often grouped based on outage durations and customer types. Most of the estimation results are classified by different types of customers (residential, industrial, commercial, agricultural, etc.). Some of the results provide different values for different outage duration. None of the above-mentioned methods considered important customers, i.e. health care centers and schools as a customer category and neither included the estimated cost. In addition, none of the results differentiated and considered real-time weather conditions when the outage occurs. This may influence the level of customer costs tremendously including the health impact and economic loss. Tracking weather condition hazards in real-time reveals quite different influence to various customer categories not considered before, such as the health impact and the inconvenient transportation impact, which depend on the loss of electricity. In this Dissertation, those influences are included in the customer costs and customers are classified into several categories based on the severity of power interruption.

3.5 Electricity Grid Support

The service providers who have the ability to aggregate customers may be either utility companies or independent service providers that represent utility customers [80]. To ensure the efficient deployment of the IEVCSs when selected and called upon, the program of DSM and OM can be applied by distribution system operators, during the normal operation or fault condition respectively. It enables customers' participation to assure a reliable energy supply. In this scenario, customers would be participating in the DSM or OM programs controlled by distribution system operators to support the customer action in response to the risk caused by weather impacts on the continuity of electricity supply in real time.

Different techniques for DSM and OM have been evaluated in earlier studies [19-21]. References [45, 81-82] discuss the benefits of using PEVs as energy storage by serving in two modes, G2V and V2G through DSM. Several demand response strategies of PEVs are illustrated in [83-86]. Reference [82] compares non-controlled charging, DSM and V2G integration strategies to smooth the residual load in 2020 and 2030. References [87] and [88] explore the financial incentives necessary to encourage PEV owners to participate in demand response programs. Reference [89] explores the potential impact of PEV market penetration on demand response in order to outline the most effective manner of using these resources. For OM, the benefits of using PEVs as energy storage are discussed in [81] and [90]. Reference [91] proposes the integration of OM tasks in the distribution system and illustrates its necessity. A process of improving information to manage the restoration of distribution facilities damaged by large-scale storms is described in [92]. Reference [93] describes the impact of government, regulator, shareholder, and customer on the development of utility OM system in the 21st century. A control scheme based on the multi-agent system concept for OM system is introduced in [94].

There are some references integrating PV generation and energy storage in analyzing the impact of PEVs [19] or considering the risk of supply insecurity with PEVs under weather impact [21]. However, the benefit of the grid integration of PEVs with mobile battery storage, fixed BESS and PVs and their participation in DSM and OM to correctively mitigate the weather-caused risk for customers has not been studied.

3.6 Conclusion

This chapter discusses literature survey of the related topics studied in this dissertation. The prior research is described and the problems that still need to be solved are analyzed. As a result, the following issues are still outstanding:

- A statistical model based on actual data to estimate PEV charging demand considering different scenarios of vehicle types, battery capacities, penetration level, market shares, etc. needs to be established. This leads to the contributions described in Chapter IV.
- The optimization algorithm to coordinate PEV charging stations with PV generation needs to consider more factors in the objective function, but the complexity and computational time needs to be reduced to realize the real-time coordination. This leads to the contributions described in Chapter V.
- The customer interruption cost analysis methods did not differentiate customer categories and consider real-time weather condition. This leads to the contributions described in Chapter VI.

- The benefit of the grid integration of PEVs with mobile battery storage, BESS and PVs has not been explored in mitigating the weather impact on customers. This leads to the contributions described in Chapter VII.

IV. SIMULATION MODELS

4.1 Introduction

In this chapter, several simulation models to be utilized in the following optimization and control algorithms are established. The proposed statistical model of PEV consumption and multi-tiered pricing scheme to validate the first scenario in the hypothesis is described. The corresponding hypothesis is that such PEV consumption model and pricing scheme can be used to help better coordinate the potential PEV charging/discharging and provide more incentives for PEV users to help reduce the PEV charging impact on the grid.

4.2 Integrated PEV Charging Station (IEVCS)

An IEVCS located in the built environment shown in Figure 3 is considered in this research. The building is connected to the same bus as the IEVCS components, namely PV panels, and fixed battery energy storage. The PEVs with mobile battery storage are assumed to support both the charging and discharging mode. Fixed battery energy storage operates in the two modes as needed. The output power of PV generation is strongly affected by ambient weather conditions. The built environment, which is the human-made space in which people live, work, and recreate on a day-to-day basis, is where the customers are located. Also, the smart IEVCS is interfaced to the power grid, so it is interacting with both end-users and grid.

The IEVS considered in this research is assumed to be located in the parking lots inside or close to the commercial building. It is rational and beneficial to supply the load demand of the building when the IEVCS has excess power supply available, instead of directly injecting power back to the grid. It will be better if the imbalance between the supply and demand can be self- ingested. In this research, the building is integrated with the IEVCS, and the load of the

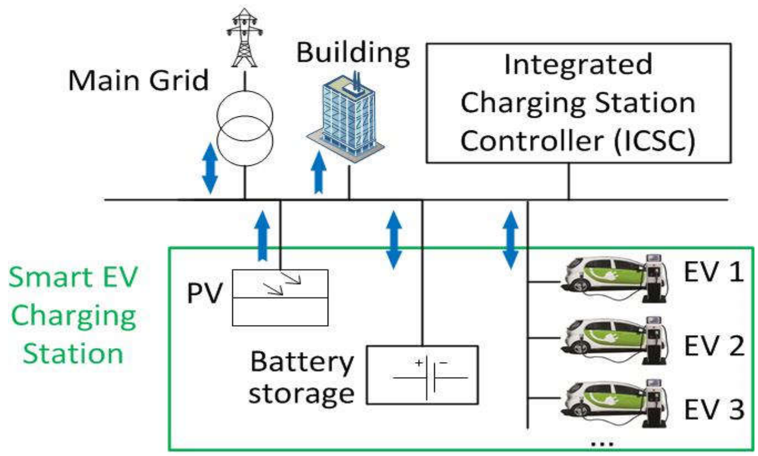


Figure 3: Network of Integrated PEV Charging Stations (IEVCS)

building is considered as a “responsibility” for the IEVCS. Therefore, the load of the building is directly supplied by the IEVCS as needed. The profit or the load loss cost will also be attributed to the integrated charging station owner.

With proper design of coordination and control, the integrated system can run in different operating scenarios. Figure 4 shows examples of different power flow scenarios of the integrated system. Power flow directions vary according to the amount of power PV panels can output, available power supply from the power grid, power demand from PEV (with mobile battery storage) charging, the status of fixed battery energy storage, electricity price, etc. Power exchange schedules will also be different with different optimization objectives.

As shown in Figure 3, PV installation can only generate power and building load can only consume power. The power flow for PEVs with mobile energy storage, BESS and main grid is bidirectional. In this study, it is allowed to sell power back to the main grid in case the PV generation can provide more power than the building interfaced to IEVCS needs or if the grid needs additional power supply during peak hours or in case of contingency. As an integrated system, the PV generation should always supply the load inside the integrated system first according to the priority of the load types,

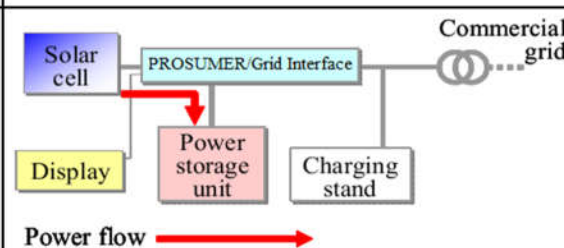
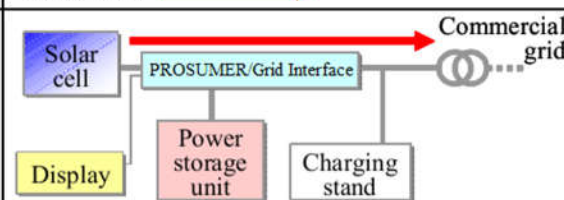
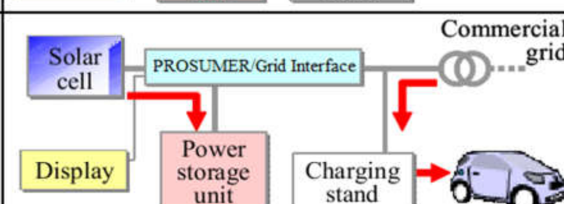
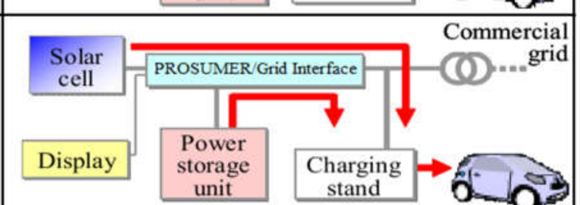
Mode	Power Flow Scenarios
Mode 1: When $P_{EV} = 0$, $P_{PV} > 0$, Battery Storage is not full	
Mode 2: When $P_{EV} = 0$, $P_{PV} > 0$, Battery Storage is full	
Mode 3: When $P_{EV} > 0$, $P_{PV} > 0$, Battery Storage is not full, electricity price is low	
Mode 4: When $P_{EV} > 0$, $P_{PV} > 0$, $P_{EV} > P_{PV}$, electricity price is high	
...	...

Figure 4: Examples of Power Flow Scenarios

including the PEV charging demand, BESS charging demand, and building load demand. When the main grid needs additional power supply, the PEV charging demand, BESS charging demand and the flexible types of load demand from the building can be adjusted or shifted. The key constraint to meet is to try not to cause any cost of expected energy not supplied (EENS). Due to the charging/discharging efficiency of batteries, fixed BESS is not the preferable source of power if another power source is available, such as PV or power grid. When the power demand from PEV charging is higher than the amount of power PV can generate, fixed BESS may be scheduled to discharge to supply the rest of power demand.

4.3 Statistical Model of PEV Consumption*

Two main places to recharge the PEV batteries are either at home or in corporate or public parking locations equipped with charging stations [22]. Due to the long waiting time for the charging to complete, it is possible that the PEV owners will leave the vehicles at the charging station close by their workplace or on their way to work if there are shared parking places for commuters. In this study, public charging stations located at convenient points on the way to work, or close by the working area are considered, and the estimated electricity consumption is for one targeted charging station.

The statistical methodology we use is an integration and improvement of the existing approaches [33-40] in estimating the PEV (with mobile battery storage) consumptions. The actual survey data from NHTS [42] is utilized to build the statistical

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model of each key variable for each PEV. Different types of vehicles, battery capacities, percentages of market shares for each type, levels of PEV penetration are considered.

In order to generate PEV (with mobile battery storage) charging schedules and model the charging need for each charging station at any time point, three random variables to build the stochastic model are studied:

- Starting time of charging,
- SOC (State of Charge),
- Total number of PEVs being charged

The PEV charging load of a single PEV charging station is determined by the stochastic distribution considering the starting time of charging, SOC, as well as AER (range of distance of a fully charged PEV), battery technology, charging level, and the amount of energy required to recharge [37]. The relation among the variables is shown in Figure 5. The starting charging time is determined by drivers' behavior and the battery capacity of the vehicles. The remaining SOC in the battery when arriving at the charging place relates to the miles driven, the capacity fading of the battery, and customers' driving behavior. The total number of PEVs being charged is determined by market penetration of PEVs in that target area. It also depends on the charging start time, the remaining SOC and how fast the charging is. Moreover, the output of the estimated electricity consumption of PEV charging can be used for centralized feedback control in order to reduce the charging impact on power distribution systems.

Figure 6 shows the flowchart of the proposed statistical analysis. The first step is to consider the proposed details on PEV charging characteristics. After developing

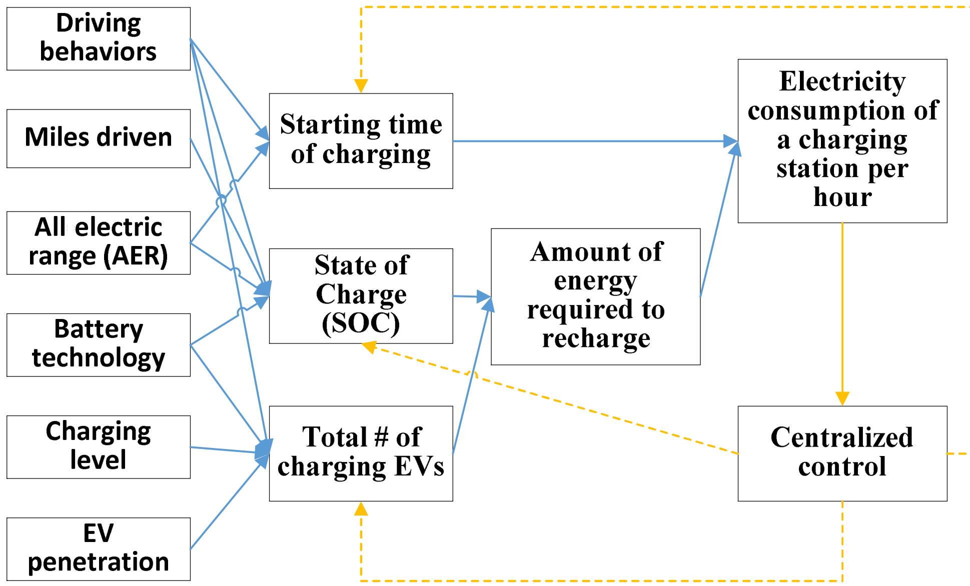

Figure 5: Relation of the PEV variables

statistical descriptions of each random variable, the uncertainties of the variables are integrated and the joint stochastic model is obtained. Based on the stochastic model, the time-variant PEV charging demand is estimated with an input of the PEV penetration.

4.3.1 Characterization of Charging Behavior

- Behavior of Miles Driven

Miles driven data can be obtained from survey results of NHTS [42]. As shown in Figure 7, with miles driven d as x axis and probability as y axis, the miles driven data best fits Weibull distribution, with shaping parameter $k = 1.5311$, and scaling parameter $\lambda = 35.044$.

$$f(d;\lambda,k) = \frac{k}{\lambda}\left(\frac{d}{\lambda}\right)^{k-1} e^{-\left(\frac{d}{\lambda}\right)^{k}}, \quad d \geq 0 \tag{1}$$
$$= 0 \qquad\qquad\qquad , \quad d < 0$$

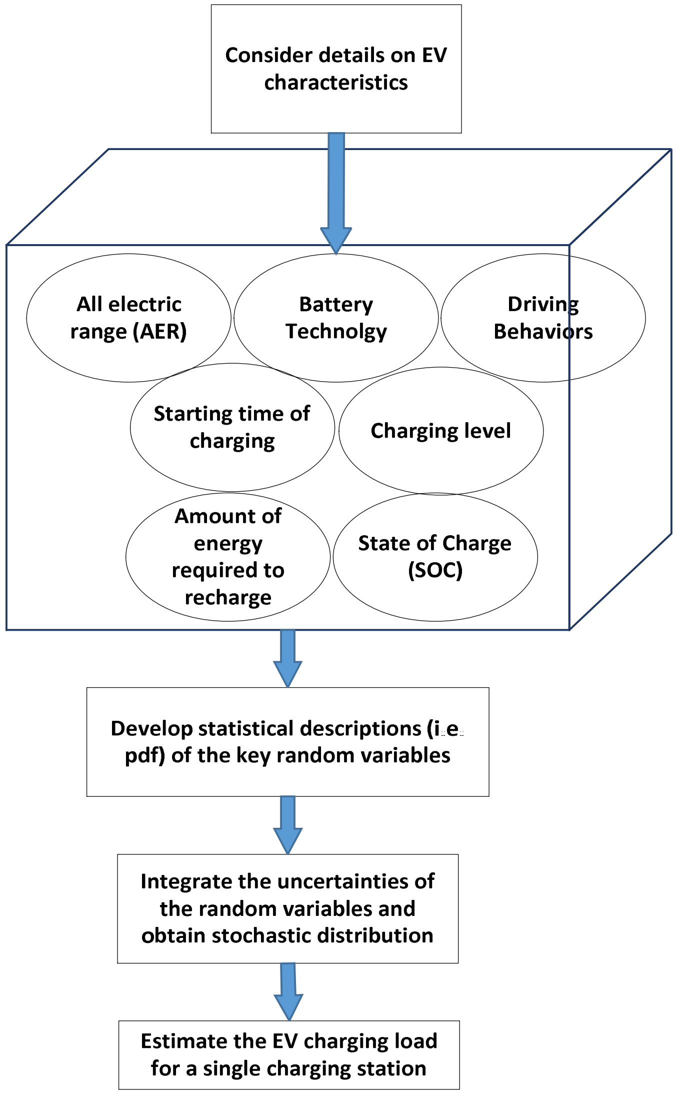

Figure 6: Flowchart of the Statistical Analysis

Numerical integral is utilized over an interval of 5 miles to calculate the probabilities using the above equation. The curve fitting result is shown in red line, while the probabilities are shown in blue bars.

- Behavior of Start Time of Charging

If daily arrival time to work place is used to estimate the charging start time, the daily travel data can be obtained from survey results of NHTS. As shown in Figure 8,

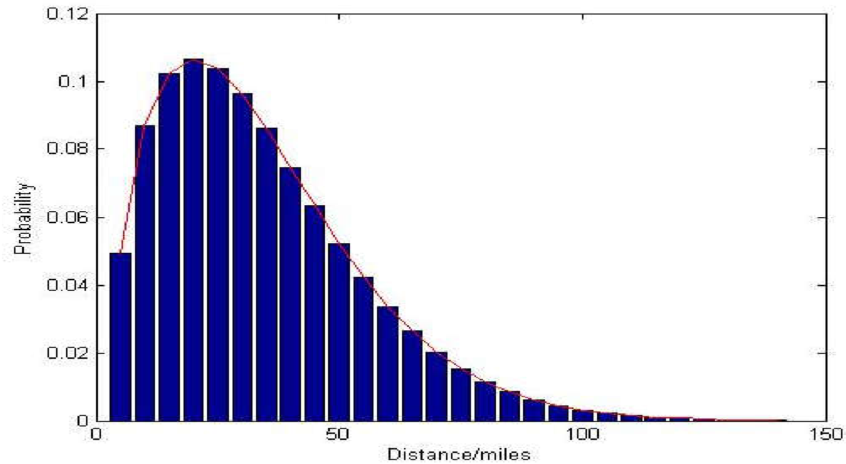

Figure 7: Miles Drive Data and Probability Distribution

with hour of a day as x axis and probability as y axis, the start time of charging data best fits log-logistic distribution, with shaping parameter $\alpha = 8.5$, scaling parameter $\beta = 6.8$, and location parameter $\gamma = 0.65$.

$$f_{\mathrm{ST}}(\tau;\alpha,\beta,\gamma) = \frac{\alpha}{\beta}\left(\frac{\frac{\tau}{0.93}-\gamma}{\beta}\right)^{\alpha-1}\left[1+\left(\frac{\frac{\tau}{0.93}-\gamma}{\beta}\right)^{\alpha}\right]^{-2} \tag{2}$$

Numerical integral is utilized over an interval of 1 hour to calculate the probabilities using the above equation. The curve fitting result is shown in red line, while the probabilities are shown in blue bars.

The charging station provides two options for the connected PEVs, charging and discharging. In addition, discharging bonus is provided as incentives to attract PEVs to be charged at work place, rather than at home. Thus, the arrival time to work place and the daily miles driven data are used.

When NHTS survey data is used to estimate charging start time, it means, uncoordinated charging scenarios are considered. As shown in Figure 5, to intelligently control the PEV charging consumption, the PEV charging start time needs to be coordinated.

- Behavior of State of Charge (SOC)

$$\begin{aligned} \mathrm{SOC} \triangleq g &= \left(1 - \frac{\mu d}{AER}\right) \times 100\%, \text{ if } d \le AER \\ &= 0 \qquad\qquad\qquad\quad , \text{ if } d > AER \end{aligned} \tag{3}$$

For $d > AER$, the distance exceeds the driving range of the vehicle. It is possible that due to different batteries' charging properties, the minimum SOC may not be zero. In this study, we assume that the SOC becomes zero (indicating 0% left in the battery) when the vehicles' driving distance reaches their *AER*, because the *AER* will change accordingly when the minimum SOC changes. In this case, it will force the drivers to charge immediately, in other words effecting the start time of charging variable. AER indicates the maximum miles as percentage of distance driven in electric mode. In (3), it

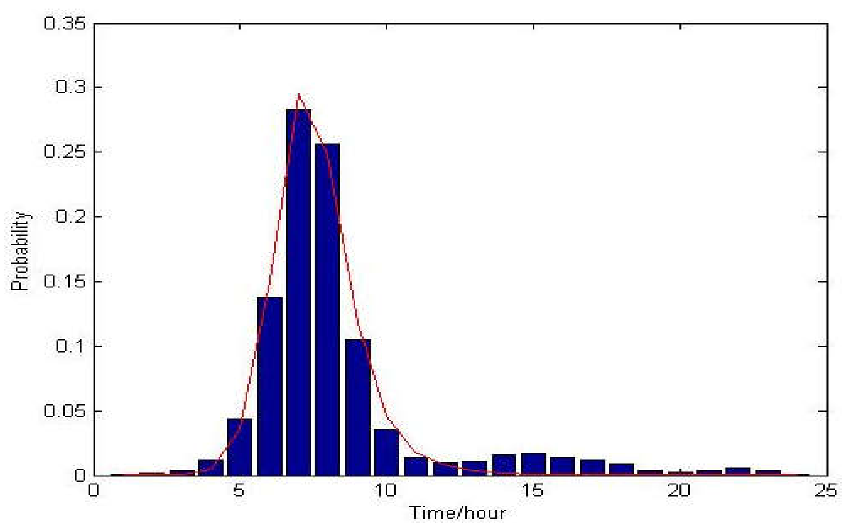

Figure 8: Start Time of Charging Data and Probability Distribution

is assumed that the battery is fully charged before the start of driving. Since the electricity demand for the trip is what we really consider, the SOC after the miles driven can be adjusted by substituting 1 to different initial SOC values. In other words, it is not required to fully charge the battery, but it should be sufficiently charged for the trip. Charging can also be completed after the driving time to supplement the consumed part. Zero SOC does not mean that the battery will be consumed completely at once, but that if the vehicle is going to be driven d miles, at least the whole battery capacity needs to be charged in that day. Since our target is one charging station near work place, we will not consider the extra charge needed. Thus, for the trips exceeding AER, it is believed that the customers wish to charge the vehicles to the maximum as needed for the long trips.

In fact, the SOC also depends on the driving pattern of the driver and other factors, so it is a nonlinear function of many other uncertain factors. Since the purpose of the study is to build a general model for PEV charging demand, linear relationship is utilized at this stage. More accurate relation function can be considered in future research.

Given the distribution of *d*, and the relationship between *s* and *d*, we may derive the distribution of *s*.

$$f_S(s) = \frac{AER}{\mu}\frac{k}{\lambda}\left(\frac{AER(1-s)}{\mu\lambda}\right)^{k-1} e^{-\left(\frac{AER(1-s)}{\mu\lambda}\right)^{k}}, \; s<1 \tag{4}$$

We may plot the probabilities of SOC, shown in Figure 9, which is calculated using numerical integral over an interval of 10%.

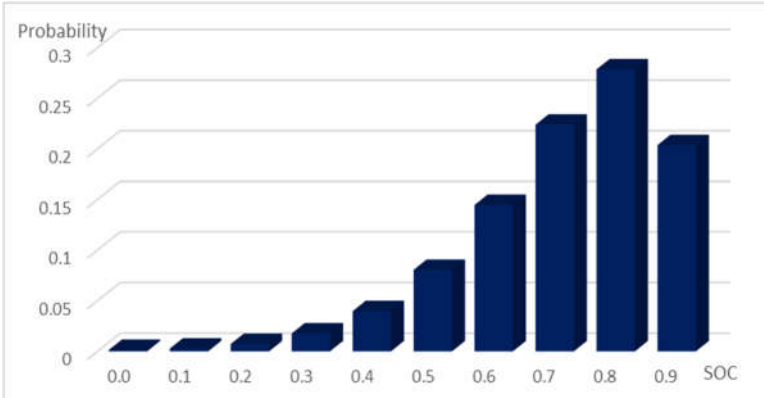

Figure 9: Probability Distribution of SOC

4.3.2 Joint Probability of SOC

Based on the charging level, SOC is assumed to increase r per hour. Therefore, if we consider the charging demand at time t, the PEV that start to charge at time t-1 with initial SOC of s-r, has the same impact for time t+1 as that start to charge at time t with initial SOC of s.

Therefore, the probability that SOC takes the value s at time t is:

$$p(s,t) = \sum_{j=1}^{t} p_{ST}(j)\, p_S\left(s - r(t-j)\right) \tag{5}$$

Where $p(\cdot)$ denotes the discretized probability, as compared to $f(\cdot)$, which is a continuous distribution function. If we consider a given time *t*, all the possibilities of $p(s,t)$ at time *t* should add up to one.

$$p(:,t) = \sum_{S} \sum_{j=1}^{t} p_{ST}(j)\, p_S\left(s - r(t-j)\right) \tag{6}$$

The right side of the above equation does not equal to 1. It is noticed that the deficiency is due to the neglect of $s = 1$. Thus, we need to consider the situation when no charging is required. In this case,

$$p(1,t) = 1 - \sum_{s=0}^{0.9} \sum_{j=1}^{t} p_{ST}(j)\, p_S\left(s - r(t-j)\right) \qquad \text{, if } s = 1 \tag{7}$$

4.3.3 Collective Behavior of PEVs

For each PEV i, with remaining battery level s, at certain time t, the charging demand needed is formulated as

$$\begin{aligned} \eta En_{EV}^{i,t,s} &= \left(SOC^f - SOC^{i,t,s}\right) C_{cap}, \text{ if } SOC^f - SOC^{i,t,s} < r \\ &= r \times C_{cap} \qquad\qquad\qquad \text{, if } SOC^f - SOC^{i,t,s} \geq r \end{aligned} \tag{8}$$

Where η is a constant number for charging efficiency, SOC^f is a constant number in this study (in the case of controlled charging, SOC^f is not constant), $SOC^{i,t,s}$ is a random variable, and C_{cap} is the usable battery capacity that depends on the type of vehicles and corresponding AER.

$$C_{cap}^{l} = ECM^{l} \times AER \tag{9}$$

Where ECM is the estimated electrical energy consumption per mile proposed by Pacific Northwest National Laboratory (PNNL) [95]. The collective behavior of $N_{EV}^{t,s}$ PEVs charging at the same charging station can be characterized as:

$$\begin{aligned} \eta En_{EV}^{t,s} &= \eta \sum_{i=1}^{N_{EV}^{t,s}} En_{EV}^{i,t,s} \\ &= \sum_{l=1}^{4} \sum_{i=1}^{\rho^l \times N_{EV}^{t,s}} \left(\min(r, SOC^f - SOC^{i,t,s})\right) C_{cap}^{l} \end{aligned} \tag{10}$$

Thus, the original problem can be simplified as: given the joint probabilistic distribution of $p(s,t)$, find the expected value of $En_{EV}^{t,s}$, for each hour.

4.3.4 Expected Value of Initial SOC for one PEV

Based on statistic theory, the expected value of $SOC^{i,t,s}$ can be formulated as:

$$E(s)=\sum_{s=0}^{1} sp(s,t) \tag{11}$$

Where

$$p(1,t)=1-\sum_{s=0}^{0.9}\sum_{j=1}^{t} p_{ST}(j)\, p_S\left(s-r(t-j)\right) \quad \text{, if } s=1 \tag{12}$$

$$p(s,t)=\sum_{j=1}^{t} p_{ST}(j)\, p_S\left(s-r(t-j)\right) \quad \text{, if } s\neq 1 \tag{13}$$

4.3.5 Expected Value of Electricity Consumption for one Charging Station

Taking the expectation for both sides of (10), we have:

$$\begin{aligned} E\left(En_{EV}^{t,s}\right) &= \sum_{l=1}^{4}\frac{C_{cap}^{l}}{\eta}\left(\sum_{i=1}^{\rho^{l}N_{EV}^{t,s}} E\left(\min(r,1-s)\right)\right) \\ &= \sum_{l=1}^{4}\frac{C_{cap}^{l}}{\eta}\rho^{l}N_{EV}^{t,s}\left(E\left(\min(r,1-s)\right)\right) \end{aligned} \tag{14}$$

Where

$$N_{EV}^{t,s}=\frac{\psi}{\delta}\times\varepsilon\times\theta \tag{15}$$

The total amount of charging PEVs is a random variable. If we regard each PEV as a stochastic target, there will be one more redundancy if the number of charging PEVs is considered as an individual random variable. Therefore, we only need to consider the total amount of PEVs in the target area, which is $N_{EV}^{t,s}$, and market shares for each vehicle type.

Last, the capacity of a charging station may be limited due to the charging limitation of the specific distribution feeder j where the charging station is located, e.g. limited PEV market penetration, limited charger number n. Thus, the constraints are as follows,

$$En_{EV,j}^{t,s} / t \le P_{\max}^{j} \tag{16}$$

$$\theta \le \theta_{\max}^{j} \tag{17}$$

$$n \le n_{\max}^{j} \tag{18}$$

Where P_{max}^{j} is determined by the capacity of the specific feeder; θ_{max}^{j} and n_{max}^{j} are also affected by how the PEV charging can be coordinated. Since the maximum charging rate for each charger is fixed in a charging station, n_{max}^{j} is decided by P_{max}^{j}. As long as (18) is satisfied, all the three constraints are satisfied. If the simulation result at *t* shows that it requires more than n_{max}^{j} chargers, i.e. $> n_{max}^{j}$, the $En_{EV}^{t,s}$ at *t* should be adjusted to $En_{EV,j}^{t,s} = P_{max}^{j} * t$.

4.3.6 Use Case Study

A use case study is used to demonstrate the statistical modeling of PEV consumption. Available data are survey results of daily travel data and mile driven data, which can be obtain from NHTS. The probability distributions of SOC and Start time of charging are derived by curving fitting the probability distributions of given data and survey results, and then discretized in acceptable resolutions. Output data should be the electricity demand from PEV charging for one charging station at each hour.

Based on experiences, $\eta = 83.33\%$, $SOC^{f} = 100\%$. The value of ECM and market shares for each vehicle type are shown in Table 1 [33, 42]. Since the charging rate is assumed to be 7.2 kW/h, the SOC is assumed to increase 20% per hour. The interval of index t is assumed to be an hour. Thus, $r = 0.2$ and the estimated value will be the electricity demand within the hour. The target area is assumed to have a population of 5000 with 50% PEV penetration. Through MATLAB simulation, the expected value of $SOC_{i,t,s}$ can be calculated, shown in Table 1 and demonstrated in Figure 10.

Table 1: Expectation of SOC

Vehicle type (l)	**1** Compact sedan	**2** Mid-size sedan	**3** Mid-size SUV	**4** Full-size SUV
ECM (kWh/mile)	0.26	0.3	0.38	0.46
Percentage (%)	51.48%	10.35%	23%	15.17%
Battery capacity (kWh) for PHEV100	26	30	38	46

Substituting (14) with actual values, we have

$$E\left(En_{EV}^{t,s}\right) = N_{EV}^{t,s}\left(E\left(\min(r, 1-s)\right)\right)\sum_{l=1}^{4}\frac{ECM^{l}\times AER^{l}\times\rho^{l}}{0.8333} \tag{19}$$

Final results of electricity consumption for a charging station are shown in Table 2 and demonstrated in Figure 11.

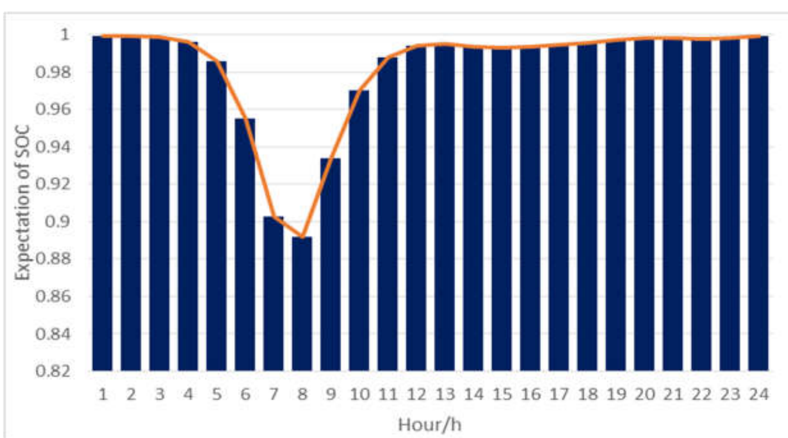

Figure 10: Expectation of SOC at time t (1-24h)

The expected number of charging PEVs is calculated based on the expectation of the electricity consumption, as shown in Figure 12. If the limitation of the charger number is 200 as an example, the expected number of charging PEVs and electricity consumption need to be adjusted accordingly, as shown in Figure 11 and Figure 12.

By adjusting the value of parameters used in the algorithm, the expected results can be obtained for different cases. PEV schedules can be assumed for each use case study by making it match the expected PEV consumption results, if a general assumption or forecast of PEV charging scenarios is needed.

Table 2: Electricity Consumption of a Charging Station

Hours (h)	**Expectation (kWh)**	**Hours (h)**	**Expectation (kWh)**
1	13.33316916	13	159.6805307
2	13.89383688	14	195.9353062
3	36.4158834	15	219.386913
4	120.4460023	16	204.465763
5	428.5495602	17	177.8155963
6	1376.845181	18	141.0527576
7	3040.768944	19	83.37086034
8	3488.105237	20	48.82979993
9	2245.234638	21	47.91638331
10	1047.928805	22	70.50275645
11	424.2160016	23	58.49847578
12	203.7457454	24	28.36626053

4.4 Multi-tiered Pricing Scheme*

Once substantial number of PEVs is in use, the electric power industry would face a new challenge of power demand surge, especially if the customers would prefer a rapid charging of their vehicles similar to the fast gasoline refilling. The financial benefits can hence encourage customers to choose an optimal time for charging their vehicles. If the pricing is calculated with reference to the total available power in the

* Part of this section is reprinted with permission from “A Multi-tiered Real-time Pricing Algorithm for Electric Vehicle Charging Stations,” by Q. Yan, I. Manickam, M. Kezunovic, L. Xie, IEEE Transportation Electrification Conference and Expo (ITEC’14), Jun. 2014. ©2014 IEEE

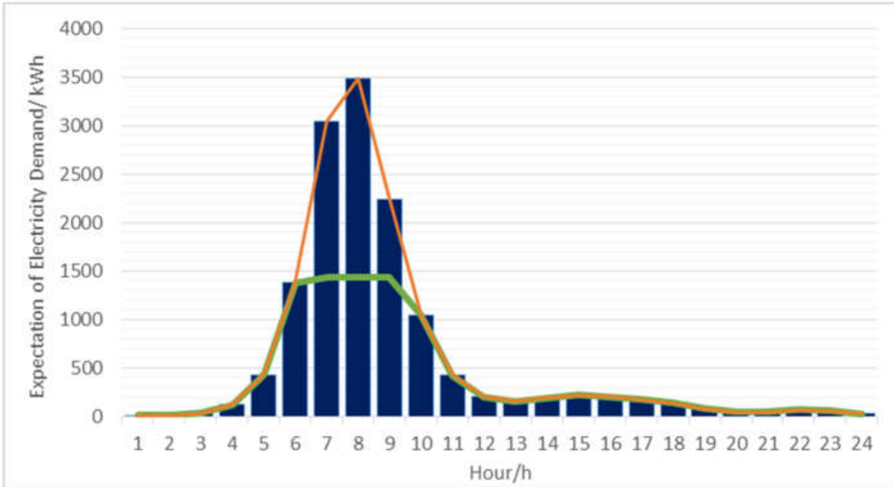

Figure 11: Expectation of Electricity Demand at Time t (1-24h)

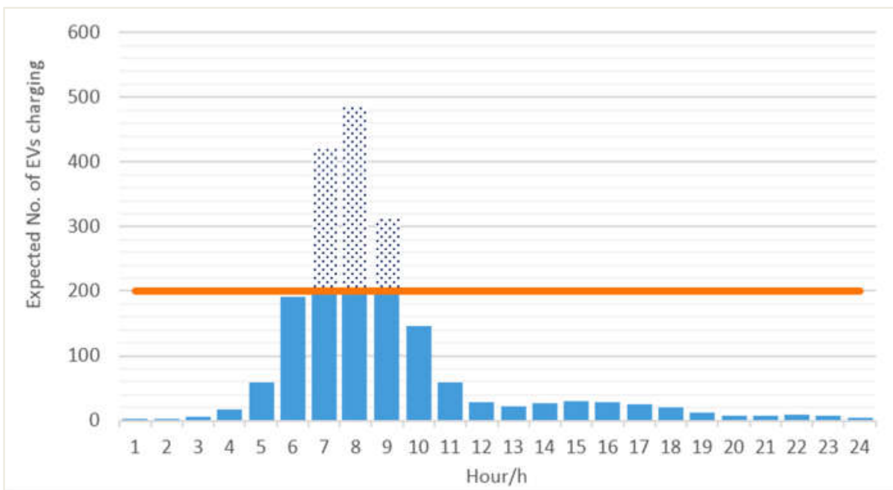

Figure 12: Expected Number of Charging PEVs at Time t (1-24h)

grid, it will encourage the customer to charge the vehicles during off-peak hours and will avoid vehicles being charged at the peak load periods. This will lead to an increase in the utilization of the power grid. Currently in China, the electricity pricing mechanism includes catalog price, stepwise power tariff (SPT) and time-of-use (TOU) price [96-98]. TOU price varies in different periods of a day based on the electricity demand, e.g. peak load, load valley, while stepwise tariff has incremental prices for higher consumption levels. Some research has been focused on controlling PEV charging loads using TOU price [87, 96-102]. Most of the papers investigated how to apply TOU price to formulate charging scheme. Although most of the papers utilized fixed value of prices, real time pricing schemes has also been studied to fluctuate on a day-ahead or hour-ahead basis [103]. The real time electricity consumption has not been considered when deciding the real time price settings in the above-mentioned pricing schemes.

In this research, a new multi-tiered pricing system is developed for charging the PEV (with mobile battery storage) customers based on the data from predicted and actual load cycle. The logic of the proposed pricing structure is similar to the combination of the existing TOU electricity pricing and the stepwise electricity pricing. The difference is that the proposed pricing structure takes both day-ahead forecasted data and real-time load data into consideration and the zone partitions are updated every day automatically. In addition, the proposed display board will not only show the customers the real-time charging price but also the customers will be aware of the predicted price variation.

4.4.1 Effect on Load Cycle

Figure 13 depicts how the load cycle of a typical city with the population of approximate 300,000 is modified when an average 100 PEVs are charged every hour. It is assumed that each PEV is charged at the rate of 60 kW/h using fast charger at charging stations. The load profile is obtained from the public website of Electric Reliability Council of Texas [104].

In practice, the number of PEVs plugged in for charging varies indeterminately, depending on customers' inclination and convenience. Figure 14 predicts such a scenario with a random number of vehicles charging over time. Heavy intermittent charging load

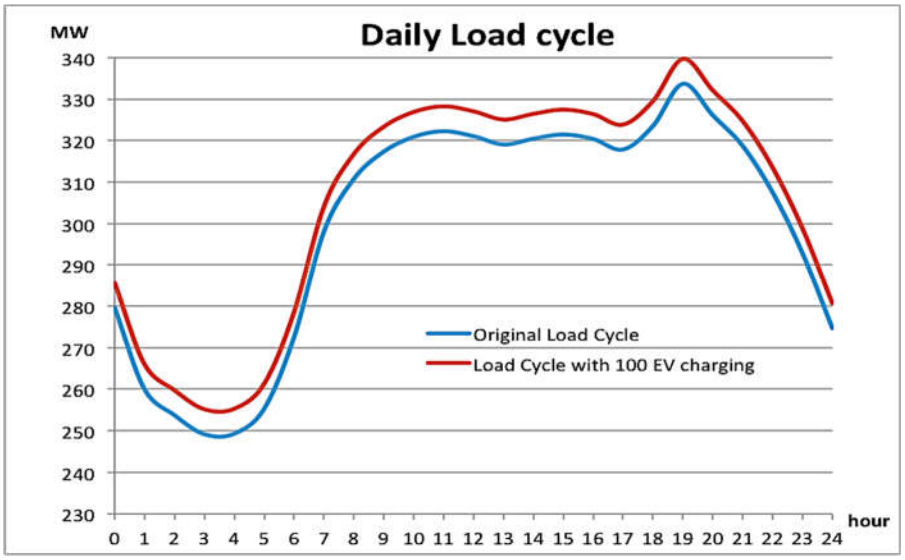

Figure 13: Effect on Load Cycle When 100 PEVs Charging

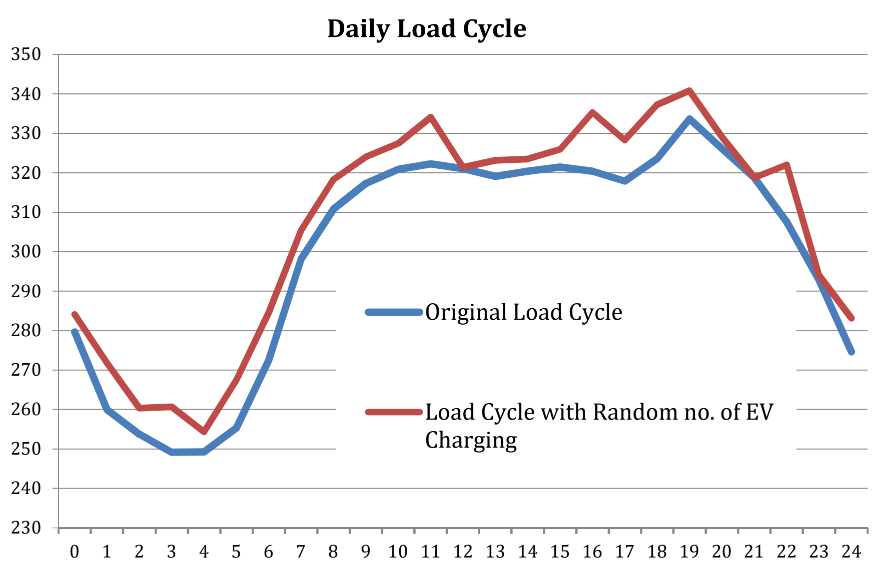

Figure 14: Effect on Load Cycle with Random no. of PEVs

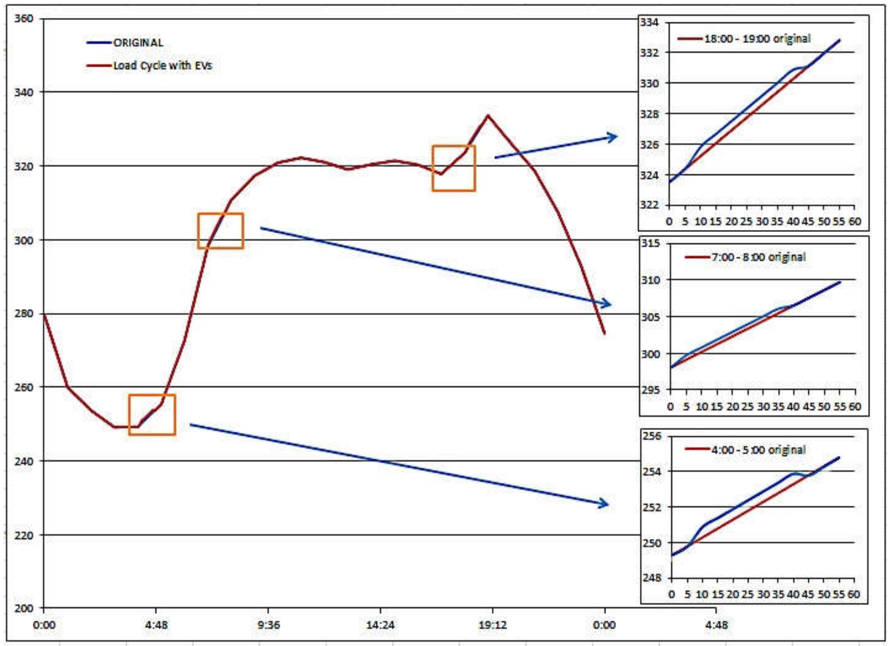

Figure 15: Effect on Load Cycle with 10 PEVs at Different Charging Times

of PEVs may create bottlenecks in the supplying capacity and expose power system to severe security risks [96].

In order to have a closer picture for individual charging, Figure 15 provides how load cycle is affected when 10 PEVs are charged at 3 different specific times.

4.4.2 Identification of Zones for Pricing

Figure 13 and Figure 14 indicate that the charging of PEVs has the potential to increase the peak load of the day. It may create much higher burden on reserve and backup generation resources and may exceed the transformer capacity, which may mean a need to upgrade the utility's local transformer or lead to early replacement [105]. In some cases, the transmission constraints may be reached so that the locational marginal prices of the whole region will be affected. Charging the PEVs during load valley hours and not during peak load hours should be highly encouraged to balance the supply and demand and flatten the load profile. To achieve that, a new real-time multi-tiered system for pricing of PEV charging is proposed. In this chapter, the formation of multiple tiers is investigated.

First, based on the day-ahead load forecast, we locate the region between the peak load and the minimum load, and then divide the obtained region into 4 equal zones. Each zone will have a unique pricing. Figure 16 shows zones 1 to 4 between peak load and the minimum load for the forecasted day.

The price of zone 3 depends on the locational marginal pricing (LMP) of that region which is updated every 15 minutes [96] while the price of zone 2 is lower than that of zone 3, the price of zone 1 is lower than that of zone 2 while the price of zone 4 is higher than zone 3. We also set zone 0 with much lower price and zone 5 with much higher price in case the real time load cycle is lower or higher than the boundaries identified earlier based on the forecasted data. Since the average electricity price of U.S. is about 0.11$/kWh, we assume the value to be the price for zone 3 in our calculation and the price difference between neighboring zones is $0.04/kWh if the zones are between peak and minimum loads.

- Calculation of Intersection Points

Load cycle-zone boundaries intersection points are important factors that affect total cost per charging. There will be different charging prices before and after intersection.

We can see from Figure 16 that the intersections of load cycle curve and the boundary line of DIVIDER2 are between 0:00 - 1:00 am (intersection 1) and 5:00 - 6:00

am (intersection 2) respectively. By applying linearization and assuming x to be the time difference between 6:00 am and intersection 2, we have

$$\frac{L_6 - B_{12}}{L_6 - L_5} = \frac{x}{1} \tag{20}$$

Where L_6 is load demand at 6:00 am, L_5 is the load demand at 5:00 am, B_{12} is the value of upper boundary of ZONE 1. Then the x is obtained as x=0.131 h. Thus, the intersection 2 at the upper boundary of ZONE 1 for that day is at 5:52:14 am. We set it to be 5:52 am.

By applying the same linearization method and assuming y to be the time difference between 0:00 and intersection 1, we have

$$\frac{L_0 - B_{12}}{L_0 - L_1} = \frac{y}{1} \tag{21}$$

Where L_0 is load demand at 0:00 am, L_1 is the load demand at 1:00 am. The y is obtained as y=0.475 h. Thus, the intersection 1 at the upper boundary of ZONE 1 for that day is at 0:28:51 am. We set it to be 0:29 am.

For the upper boundary of ZONE 2, the two intersections of load cycle curve and AVER line are between 6:00-7:00 (intersection 3) and 23:00-24:00 (intersection 4) respectively. By linearization, we have

$$\frac{L_7 - B_{23}}{L_7 - L_6} = \frac{x}{1} \tag{22}$$

Where L_7 is load demand at 7:00 am, L_6 is the load demand at 6:00 am, B_{23} is the value of upper boundary of ZONE 2, x is the time difference between 7:00 am and intersection

1. The x is obtained as x=0.262 h. Thus, the intersection 1 at the upper boundary of ZONE 2 for that day is at 6:44:30 am. We set it to be 6:44 am.

$$\frac{L_{23} - B_{23}}{L_{23} - L_{24}} = \frac{y}{1} \tag{23}$$

Where L_{23} is load demand at 23:00, L_{24} is the load demand at 24:00, y is the time difference between 23:00 and intersection 2. The y is obtained as y=0.077 h. Thus, the intersection 2 at the upper boundary of ZONE 2 for that day is at 23:04:64. We set it to be 23:05.

Applying the same method to calculate the intersections of load cycle curve and the line of DIVIDER1, the two intersections are obtained as 8:16 and 21:33.

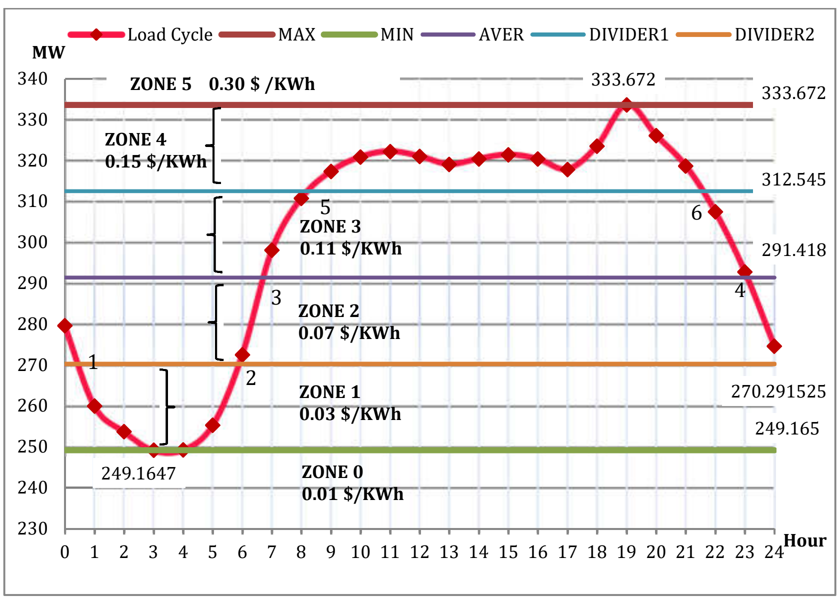

Figure 16: Effect on Load Cycle with 10 PEVs at Different Charging Times

4.4.3 Display Board Specifications

The proposed display board includes:

- Current time t: standard GPS time and local time.

- Current charging price Pr(Z(t)): the price of the zone that the current load demand lies in.
- Total charging cost C: the total estimated cost that PEV users need to pay if the vehicle starts charging at this moment and fast charging takes d=30 min. Assuming the charging power at time t is P(t), the function of the cost will be:

$$C = \int_{t}^{t+d} \Pr(Z(t)) * P(t)\, dt \tag{24}$$

- Charging time d: in this case, the charging time is assumed to be 30 min. Charging time may vary depending on different PEV battery capacity and initial state-of-charge (SOC_i). For each PEV, the charging time will have to satisfy the constraint:

$$\int_{t}^{t+d} P(t)\, dt = (1 - SOC_i\%) * Capacity\ (kWh) \tag{25}$$

- Number of vehicles left to be charged at current price: it is calculated by the difference of the current load demand and the upper boundary of the current zone. Assuming the current load is L(t), the number can be expressed as:

$$N_{current\_limit}(t) = (B_{Z(t),Z(t)+1} - L(t))/P(t) \tag{26}$$

- The next charging price after that number of vehicles being charged: it is the price of the next higher zone Z(t)+1.
- Total vehicles left to be charged at regular price: it is calculated by the difference of the current load demand and the maximum load demand of the

forecasted load cycle M. The charging price will become twice or more if the real load exceeds the maximum forecasted load of the day.

$$N_{regular\_limit}(t) = (M - L(t))/P(t) \tag{27}$$

- The predicted maximum number of PEVs left to be charged within the next 30 minutes: it is calculated by the difference of the forecasted maximum load demand within the next 30 minutes and the maximum load demand of vehicle left to be charged at regular price, it means the total cost per charging will increase within the 30 minutes.
- The number of vehicles that are currently charging $N_{current}(t)$: the customers can compare the number of vehicles left to be charged at the current price with the number of vehicles currently charging to decide when to charge his car.

This data will be sent to the ISO so that the load cycle is updated. Hence this algorithm ensures dynamic operation.

4.4.4 Flow Chart of the Proposed Algorithm

The flowchart of the proposed algorithm is shown in Figure 17. It is evaluated whether the pricing scheme can be used in the intelligent management system to attract PEV (with mobile battery storage) customers to optimally charge their vehicles. The first step is to draw the day-ahead forecasted load cycle [104] and then update it with real time load data. Once the zones are identified and the prices are allotted for each zone, the zones are fixed for that particular day. This will lead to the formation of zone 0 to zone 5. The intersection points of the load cycle with zone boundaries are found, which are used to calculate the total cost per charging at every minute in the MATLAB program. We input zone data and load cycle data to the MATLAB program to calculate the current charging price, the total current charging cost, number of vehicles left to be charged at that price, etc. The results are displayed in the proposed "Display board of a charging station" for the customers to decide their vehicle charging time. Finally, the current charging status will be reflected in the real time load cycle.

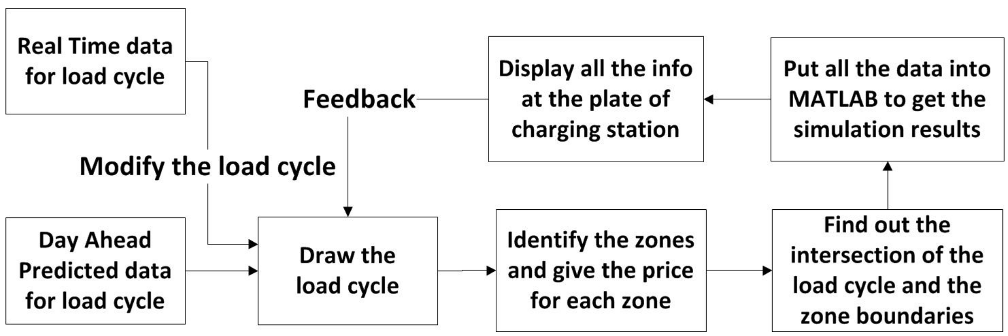

Figure 17: Flowchart of the Proposed Pricing Scheme

4.4.5 Use Case Study

The input to the MATLAB program that runs the algorithm and its simulation results showing the price for charging and other important information are presented. The MATLAB program requires the zone information and load cycle data. The load cycle data is obtained from ISO every 15 min.

1) Calculation of total cost per charging

Figure 18 shows the load cycle from 7 am to 10 am. Let's consider several charging scenarios, assuming the load is 60 kW:

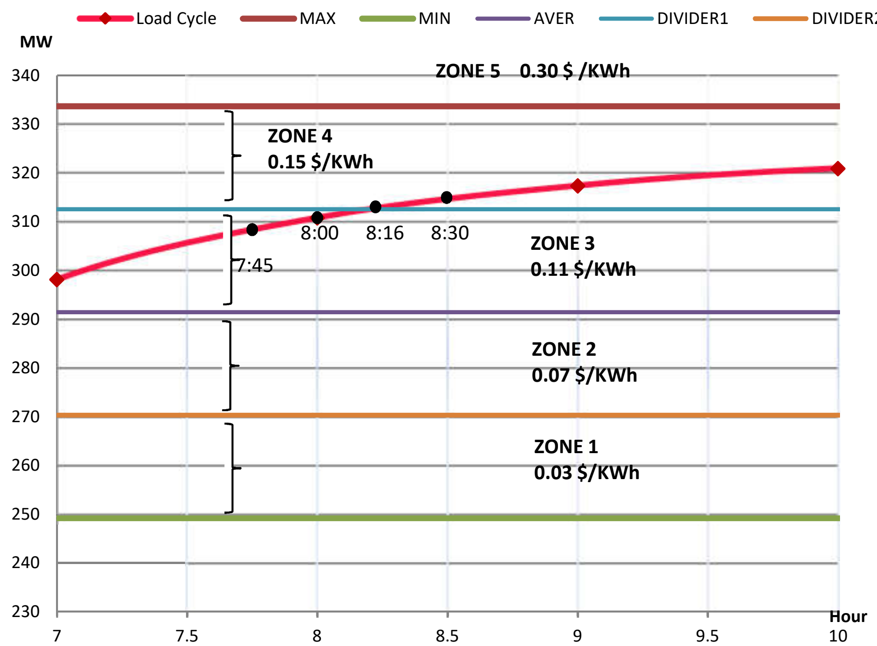

Figure 18: Load cycle from 7 am to 10 am

- Start charging at 7:45 am for 30 minutes:

When the customer starts charging at 7:45, the charging time 30 minutes are all within zone 3. Thus, charging from 7:45 to 8:15 am costs,

$$\frac{30}{60} hour * 0.11\$/KWh * 60KW = 3.3\$ \tag{28}$$

- Start charging at 8:00 am for 30 minutes:

When the customer starts charging at 8:00, the time interval 8:00-8:30 crosses two zones with the intersection point 8:16, then the total cost per charge will be the combination of two parts. From 8:00-8:15,

$$\frac{16}{60} hour * 0.11\$/KWh * 60KW = 1.76\$ \tag{29}$$

From 8:16-8:30,

$$\frac{14}{60} hour * 0.15\$/KWh * 60KW = 2.1\$ \tag{30}$$

Consequently, the total cost per charge is,

$$\$1.76+\$2.1=\$3.86 \tag{31}$$

2) Feedback from PEV charging

Figure 19 shows how the load cycle is modified and the interaction points are updated with the feedback from the real-time PEV charging data. Point 1 indicates the intersection at the original load cycle, while point 2 indicates the intersection at the updated load cycle.

The set of information delivered by the MATLAB program is shown in Figure 20 and Figure 21. Figure 20 shows the proposed display board of charging station at 7:45 am and Figure 21 shows the display board at 1:00 am.

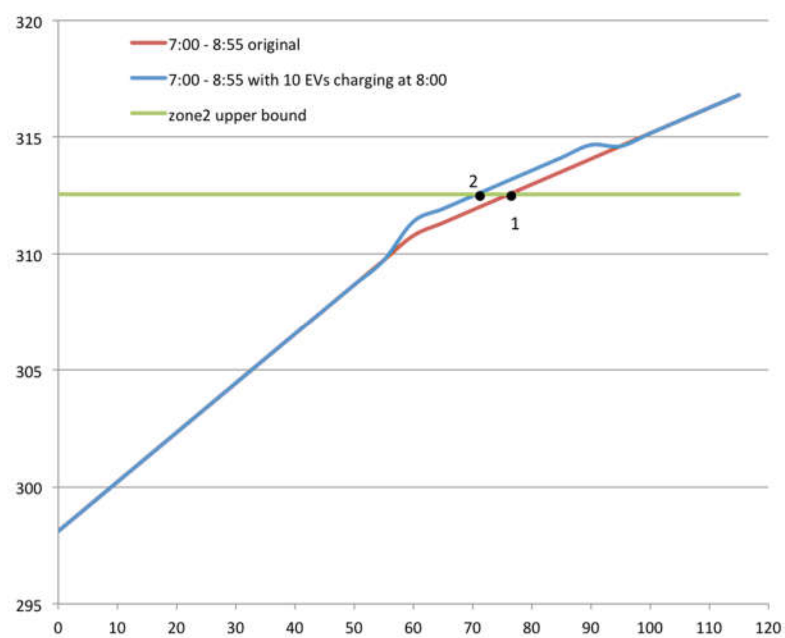

Figure 19: Feedback from PEV Charging

3) Display board

A comparison between fossil fuel (gasoline) and electric fuel is stated below:

- Assume a regular car with a tank of 14 gallons and with the average miles per gallon rate of 25. If the user fills it with fuel twice a month, then the total cost of the gas for one month with total miles driving of 700 miles is calculated as,

$$3.09\ \$/\text{gallon} * 14\ \text{gallon} * 2 = 86.52\ \$/\text{month} \tag{32}$$

- Assume an PEV with the battery size of 30 kWh, charging power of 60 kW and charging time of 30 min, the user charges it per day at night, then the total cost for one month using the price for zone 1 is calculated as,

$$0.9\ \$/\text{day} * 30\ \text{day} = 27\ \$/\text{month} \tag{33}$$

According to the specification of Nissan Leaf, we assume the electricity consumption of the PEV to be 40 kWh/100 miles. Thus, the total electric range of the PEV per month is 2250 miles, which is three times of a regular car, in this case.

4.5 Conclusion

This chapter described several simulation models established and utilized in the study: integrated PEV (with mobile battery storage) charging station, statistical model of PEV consumption, multi-tiered pricing scheme. To be more specifically,

- The structure of the IEVCS is described and different power flow scenarios are displayed, in Chapter 4.2. This is the fundamental concept before the optimal scheduling of components inside the IEVCS are established.

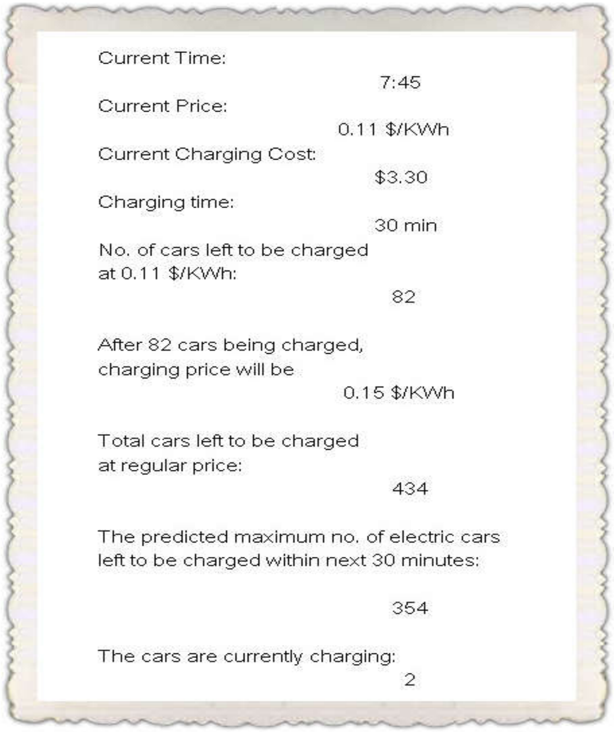

Figure 20: Display Board at a Charging Station at 7:45 am

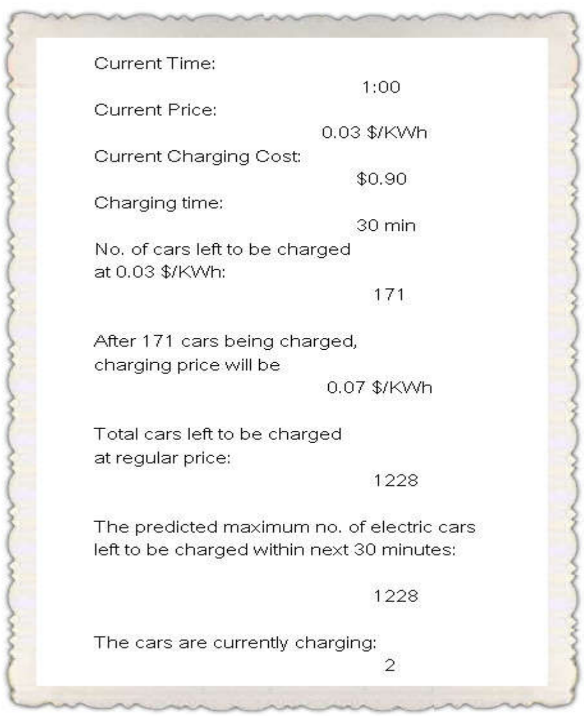

Figure 21: Display Board at a Charging Station at 1 am

- Stochastic model of PEV charging is established and probabilistic description of the electricity needs from PEV charging is derived in Chapter 4.3. As a result: 1) The PEV driving and charging characteristics are analyzed using the real statistical data. Battery technology, charging level, PEV penetration, AER, daily trip miles, starting time of charging, and SOC are taken into consideration; 2) The statistical descriptions (pdf) of the key variables is developed. The continuous functions are discretized to simulate the probability distribution; 3) The uncertainties of the random variables are integrated and interconnected; 4) Numerical experiments are implemented to verify the proposed analysis and illustrate the electricity demand that PEVs contribute to the distribution systems. The results of this study are used in the optimal scheduling and control algorithm in Chapter V and validate the first scenario listed under the hypothesis.
- A novel real-time multi-tiered electric pricing system has been proposed in Chapter 4.4. It aims to achieving higher utilization of power from the grid and decreasing the possibility of creating new peak load on account of PEV charging by encouraging vehicle owners to adjust their charging time in return for reduced electricity bills. As a result: 1) The charging price is varying with the real time electricity consumption; 2) a new display board design for PEV charging stations is proposed, which demonstrates the new pricing system and helps the customers make better decisions on their charging time; 3) the influence on the customers' charging habit will

significantly adjust the electricity demand in the distribution level and alleviate the electricity demand burden it may bring to the electricity market with the increasing penetration of PEVs. Thus, by applying the proposed electric pricing mechanism, the PEV charging patterns can be better controlled so as to help improve the performance of electric grid in terms of the utility application of demand side management. The proposed pricing system is used in the optimal scheduling and control algorithm in Chapter V and validates the assumptions raised in the first scenario listed under the hypothesis.

V. OPTIMAL SCHEDULING AND CONTROL*

5.1 Introduction

In this chapter, a four-stage intelligent optimization and control algorithm for a single bidirectional IEVCS equipped with PV generation and fixed battery energy storage, and integrated with a commercial building, as shown in Figure 3 is discussed. The simulation models described in Chapter IV are used in the proposed algorithm. As discussed in Chapter 4.2, power schedules vary with different optimization objectives. In this chapter, to minimize the overall operational cost for the IEVCS, at the same time maximally guarantee power supply is considered. The Use case to implement the proposed algorithm to validate the second scenario listed in the hypothesis that such algorithm can provide more resilience for unpredictable conditions and more reliably serve the customers is studied.

The proposed algorithm aims at maximally reducing the operational cost considering the potential uncertainties, while balancing the real-time supply and demand by adjusting the optimally scheduled charging/discharging of PEV mobile/local BESS, grid supply, and deferrable load. In spite of two objectives, it is an optimization question with one objective function, with penalty terms added to maximally guarantee the power supply. The operational cost includes customer satisfaction index, allowing the consideration of not only the visible power loss but also customers' satisfaction degree. The algorithm separates the stages into ahead-of-time optimal scheduling and real-time

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* Part of this section is reprinted with permission from "Optimized Operational Cost Reduction for an EV Charging Station Integrated with Battery Energy Storage and PV generation," by Q. Yan, B. Zhang, M. Kezunovic, IEEE Transactions on Smart Grid, Jan. 2018. ©2018 IEEE

control. Day-ahead and hour-ahead predictive data are used and model predictive control-based method is utilized for those predicted data. Operating cost optimization model is established considering the potential uncertainties and customer satisfaction indices. The load is classified by the significance and flexibility. PEV discharging is encouraged by adding and maximizing the participation bonus. Such participation bonus can attract more PEV customers to participate in the charging/ discharging program, allowing garage operators to coordinate the vehicles' charging/discharging schedules. It can further help utilities to more reliably serve the customers by coordinating both supply and demand.

The proposed chance-constrained optimization objective has been stated in stages: a) Stage I, optimization of day-ahead energy management schedules, b) Stage II, multi-tiered PEV charging price update and optimization of discharging participation bonus, c) Stage III, optimization of hour-ahead energy management schedules, and d) Stage IV, real-time control. Such algorithm provides more resilience for unpredictable conditions, provides more incentives for PEV users to participate, and better coordinates the integrated system including the building load to reliably serve the customers while lessening cost. Case studies are implemented and the comparison analysis is performed in terms of the use and benefit of each design feature of the algorithm.

5.2 Optimization and Control Algorithm

In order to coordinate the operation of the IEVCS, an optimization and control algorithm is required. The real-time control algorithm is based on the optimization results. To be more accurate in the optimization schedules and to consider the unexpected occurrence on that day, hour-ahead forecast data is used in addition to day-ahead forecast data before each hour. Since the day-ahead optimal schedules of battery charging/discharging will change the power demand profile, the PEV charging prices for each hour can be updated to track the demand change, and participation bonus for PEV discharging can be updated to satisfy PEV owners to the greatest extent and at the same time meet charging station's requirement. The output of PV generation is accepted as much as possible to provide clean energy, while the PEV mobile battery storage and BESS are utilized to balance the difference between the forecasted data and real-time data, including the PV output power change caused by the sudden weather change, PEVs not coming as expected, and the load demand difference with the forecasted load profile. PEV battery storage is mobile and tends to have the characteristics of randomness, thus the fixed BESS takes the main role to deal with the imbalance. The load demand from the building can also be adjusted according to the priority of the load types. As mentioned in Chapter 4.2, to integrate the components in the IEVCS as a unit, the imbalance between the supply and demand needs to be self-ingested first. For example, when PV generates more power than expected, if the PEVs parked in the IEVCS are in need to charging, the extra power generated by PV cannot be sold back to the grid, regardless of the electricity price. The advantages of each stage of the optimization and control algorithm are further evaluated and analyzed in Chapter 5.3.

Figure 22 describes the flowchart of the proposed four-stage operational cost reduction algorithm. Chance-constrained optimization is utilized in Stage I and Stage III, considering various uncertainties. The purpose of utilizing the method is to make the power supply of building load by the IEVCS more reliable. According to the load demand during on-peak and off-peak hours, the result from Stage I is used in Stage II to obtain new charging price based on multi-tiered pricing scheme described in Chapter 4.4 and maximum participation bonus to attract PEV (with mobile battery storage) customers to be involved in charging/discharging program for the next day, as well as to guarantee a specific maximum cost boundary. To make it a better reference for the real-time operation, Stage III optimization considering hour-ahead forecast data with prices obtained in Stage II, is implemented every hour, i.e. 15 minutes before each hour. Each simulation covers the hours from the start of next hour to the last departure time of the predicted PEV participant. To manage the difference between predicted and real data, real-time control aimed at adjusting the hour-ahead schedules is implemented in Stage IV.

The highlight of the four-stage algorithm lies in the design of the timeline spanning three time-scales, an additional stage to maximize the participation bonus for PEV discharging, and the use of proposed control scheme. The logic flowchart of the control strategy is depicted in Figure 23.

5.2.1 Scenario Description and Definition

Generally speaking, one day (24 hours) is regarded as a whole simulation cycle. However, the last PEV to stay connected in the IEVCS is usually staying past midnight. Thus, in the proposed algorithm, simulation cycle for a day is still 24 hours long (starts at midnight), but the coverage time in each simulation is not necessarily 24 hours but determined by the departure time of the PEV which is the last one to leave.

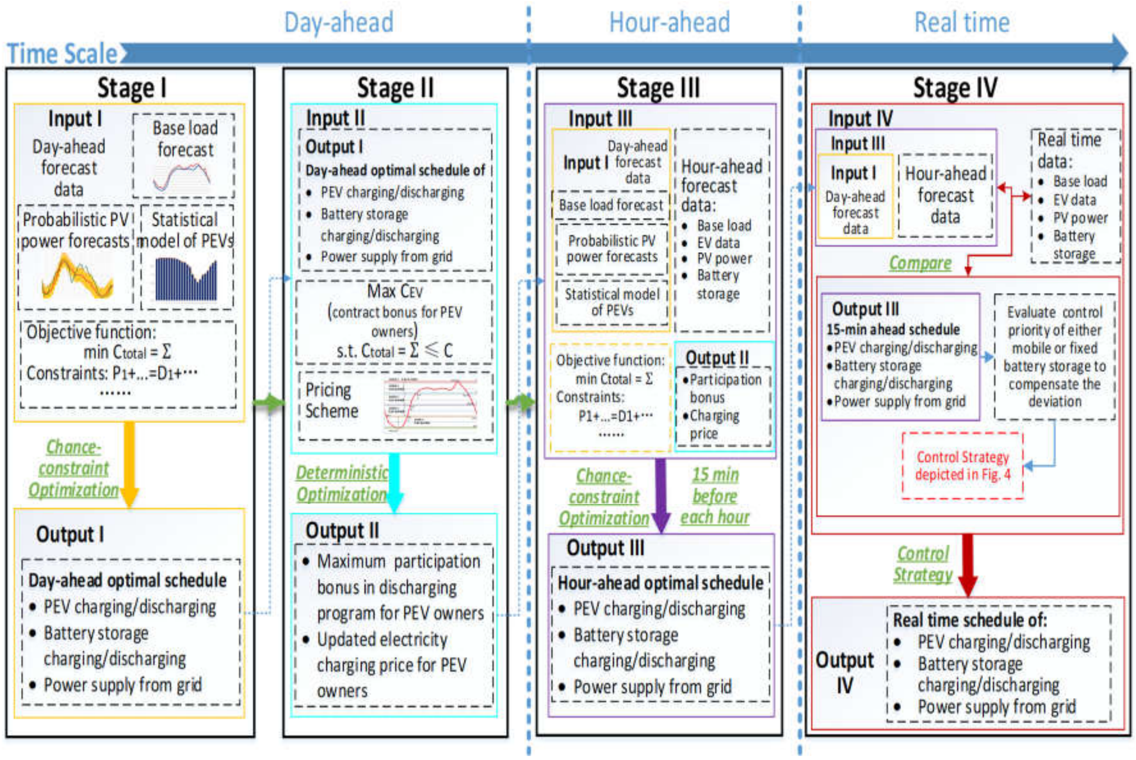


Figure 22: Four-stage Optimization and Control Algorithm

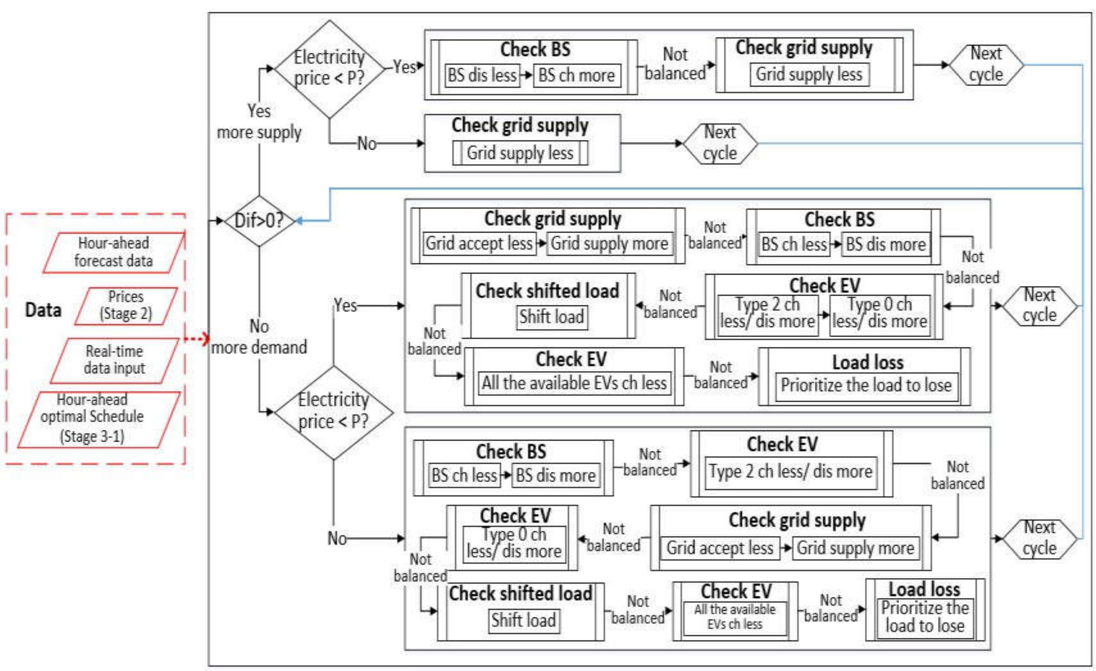


Figure 23: Flowchart of the Control Strategy

The day-ahead forecast for PEV itineraries is based on the statistical analysis of PEV electricity consumption discussed in Chapter 4.3. Let $e_i^{T^0}$ be the battery energy level when PEV i starts to connect at T_i^0, and E_i be the pre-determined target of battery energy level when disconnected. Then the energy transfer of each PEV i over the total connection time T_i should satisfy,

$$\sum_{t=T_i^0+1}^{T_i^0+T_i} e_i^t = \sum_{t=T_i^0+1}^{T_i^0+T_i} (e_i^{t+} - e_i^{t-}) = E_i - e_i^{T_i^0} \tag{34}$$
$$= SOC_i^{fn} \times e_i^{\max} - SOC_i^{in} \times e_i^{\max}$$

The load is classified into four types: critical load, power-controllable load, deferrable load and less important load. The power required by essential appliances are regarded as critical load. Such load has to be always supplied. Power-controllable load can be some flexible appliances such as thermostat load (air conditioner or water heater), which is required but can be controlled. Deferrable load requires power for a certain but shiftable duration, such as laundry machines or dishwashers. The remaining optional load is treated as less important load. The percentage of the load demand for each type is estimated based on references [106-108], as shown in Figure 24. The base load for a building is estimated based on the real load profile data from New Hampshire Electric Co-op (NHEC) [109]. The cost of expected energy not supplied (EENS) indices for each load type are determined referring to Chapter VI.

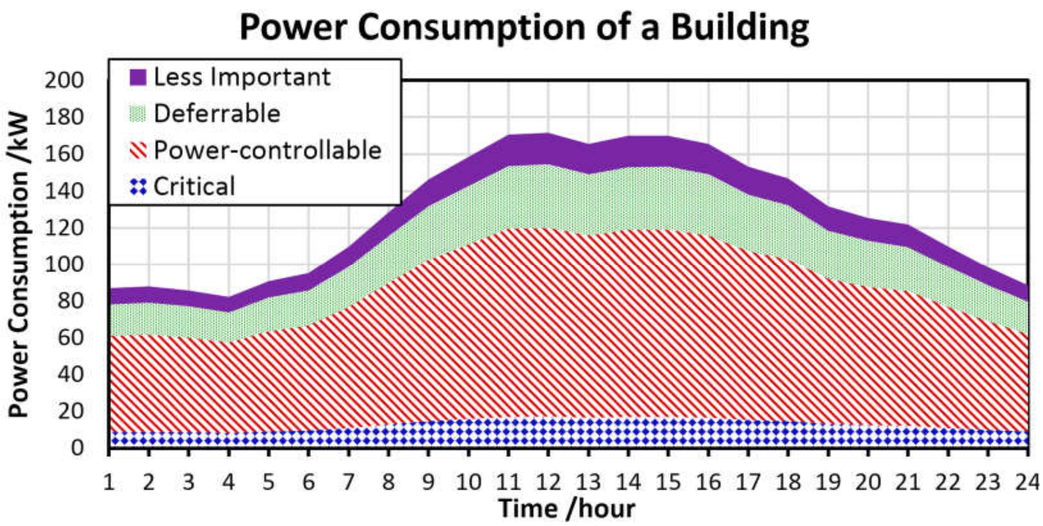


Figure 24: Power Consumption of a Building

5.2.2 Optimization Model

The improvement on the optimal planning scheme for scheduling the operation of the IEVCS lies in the classification of different load types, customer satisfaction indices reflected in the cost function, ability to provide bidirectional power flow with main grid, the impact of the operation of the IEVCS on the node voltage, etc.

The objective function of the optimization model involves cost of power supplied by the grid, operating cost of PV and fixed BESS, cost of unsupplied demand, cost of discharging PEVs and profits from charging PEVs and providing power back to the grid.

$$\min \overbrace{C_{total}}^{\text{total cost}} = \sum_t \begin{bmatrix} \overbrace{C_G^t}^{\substack{\text{cost of power}\\ \text{supplied}\\ \text{by grid}}} + \overbrace{\sum_i C_{c,i}^t}^{\substack{\text{contract with}\\ \text{participating}\\ \text{PEVs}}} + \overbrace{C_{PV}^t}^{\substack{\text{operating}\\ \text{cost of PV}}} + \overbrace{C_b^{EENS,t}}^{\substack{\text{cost of unspplied}\\ \text{demand (EVs}\\ \text{and building)}}} \\ + \overbrace{C_{BS}^t}^{\substack{\text{operating cost}\\ \text{of storage}}} - \overbrace{\sum_i Pr_i^t}^{\substack{\text{profit from}\\ \text{charging PEVs}}} - \overbrace{Pr_G^t}^{\substack{\text{profit from}\\ \text{supplying grid}}} \end{bmatrix} \tag{35}$$

$$= \sum_t \left[\begin{array}{l} \overbrace{\sum_t (\sigma \times P_G^{t+})}^{\text{cost of power supplied by grid}} + \overbrace{\sum_t \sum_i (\sigma_{EV} \times e_i^{t-})}^{\text{contract with participating PEVs}} + \overbrace{\theta_{PV} \times p_{PV}^{\max}}^{\text{operating cost of PV}} + \overbrace{\sum_t (D_b^t - b_b^t) \times c_l^i}^{\text{cost of unspplied customers}} \\ \quad + \overbrace{\theta_{BS} \times s_{BS}^{\max}}^{\text{operating cost of storage}} - \overbrace{\sum_i \left(\theta_{EV} \times \sum_t e_i^{t+} \right)}^{\text{profit from charging PEVs}} - \overbrace{\sum_t (\sigma_G \times P_G^{t-})}^{\text{profit from supplying grid}} \end{array} \right.$$

Where $C_b^{EENS,t}$ can be expressed in (36) if several buildings are connected to the IEVCS.

$$C_b^{EENS,t} = \sum_{b_1} C_{b_1}^{EENS,t} + \sum_{b_2} C_{b_2}^{EENS,t} + \cdots \tag{36}$$

$$= \sum_{b_1} \left((D_{b_1}^t - b_{b_1}^t) \times c_{b_1}^{EENS} \right) + \sum_{b_2} \left((D_{b_2}^t - b_{b_2}^t) \times c_{b_2}^{EENS} \right) + \cdots$$

Constraints: $\forall t = 1, \ldots, T$

- For each building *b*:

$$0 \leq b_b^t \leq b_b^{\max} \tag{37.a}$$

- For each PEV *i*:

$$\begin{cases} 0 \leq e_i^{t+} \leq e_i^{\max,c}, t \in [T_i^0, T_i^0 + T_i] \\ 0 \leq e_i^{t-} \leq e_i^{\max,d}, t \in [T_i^0, T_i^0 + T_i] \\ 20\% \times e_i^{\max} \leq e_i^{T_i^0} + \sum_0^t e_i^t \leq e_i^{\max} \\ \begin{cases} e_i^{T_i^0} = SOC_i^{in} \times e_i^{\max} \\ \sum_{t=T_i^0+1}^{T_i^0+T_i} e_i^t = SOC_i^{fn} \times e_i^{\max} - e_i^{T_i^0} \end{cases} \end{cases} \tag{37.b}$$

At any time, the energy in each PEV cannot be negative nor exceed the battery capacity. In addition, the number of connected PEVs should be less than the number of chargers.

- For PV:

$$0 \leq p_{PV}^{t} \leq p_{PV}^{\max} \tag{37.c}$$

- For each BESS:

$$\begin{cases} -s_{BS}^{\max,d} \leq s_{BS}^{t} \leq s_{BS}^{\max,c} \\ 0 \leq \sum_{0}^{t} s_{BS}^{t} \leq s_{BS}^{\max} \end{cases} \tag{37.d}$$

- Power constraints:

$$\sum_{i} e_{i}^{t} + b_{b}^{t} = p_{PV}^{t} + s_{BS}^{t} + P_{G}^{t} \tag{37.e}$$

- Power flow equations for each bus l:

$$p_{G_l}^{t} + \sum_{j \in l} p_{PV,j}^{t} + \sum_{n \in l} s_{BS,n}^{t} - \sum_{i \in l} e_{i}^{t} - \sum_{b \in l} b_{b}^{t} - P_{D_l}^{t} = V_{l}^{t} \sum_{x=1}^{n_l} V_{x}^{t} (G_{lx} \cos \delta_{lx} + B_{lx} \sin \delta_{lx}) \tag{37.f}$$

- Power flow constraints for the IEVCS:

$$-P_{cs}^{\max} \leq \sum_{i} e_{i}^{t} + b_{b}^{t} - p_{PV}^{t} - s_{BS}^{t} = P_{G}^{t} \leq P_{cs}^{\max} \tag{37.g}$$

- Voltage constraint:

$$V_{l}^{\min} \leq V_{l}^{t} \leq V_{l}^{\max} \tag{37.h}$$

- Bus constraints:

$$
\begin{cases}
-P_{G_l}^{\max} \leq P_{G_l}^{t} \leq P_{G_l}^{\max} \\
-Q_{G_l}^{\max} \leq Q_{G_l}^{t} \leq Q_{G_l}^{\max} \\
\sum_{x} P_{lx}^{t} = P_{G_l}^{t} + \sum_{j \in l} p_{PV,j}^{t} + \sum_{n \in l} s_{BS,n}^{t} - \sum_{i \in l} e_{i}^{t} - \sum_{b \in l} b_{b}^{t} - P_{D_l}^{t} \\
\sum_{x} Q_{lx}^{t} = Q_{G_l}^{t} - Q_{D_l}^{t} \\
\begin{cases} P_{xl}^{t} = -P_{lx}^{t} \\ Q_{xl}^{t} = -Q_{lx}^{t} \end{cases} \\
\begin{cases} -P_{lx}^{-\max} \leq P_{lx}^{t} \leq P_{lx}^{\max} \\ -Q_{lx}^{-\max} \leq Q_{lx}^{t} \leq Q_{lx}^{\max} \end{cases}
\end{cases}
\tag{37.i}
$$

Where l indicates the bus to which the IEVCS is connected. P_{G_i} and P_{D_i} include all the generators and loads connected to the same bus l. x represents all the adjacent buses if a complete power network is considered.

This optimization model aims at minimizing the overall operational cost for each element in the integrated system. This method allows PV to generate as much power as possible. Due to the charging/discharging impact of battery life and high cost of battery storage, frequently charging/discharging batteries is not recommended. Thus, fixed BESS is not the preferable source of power if other power source is available, such as PV or power grid based on the prices. The customer satisfaction indices determine that the load loss is the least wanted situation. The relationship between the electricity price, charging price and discharging participation price for PEVs determines the optimal schedule of PEV charging/discharging and power supply needed from the main grid. Indeed, the optimal solution obtained in Stage I will not be optimal once the prices are updated in Stage II. That leads to the necessity of Stage III to have new hour-ahead input and new prices for the hour-ahead optimization solution.

To save more computational time and simplify the simulation work, the optimization model is solved as DC system. The nonlinear power flow equation (37.f) is used to calculate voltage and (37.h) is checked to see if the voltage constraint is satisfied. If the constraint is not satisfied, the optimal results will be excluded and optimization will be performed again.

After reaching day-ahead optimization solution in Stage I, new charging prices are obtained by utilizing the pricing scheme in Stage II. The multi-tiered electric pricing scheme divided the load profile into five zones and assigned different charging price for each zone. Since the load profile will change after applying the optimization solution from Stage I, the charging price also needs to be updated accordingly.

5.2.3 Control Strategy

The benefit of the control scheme lies in the different scenarios differentiated by comparison results, classification of PEV groups and the logic to optimize each schedule in terms of prediction deviation, etc.

The flowchart of the control scheme is shown in Figure 23 with the input data included in the red box on the left-hand side. The value of *Dif* indicates whether more power supply is available or more demand is needed in real time. The control process differs based on *Dif*, electricity price, $C_b^{EENS,t}$, etc.

These divide the control scheme into four scenarios, in which the checking sequences are different. The underlying principles are as follow:

- Output power from PV is accepted as much as possible.

- Power injection in one bus node is limited and the bus voltage should always be within an allowable range during the real time control.
- Real-time data need to be compared with predicted data for PV output power, electricity demand of a building, available PEV and current status, SOC of BESS.
- PEVs are classified into three groups according to their charging demand and departure time: 1) must participate at this time slot to meet the demand, 2) can be flexible load, 3) the same as predicted, and thus remain the same as scheduled. If a certain PEV is not scheduled for charging in this time slot in the hour-ahead schedules, the real-time control will not change the schedule unless necessary.
- Different scenarios are separated, where the checking logic and priorities are defined for each scenario.
- When more power is supplied than predicted, reduce power supply from the main grid if real time electricity price is high, while reduce power supply from BESS or restore the extra power to BESS if real time electricity price is low.
- When the power demand at real time is more than the predicted power demand,
    - Increase the power supply from BESS first if real time electricity price is high; Increase the power supply from main grid first if price is low.

- If BESS and main grid cannot balance the extra demand, the charging/discharging schedules of group 2 PEVs can be adjusted.
- The schedules of group 3 PEVs can be adjusted if the power is still not balanced.
- Type 3 load can be shifted to later time slots if load demand change is necessary.
- If load loss is inevitable, the priorities are based on the cost of energy not supplied indices for each load type.
- The control scheme reserves power in case some large deviations with predicted data occur.

In fact, the real situation of the PEVs coming to the IEVCS is highly uncertain, thus it is pretty possible that the scheduled PEVs in the prediction are not coming, more PEVs come than predicted, scheduled PEVs come later or earlier, or status of the battery is very different from predicted data, etc. All the above-mentioned scenarios are considered in the control scheme to best match the real situation. The algorithm is briefly presented below.

Algorithm: Real Time Control Strategy

load: hour-ahead optimal solution

input: hour-ahead forecast data, real time b_b^t, p_{PV}^t

output: real time scheduling of $P_G^{t+}, P_G^{t-}, e_i^{t+}, e_i^{t-}, s_{BS}^{t+}, s_{BS}^{t-}$

1. **update** *t,* **input**
2. initiate real time scheduling by hour-ahead optimal solution
3. classify existing PEVs and check *Dif*
4. **if** *Dif>0*

Check example:

$$\text{if } \sigma < \sigma_{\lim} \rightarrow \text{if } \begin{cases} p_{BS}^{t} + s_{BS}^{t+} - s_{BS}^{t-} + Dif > s_{BS}^{\max,c} \\ \text{or } Dif > r_{BS}^{avl,c} \text{ or } Dif > r_{BS}^{c} - s_{BS}^{t+} \end{cases} \rightarrow$$

$$\begin{cases} \Delta s_{BS}^{t+} = \min(r_{BS}^{avl,c}, s_{BS}^{\max,c} - (p_{BS}^{t} + s_{BS}^{t+} - s_{BS}^{t-})) \\ \Delta P_{G}^{t-} = Dif - \Delta s_{BS}^{t+} \end{cases}$$

$$\text{else } \rightarrow \Delta s_{BS}^{t+} = Dif$$

$$\text{else } \rightarrow \Delta P_{G}^{t-} = Dif$$

5. **elseif** *Dif<0*, **check …**
6. **jump to 1 until** next hour
7. **end**

5.2.4 Comparison with the Basic Control Scheme

The basic control scheme does not consider the priority criteria in the proposed control scheme. The basic control is needed in real time due to the inevitable existence of the difference between predicted value and real data. The IEVCS always tries to store extra energy to the fixed BESS first and supply extra demand from the main grid to meet the charging/ discharging efficiency of the battery.

To evaluate the validity of the proposed algorithm, the comparison is carried out to show the benefits of having the Stage II, Stage III and Stage IV, respectively. Thus, results from using Stage I and Stage II electricity prices and participation bonus, results from using day-ahead forecast data and hour-ahead forecast data, and results from using the basic control scheme vs. the proposed control scheme are compared. Also, the results of using 24 hours as a cycle vs. flexible hours based on the last departure PEV are compared.

5.3 Use Case Study

In order to implement the proposed optimization and control algorithm, case studies are conducted to evaluate the necessity and benefit of each design feature of the algorithm.

According to the day-ahead forecast data for PEVs, 29 hours are covered in each hour-ahead simulation. Based on the statistical method described in Chapter 4.3, 39 PEVs are considered in this use case study, and their forecasted connection time duration is displayed in Figure 25. The predicted output power from solar panels as shown in Figure 26 is based on [110]. Operational cost for PV and fixed BESS is assumed based on [111] and [112]. The capacity of the fixed BESS is assumed to be 113.4 kWh and maximum charging/discharging rate is 70.875 kW/hour. The maximum output power of PV is assigned to be 153 kW. The target area is assumed to have a population of 300 with the PEV penetration of 30%. According to the population and PEV penetration, 18 chargers are assumed to be installed in the IEVCS, so no more than 18 PEVs can be connected and exchange power at the same time. The charging rate for each charger is set at 7.2 kW/h.

In this simulation, the building and the IEVCS including PV generation, PEV chargers, and fixed BESS are connected to the same bus. The whole integrated system in Figure 3 is connected to bus 18 in IEEE 33 bus test distribution system [113]. Case studies are implemented in MATLAB environment and comparison analysis is performed. Summary observations and conclusion for each comparison are elaborated in Table 3.

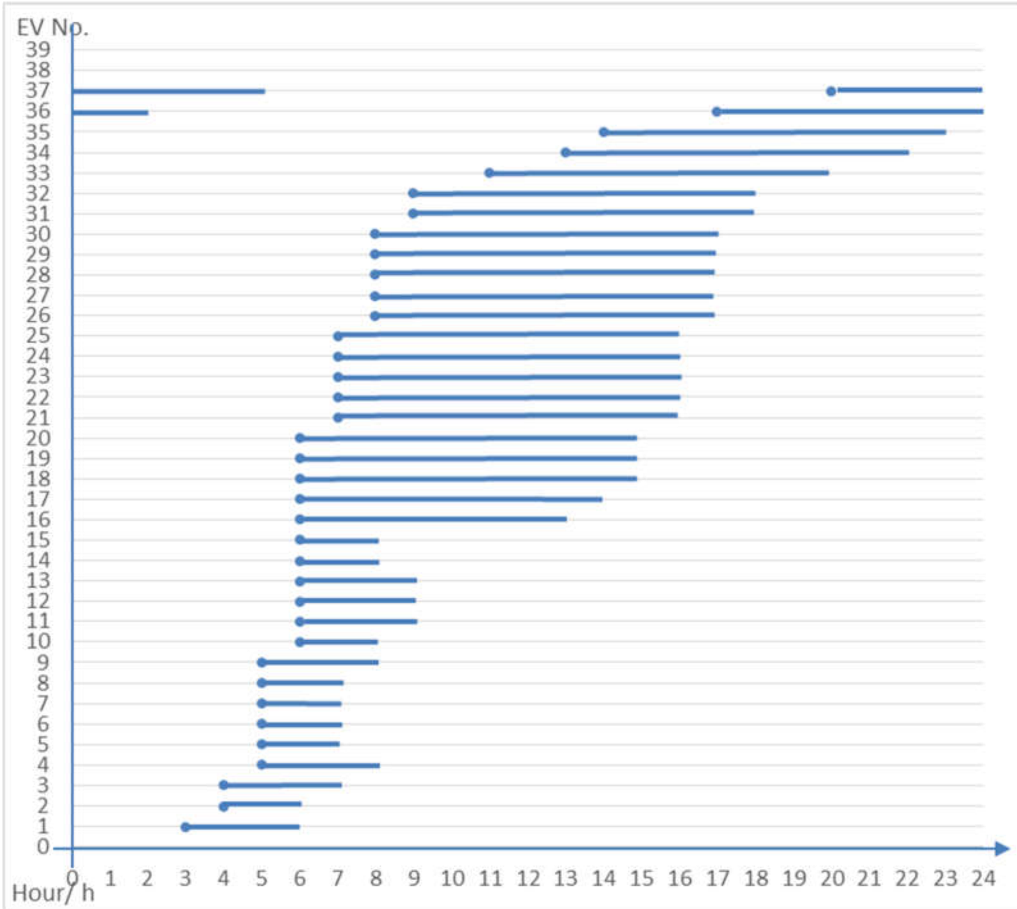


Figure 25: EV Forecast Data: Connection Time

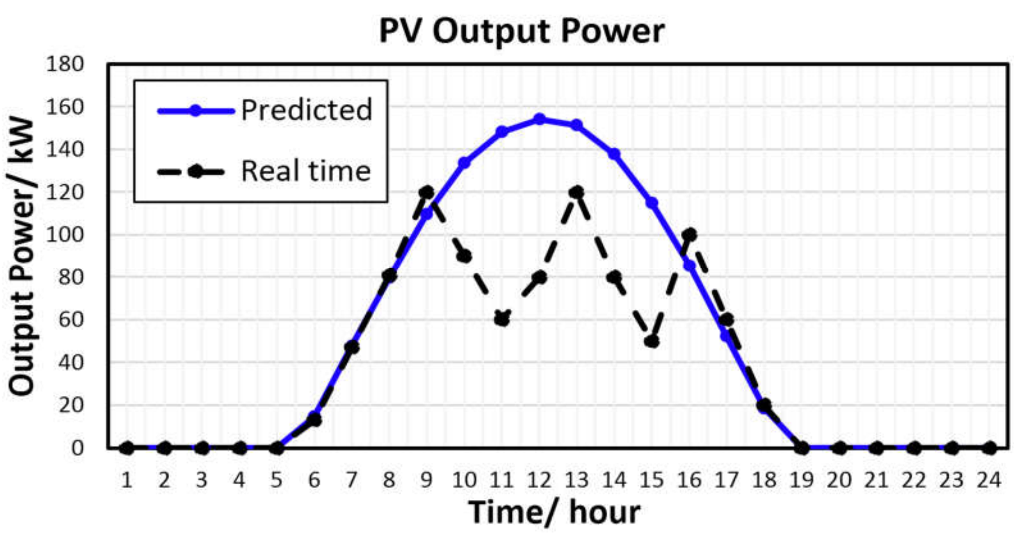


Figure 26: Predicted Output Power from PV

Table 3: Comparison Results and Analysis

Evaluate	**Section**: Case vs.	Observation	Conclusion
Stage III: Hour-ahead schedules	**IV-A**: Day-ahead schedule (case 1) vs. Hour-ahead schedule (case 2)	• In case 2, battery storage stores more energy during low electricity price hours 2-7, which saves more cost during hours 10-15 (there is a quite large deviation of PV output power from hour 10-15 in Fig. 5). • In case 1, few deferrable loads supplied during high electricity price hours 8-11 give load burden to later hours. The situation became worse due to the unforeseen output power deviation from PVs. • The impact is accumulated with time causing significant load burden for the last several hours. The overall cost in case 1 is 15 times of case 2.	It can be concluded that using hour-ahead forecast data in the optimization model is better.
Stage IV: Real-time control	**IV-B**: Hour-ahead schedule (case 2) vs. Real-time control (case 3)	• The change of battery storage SOC seems quite similar except more discharge is scheduled in hour 10 (case 3). • Due to different initial SOC of battery storage, deferrable load in hour 11 for case 3 is less than in case 2. • PEV charging/discharging schedules are different in several time slots, but the overall PEV consumption is the same. • There is a significantly higher cost at the end of day for case 2, and the overall cost of case 2 is 1.55 times of case 3. • In case 3, more power supply is accepted from grid in several time slots even though the electricity price is not low. It may cause the overall cost to increase more or less if predicted data is quite accurate, but it will save a lot of cost if some unpredictable conditions happen.	• The proposed control scheme is more suitable for unfavorable conditions. • Load profile is not simply flattened as in the traditional demand response since the grid is not the only source of power. PV generation, fixed energy storage and PEV mobile energy storage are integrated in the network, which makes it hard to intuitively predict the optimal solution for the overall operation. The target is to reduce the operational cost for the IEVCS.

Table 3 Continued

Evaluate	**Section**: Case vs.	Observation	Conclusion
Extended coverage time	**IV-C**: 24h (case 4) vs. extended coverage (case 1)	• The load loss happens in both cases, causing high cost due to the customer satisfaction related indices being low in the cost function. • More deferrable load is supplied during high electricity price hours and the utilization ratio of the fixed battery storage is higher in case 1. • Case 4 has more load loss and overall cost is about 1.4 times of case 1.	The use of extended coverage hours gives higher tolerability and flexibility for unpredictable circumstances.
Stage II: Price update	**IV-D**: Stage I vs. Stage II price	The costs with Stage II price are higher than those with Stage I price, but the differences are small enough to be neglected.	It is beneficial to update prices since higher bonus can attract more PEV customers to park and charge there.
Stage I&III: Chance-constrained optimization	**IV-E**: None vs. Base case vs. More reliable case	• More energy is reserved in the fixed battery storage when *Rei* is higher (more reliable) in case a fault happens. More reliable case tends to have less cost induced by the energy not supplied when fault happens. • The cost due to the energy not supplied during fault is very low during hours 5-14, since the PV generation is quite active during those hours.	The adoption of chance-constrained optimization will lead to lower loss especially when the fault happens.

5.3.1 Day-ahead Schedule vs. Hour-ahead Schedule

This comparison shows whether the cost will decrease if hour-ahead schedules instead of day-ahead schedules are used. Obviously, hour-ahead forecast is more accurate. In the proposed algorithm, it is possible that using hour-ahead data may cause higher cost. Optimization for hour-ahead schedules need to be implemented every hour and up to 29 hours are covered in each simulation. Since the deferrable load in hour 1-24 may be shifted to hour 25-29, the shifted load needs to be compensated at later hours to guarantee all the deferrable load (1-24) are supplied within a day (24 hours). Each hour-ahead simulation may output different schedules for the deferrable load supply. Even though the hour-ahead schedule may give more optimized schedule for the current time slot, it may induce more burden to later hours. It is still meaningful to compare the results of using day-ahead and hour-ahead schedules. The comparison results of battery storage SOC, deferrable load consumption, PEV consumption, and hourly cost, are shown in Figure 27.

5.3.2 Hour-ahead Schedule vs. Real-time Control

This comparison shows whether the results will be improved if the proposed control scheme is used, as shown in Figure 27. In this study, a relatively unfavorable situation is assumed where the PV output power is not quite as predicted, especially during low electricity price hours when the load schedule is supposed to be higher. This scenario is reasonable since in real life PV output power can be fairly uncertain and flexible as sunlight changes.

5.3.3 Coverage Time of 24h vs. the Departure of the Last PEV

This comparison shows whether covering the individual connection time intervals of all the arrived PEVs is better than a fixed 24 hours. Even though the coverage time in the simulation is extended, the control cycle of a day always starts at midnight and ends at the next midnight. The reason for extending the simulation coverage time is that splitting the connection time of PEVs into two days is not desirable and assigning a new target SOC at the end of a day will limit the optimization results. For example, a PEV may arrive at 10 pm with an initial SOC of A and may leave at 5 am the next day with the target SOC of B. If it is the last car to leave the IEVCS, the coverage time in the simulation will be 29 hours. If the coverage time is set to be always

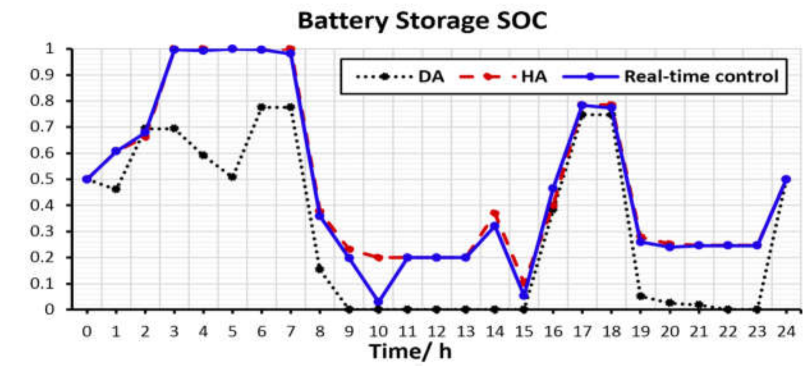
24 hours, it is necessary to assign a temporary target SOC at the end of the first day, which will narrow the feasible region of the optimization model. Extending the coverage time may bring more uncertainties since the deferrable load that are scheduled to be shifted to extended hours (25-29) need to also be reflected within 24 hours. Making the comparison is still necessary. To simplify the simulation, we use the case 1 in Subsection A to represent the use of extended coverage time and use the coverage time of 24 hours in the same model. The comparison results of deferrable load consumption, fixed battery storage SOC, and hourly cost are shown in Figure 28.

5.3.4 Stage I Prices vs. Stage II Prices

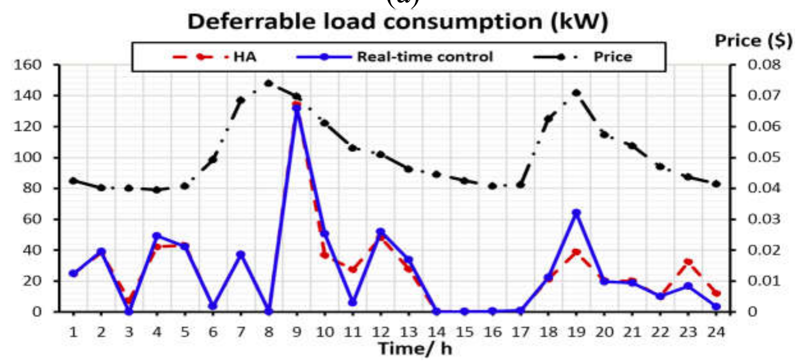
This comparison demonstrates whether using the updated prices from Stage II will cause any negative impact on the cost. In the proposed algorithm, PEV charging prices and discharging participation bonus vary with time and are based on the load profile. The load consumption will change after the day-ahead predictions give new building consumption schedules and PEV charging/ discharging schedules. In order to provide more incentives to PEV customers, the discharge bonus is maximized. Larger bonus value will lead to higher cost for the IEVCS, so a maximum cost limit C is guaranteed as a constraint. Undoubtedly, if the updated bonus value in Stage II is much higher than original value in Stage I, the cost will be increased accordingly when discharging is needed. As a tradeoff, it will lower the priority of discharging PEVs with mobile battery storage when extra supply is needed. The comparison results of the hourly cost from case 1 to case 4 are shown in Figure 29.

5.3.5 Computational Efficiency Analysis

Computational efficiency is a requirement for simulations. As discussed in Chapter 5.2.2, the optimization model is solved as DC system in this research to save computational time. The computational time for hour-ahead optimization in Stage III is about 16.931227 seconds on a computer with quad core processor (1.6 GHz Intel i5) and 8 GB RAM. It takes another 0.013601 seconds to run the simulation to obtain the estimated real time data from the most recent real-time control for hour-ahead optimization. In the use case study, the hour-ahead optimization is implemented 15 minutes before each hour. But the computational time allows the gap to be as short as 30 seconds before each hour, to leave some redundancy. For the real time control, each simulation takes about 0.034030 seconds on a computer with dual core processor (2 GHz Intel i5) and 8 GB RAM, including extracting real time data as input. The value may change for each simulation, but the difference remains within 0.02 seconds. Compared with the algorithm in [59] with a computational complexity of $O(T^3)$ and computational time of the range 1-10 seconds, the proposed control algorithm is quite fast. In this use case study, the real-time control is implemented every 15 minutes, but it can be easily adjusted to shorter intervals. The computational time allows the real time control to be implemented for each second. Note that the computational time is based on the operational speed of individual computers. In conclusion, the control algorithm is pretty computationally efficient.



(a)



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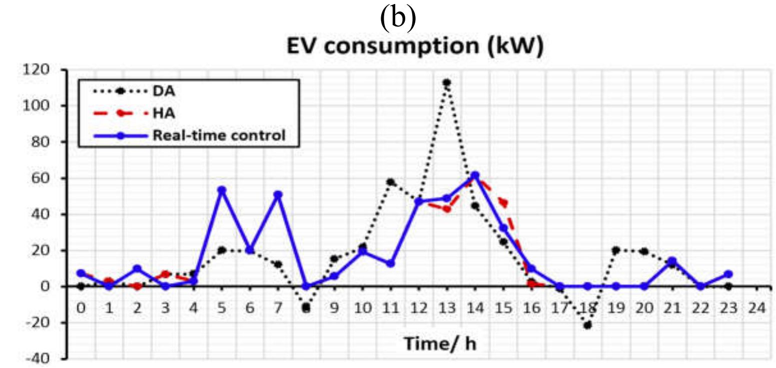

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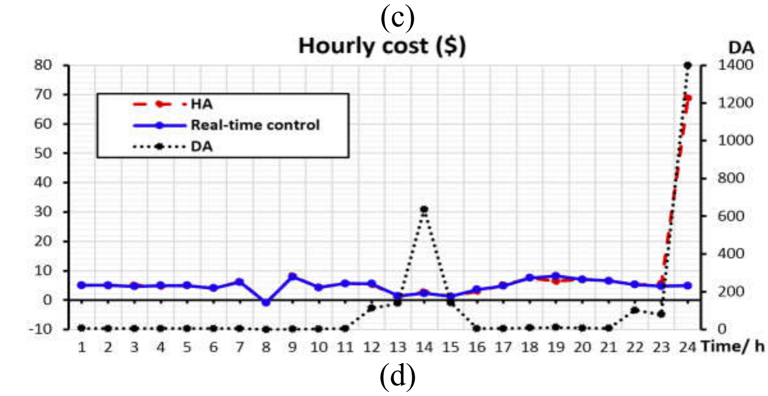
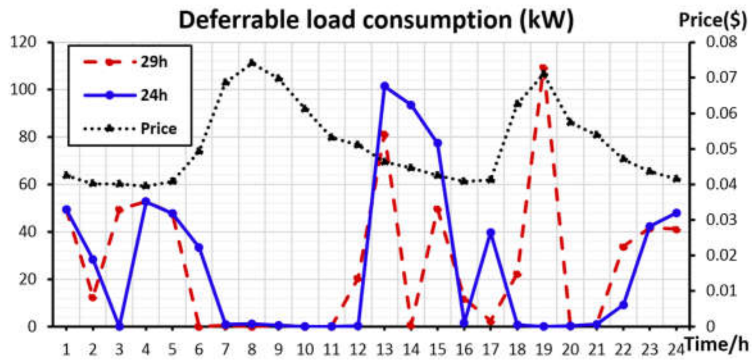
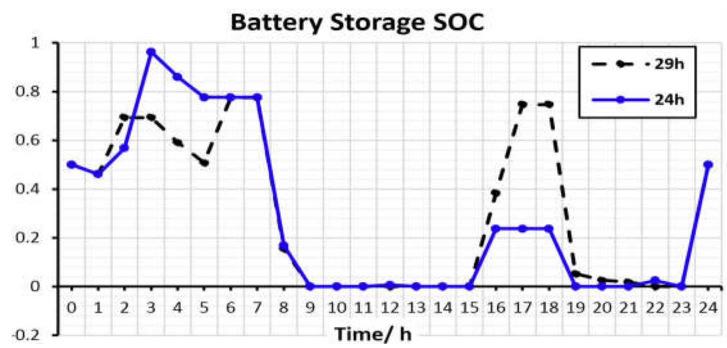


(d)

Figure 27: DA vs. HA vs. real-time (a) Battery storage SOC comparison (b) Deferrable load consumption comparison (c) PEV consumption comparison (d) Hourly cost comparison



(a)



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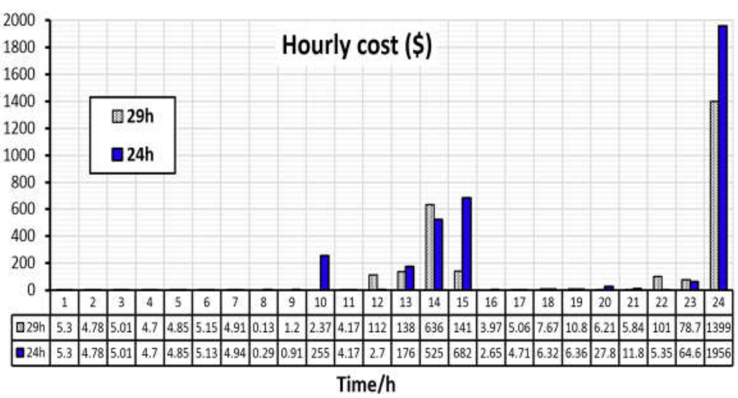

(c)

Figure 28: 29h vs. 24h (a) Deferrable load consumption comparison (b) Battery storage SOC comparison (c) Hourly cost comparison

The results of the proposed four-stage algorithm are compared with the results of directly applying the proposed optimization model in real time which will make the solution more optimal. The comparison results indicate that the performance gap of the total cost is smaller than 0.4%, but the proposed four-stage algorithm saved a lot more

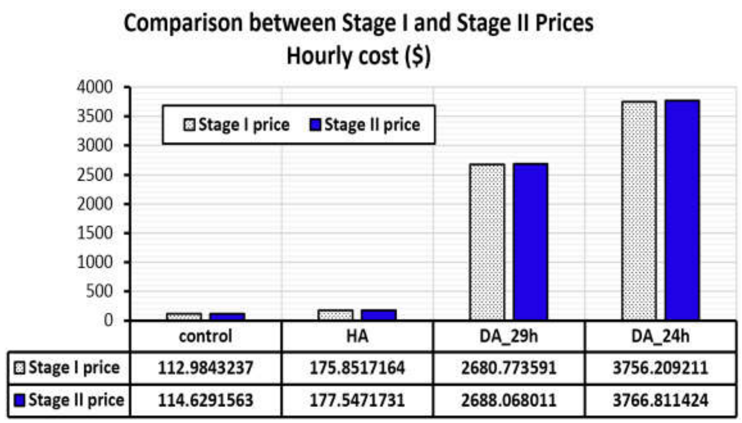

Figure 29: Hourly Cost Comparison between Stage I Price and Stage II Price

computational time in real time control.

5.4 Conclusion

In this chapter, a four-stage optimization and control algorithm is proposed for the purpose of reducing the operational cost and maximally guarantee the power supply of the smart IEVCS. The components of the IEVCS are effectively integrated as a unit in the market. This chapter fits the “Optimization & Control Algorithm” term under the “Single IEVCS” branch, as shown in Figure 1, and validates the second scenario under the hypothesis discussion.

The proposed algorithm spans three time-scales, has an additional Stage II to deal with PEV charging/ discharging prices to attract customers to participate, and offers a novel control scheme design to improve the operational performance. The following are some major findings:

- By using the extended coverage hours, no temporary parameter needs to be assigned, and also the integrated station is more prepared for unpredictable condition.

- It is beneficial for both PEV customers and charging station owners to use updated PEV charging price and discharging program participation bonus in Stage II.
- Using the hour-ahead forecast data to optimize the schedules will not only provide more accurate data, but also dramatically decrease the overall cost.
- The proposed control scheme provides higher tolerability for unpredictable circumstances.

This algorithm can easily be applied to IEVCS connected to any other types of building by replacing the predicted load profile, consumption percentage of each load type and predicted PEV consumption (probability distribution of arriving time) as needed.

VI. WEATHER-RELATED RISK ASSESSMENT*

6.1 Introduction

Heavy rain, strong wind, unusual heat, thunderstorm, hail, ice buildup, tornados, etc. can lead to power outages. When a tree limb touches a power line due to the bad weather condition, protective equipment may initiate a breaker operation to disconnect the feeder and shut off the power flow to the customer. As a result, customers served by the interrupted feeder will be out of power until service is restored. The falling of power lines/poles can also directly lead to power outage. The same consequence results from the vehicle crashes involving utility poles or equipment, which may be caused by dense fog leading to low visibility. According to the historical outage data (2012-2014), about 33.33% of the historical outages are caused by weather [16]. Electricity supply outage can result in substantial damage to customers because of spoiled perishable materials, production loss, broken equipment, health impact, income loss, extra mitigation expenses, etc. [23]

The focus of the dissertation on risk assessment particularly concerns the improvement of the worth of loss. CIC is closely related to the degree of customers' dependence on electricity supply [23], thus it was formulated to be a function of outage parameters and customer features. To estimate the customer loss from a weather-related power failure, the CIC formulation needs to be improved to consider the financial loss and health effect caused by the weather elements, in addition to the previous economic

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value for EENS. Important customer categories such as health care centers, schools, fire stations are particularly of concern. We look at a variety of weather factors and evaluate the probability of blackouts and the corresponding customer financial and health impact under the forecasted weather conditions. We then develop the risk assessment of the weather-related outage impact on different customer categories, making the assessment of customer cost more accurate and comprehensive. Such risk assessment can benefit distribution system operators and utility customers by allowing them to be prepared for the impending risk, which is the Use case #3 of the hypothesis validation.

6.2 Weather Impacts*

6.2.1 Weather Data

Four types of weather data are of interest in this dissertation: i) historical measured weather data used for training of the prediction model, ii) historical weather forecast data (past) used for testing of the prediction model, iii) weather forecast data (future) and iv) current real-time measurement used in the trained prediction model for real time decision-making.

Historical weather data can be extracted from land-based station data, radar or satellite data, [114]. In this research the land-based station data has been used. In case of land-based stations the interpolation techniques need to be applied in order to provide wide-area weather conditions that can be mapped using GIS software such as ESRI ArcGIS, [115].

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Based on collected historical weather data and real-time measurements, weather forecast algorithms are developed. There are several services that provide weather forecast data such as National Digital Forecast Database (NDFD) [116] that provides short-term (next 3-7 days) and long-term (next year and a half) weather prediction for variety of weather parameters. NDFD uses Numerical Weather Prediction (NWP), which is taking current weather observations and processing it using different numerical models for prediction of future state of weather. These services make weather predictions using one of numerical models such as Global Ensemble Forecast System (GEFS), Global Forecast System (GFS), North American Mesoscale (NAM), etc. [117].

Weather parameters that are of great importance for analyzing power system outages are: temperature, precipitation, humidity, wind characteristics, storm, hail, ice storms, and severe wind probabilities, lightning characteristics and frequency maps, etc.

Geographical Information System (GIS) software is designed to enable storage, manipulation, analysis and visualization of all types of spatial data. Together with Global Positioning System (GPS) it enables spatio-temporal analysis of extensive data sets that play the key role in integrating big data for various electric power system applications, [118]. In this research, weather data, and customer related data are ingested, cleansed, curated and visualized in the GIS software. Spatio-temporal databases offer the possibility of simulation or prediction of strategic events. GIS database contains two types of data: 1) *Spatial data* containing location and the shape of components on the map; 2) *Attribute data* containing features of objects on the map. There are two basic structures for storing and manipulating spatial data: 1) *Raster data* (grid data) is a grid of cells where each cell has a unique value of targeted information; 2) *Vector data* uses geometry rules to represent shapes using points, lines and polygons.

The key components of modern GIS software, such as ESRI ArcGIS [115] that enable spatial integration of data are:

- Data coming from various sources can be presented in several map layers.
- Spatial relationships such as topology and networks. Topology is used to manage boundaries between features, while networks describe connectivity between spatial objects.
- Extensive set of geoprocessing tools helps user to manipulate and combine different layers.
- Extension Manager allows user to develop and distribute additional processing tools and models.

6.2.2 Weather Impact on Outages

Severe weather includes any meteorological phenomena that have potential to cause faults but not devastated destruction. Some of the conditions typically considered severe are: high winds, hail, ice storms, excessive precipitation, thunderstorms, downbursts, lightning, tornadoes, waterspouts, tropical cyclones, etc. Catastrophic weather is a type of severe weather where events have exceeded the predicted amount of severity and caused tremendous damage to the area. In this research seasonal severe weather (not the catastrophic type) is considered.

Weather impact on outages in power systems can be classified into two groups:

- *Direct impact to utility assets*: This type of impact includes all the situations where severe weather conditions directly caused the component to fail. Examples are: lightning strikes to the utility assets, wind impact making trees or tree branches come in contact with lines, etc. In this case the outage occurs during the time of impact. When post fault analysis is performed these types of outages are marked as weather caused outages.
- *Indirect impact to utility assets*: This type of impact accrues when weather didn't directly cause the outage but instead created the situation in the network that indirectly caused the component to deteriorate over period of time and eventually to fail. Examples are: hot weather conditions increasing the demand thus causing the overload of the lines resulting in the feeder sags that can cause faults, exposure of assets to long term weather impacts causing component deterioration, etc. In this case the outage can occur after the time of impact. In post-fault analysis this type of outages is marked as equipment failure.

Since the risk assessment of the outages occurring during the time of weather impact are considered in this dissertation, the focus is on the direct impact of weather to utility assets. Thus, when analyzing outage data only group of data marked as weather causing immediate outages has been used.

6.2.3 Weather Impact on Customers Under Outage

In terms of the duration and cause of the failure, power interruptions can be classified into three types: momentary, sporadic and chronic interruptions [119].

Momentary interruptions are due to switching actions, while sporadic interruptions are mainly caused by severe weather condition which tends to last longer, affect larger number of customers, cause longer restoration time due to the affected transportation or unavailable resources and finally lead to high financial impacts. The chronic interruptions occur more regularly and are generally caused by forced load shedding.

Power supply interruption can bring extensive cost to customers in the way of spoiling the perishable materials/food, damaging equipment, causing production loss, income loss, health impact, and extra mitigation expenses [23]. Severe weather conditions can aggravate the power supply interruption impact by the change of temperature (either heat wave or cold front), unusual humidity, heavy precipitation, high wind, poor visibility, etc. For indoor customers, temperature and humidity will be the main factors. Once the ambient condition is out of human's comfort range, it may lead to extensive health issues, especially for people with injury or illness. For the patients who are extremely dependent on the health appliances such as medication infusions, dialysis, or respirators which require electric power to operate, the outage may cause very serious health problems and it can be deadly even with only a few hours of outage in many cases. Appliances as simple as heaters or fans can also cause health issues when they are not working under extreme temperatures. Strokes can be triggered in a freezing house in winter without heater or a sweltering house at peak summer without any air condition. The same applies to others requiring certain condition to survive, such as tropical plants or pets. Besides the personal health, safety issues may also arise by the increased robbery rate due to the non-operating street lights and security system. [120]

The extent of the weather impact on different customer categories varies. Residential customers may not be affected by wind or rain if they stay inside, while the thunderstorm may ruin the uncovered crops or damage the outdoor equipment for some industries. Commercial stores may lose business due to the interrupted transportation caused by poor weather. The same impact also affects the goods transport for industries and patient transfer for health centers, etc. Property loss and business interruptions are usually considered when estimating the customer impact, because such losses are obvious and easy to be quantified.

Evaluating the health impact on the customers would be helpful in designing a methodology for calculating and estimating the possible customer financial and health loss under outage caused by unusual weather factors and quantify it as an impending event risk value [121]. This research considers weather impact on different customer categories in different time intervals, incorporates the weather factors into the models in evaluating the customer cost, and implements a risk assessment of customer impact caused by the weather-caused power outage. The results can be used by the utilities as a reference of how serious the customer may have to suffer from the upcoming event and whether certain mitigation measures are necessary to avoid the loss.

6.3 Risk Assessment Formulation

Risk is an estimate of the probability of a hazard-related incident or exposure occurring and the severity of harm or damage that could result [122]. Risk assessment is an analytical tool to assess the probability of adverse impact, while risk management is a systematic process to accept a risk and/or implement actions to mitigate the probability of occurrence or harmful consequences to an acceptable level [123].

Customer data has been integrated with weather and GIS data in order to develop framework for prediction of impact of different weather conditions on customers. Prediction model has been trained using historical outage data that are spatially and temporally correlated with weather parameters measured at the time of outage. Then, real-time weather forecast data has been used to predict risk to customers in case of an anticipated weather conditions.

Overview of the proposed method is presented in Figure 30. First, the above-mentioned data are collected and ingested by the GIS software. Then such data is correlated and utilized to estimate: a) the probability of outage caused by the unfolding weather condition, b) customer interruption cost indices for each customer area (can be feeder area or hazard area), and c) the corresponding customer risk indices. Last but not least, the risk results are visualized to show the possible impact of the forecasted weather conditions on the customers in GIS map.

6.3.1 Risk Analysis

According to standards, risk involves three principle variables: hazard (threat), vulnerability (likelihood), and consequence (financial impact) [122, 124]. The risk assessment framework used in this research presented in Figure 31 is formulated as follows, [125]

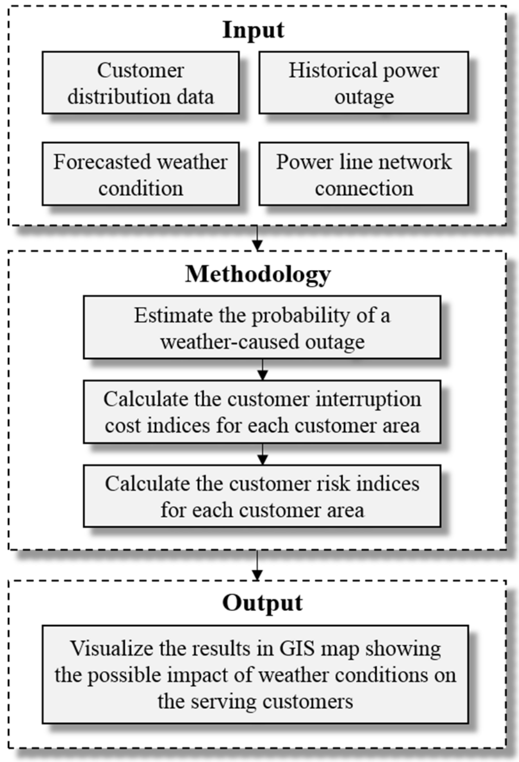


Figure 30: Customer Impact Evaluation Framework

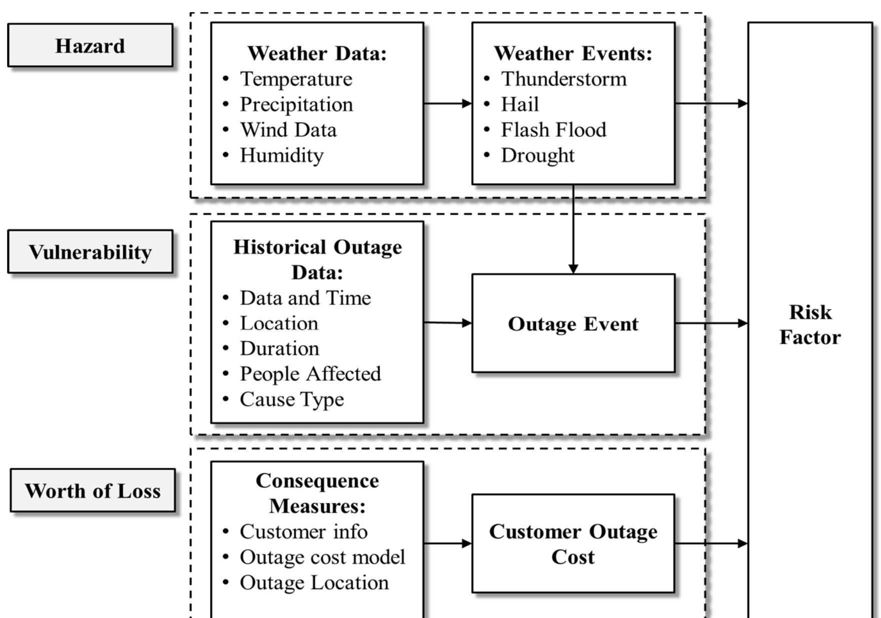


Figure 31: Risk Analysis for Customer Impact

$$R = P[T] \cdot P[C|T] \cdot u(C) \quad (38)$$

Where *R* is the *State of Risk* of the customer impact from the upcoming weather conditions, *Hazard P [T]* is the probability of a *Threat* intensity *T* (i.e. a certain weather condition that may cause power outage), *Vulnerability P [C|T]* is the probability of power supply failure in that area (estimated according to the correlation of historical outage data and historical weather data), and *Worth of Loss u(C)* is an estimate of customer interruption losses in case of the power supply failure.

Following the outline in Figure 31, *Hazard* map is developed solely based on historical weather data. Probabilities for a specific severe weather condition are estimated based on historical frequency of occurrence of such events in an area, so this factor describes how likely certain weather conditions will occur in the area. The following weather parameters are observed: temperature, humidity, precipitation, and wind speed. The weather conditions have been classified in several groups based on values of the listed parameters. Then hazard probability has been assigned to each of these groups based on weather forecast data.

The main data that drives building of *Vulnerability* map is historical outage data. Vulnerability analysis uses historical outage and weather data to summarize the relation between weather condition and outage probability and predict the conditional probability of a blackout in case of predicted weather. Based on this information the probability that specific weather condition will cause the fault and loss of power to the customer is estimated.

Worth of loss considers customer information, i.e. how many customers are disconnected and what is the expected duration of outage, what is the type of customer in the area (residential, commercial, industrial), are there any loads of special interest (hospitals, schools etc.).

6.3.2 Weather Driven Customer Impact Analysis

In this research, the historical weather data together with customer indices have been used to develop a predictive model that estimates what is the risk for customers in case of a predicted weather conditions provided by national forecast services.

From the perspective of customers, the CIC is correlated with the degree of the customers' dependence on the electricity [23]. It is stated to be a function of customer characteristics and interruption features. If weather condition is taken into consideration, then the formulation needs to be improved. Thus, in order to evaluate the customer loss in terms of weather-caused power failure, besides the previous model of estimating the economic cost during an outage, the total cost also needs to include the additional financial impact that the bad weather condition may bring to increase the original cost and the health impact the weather condition may cause for the customers without electricity supply. The total costs are formulated comprising of three monetary terms, as follows:

$$Loss^{i,HA} = CDF^{i,HA}(dr, s, d, wk, cf) + EL^{i,HA}(EF, cf, dr) + HL^{i,HA}(EF, cf) \tag{39}$$

where the estimated *Loss* at target time *i* for each hazard area *HA* includes three monetary terms: existing *CDF*, additional economic loss *EL* caused by unusual environmental features *EF*, and health loss *HL* under outage. *EF* includes all the weather elements that may influence the customer cost, including temperature *tp*, humidity *hu*, storm type *st*, wind speed *ws*, precipitation *pr*, and others *ot*. Once *t* is targeted, season *s*, time of a day *d*, day of a week *wk* are given. *HA* is determined by the forecasted weather. The interruption duration *dr* can be statistically estimated based on the historical blackout event data and the forecasted weather condition. Customer features *cf* comprise customer type, number of people, time schedule at *i*, presence of interruption-sensitive equipment and back-up equipment or generators, etc. [126-127].

Specifically, the three terms in (39) are defined respectively:

$$CDF^{i,HA} = \sum_{\substack{lp=1 \\ lp\epsilon HA}}^{L} CL^{lp}(dr, s, d, wk, cf) \cdot EENS_i^{lp} \tag{40}$$

$$or \qquad CDF^{i,HA} = \sum_{\substack{lp=1 \\ lp\epsilon HA}}^{L} CE_{dr,s,d,wk,cf}^{lp} \tag{41}$$

At load point *lp*, *CL* represents the interruption cost per kWh ($/kWh) while *CE* represents the interruption cost per event. *L* is the total customer number based on the size of each hazard area. *EENS* can be reliably predicted if based on smart meter measurement. According to the data availability and accuracy, either (40) or (41) can be chosen to estimate *CDF*.

$$EL^{i,HA} = \sum_{\substack{lp=1 \\ lp\epsilon HA}}^{L} \{ACL^{lp}(dr, s, d, wk, cf) \cdot AE_{EF,i}^{lp} + O_{EF,i}^{lp}\} \tag{42}$$

where ACL is the interruption cost for additional unsupplied energy AE for each lp and O represents other financial losses caused by weather, i.e. spoiled food/material, damaged equipment, production loss. These can be estimated based on the type and severity of the forecasted bad weather condition.

$$HL^{i,HA} = \sum_{\substack{lp=1 \\ lp \epsilon HA}}^{L} f_{cf}^{lp}(EF) \tag{43}$$

where f is the function to calculate the health cost for each lp in terms of the cf. The function can be expressed as follows.

$$f_{cf}^{lp} = cs^{lp} \cdot ec^{ct} \cdot \begin{bmatrix} \alpha^{ct} \cdot |tp - tp^{s}| + \beta^{ct} \cdot |hu - hu^{s}| + \gamma^{ct} \cdot g(st) + \\ \delta^{ct} \cdot |ws - ws^{s}| + \varepsilon^{ct} \cdot |pr - pr^{s}| + \theta^{ct} \cdot k(ot) \end{bmatrix} \tag{44}$$

where $\alpha^{ct}, \beta^{ct}, \gamma^{ct}, \delta^{ct}, \varepsilon^{ct}, \theta^{ct}$ are the weight coefficients to express the impact of each weather element on the customer type ct. cs is the customer size at lp, and ec is the equivalent economic cost of health impact based on the medical cost standard. The value with a superscript s indicates the threshold of the parameter's normal range there. Since storm type is not a quantitative value, functions g and k are used to present the corresponding impact. All the coefficients can be set by utilities in their geographic and climate circumstances.

6.4 Use Case Study

6.4.1 Spatio-temporal Data Integration

In Figure 32 processing steps for risk analysis are shown. The following data layers have been used as input data: electric network GIS data, weather data, customer type data, population count, and historical outage data.

As part of preprocessing in Figure 32, all historical and static data are analyzed in order to provide training datasets for the prediction model. Here historical outage data is used to select time instances of interest. Then weather parameters are selected for those times. Static maps such as population count, customer distribution and points of interest are used to calculate what the associated losses for observed outages are. It is to be understood that this data is changing over time, but since the change and data availability comes once in every few years, it is considered static in this study, compared to weather data which may change every few minutes to every few hours.

As part of the real-time analysis in Figure 32, weather forecast data obtained from NDFD is downloaded every three hours. This data is then overlaid with network data and static customer data. The risk model uses training data and weather forecast data to evaluate the risk for customers in case of weather conditions predicted by weather forecast.

In order to implement the risk assessment methodology, two cases are studies: one is in Fort Pierce network in Florida with feeder information available, while the other one is in Harris County network in Texas with hazard areas created based on forecasted weather conditions.

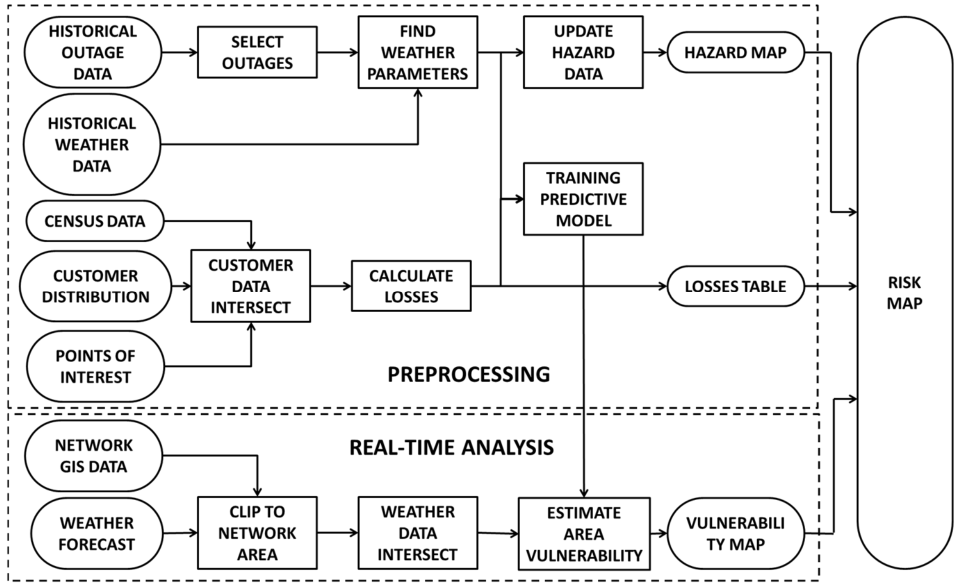


Figure 32: Spatial Integration – Processing Steps

6.4.2 Use Case Study 1: Florida Network

Two kinds of weather data are used in this use case study:

- Historical weather data coming from weather stations:
    - Ft. Pierce Arc (temperature, precipitation, wind)
    - St. Lucie County International Airport (temperature, precipitation, wind)
    - Fort Pierce 2.8 SSE (precipitation)
    - Ft. Pierce (temperature, precipitation)

  Historical data for the period of 5 recent years were obtained starting from January 1st 2010 until December 31st 2014.
- Weather forecast data coming from National Digital Forecast Database (NDFD). Data for temperature, humidity, precipitation and wind for the next

3 days is used for prediction model. Data is updated every 3 hours. Data resolution is 3 hours.

In this use case study, the Florida network is selected to demonstrate the results since the information about distribution lines is available [128]. Then, the customer distribution data needs to be collected. Such data are customer population distribution, customer type, facility locations, etc. Next, the network is split into small polygons as customer service areas per distribution feeder. Then all the customer data layers are clipped to each area and the customer info summarized based on the clipped data layers (customer population, customer types and corresponding numbers for each type, and disable people numbers). The customer info in each area is imported to the models of customer cost, and the corresponding risk index for each area is calculated based on the risk assessment theory. The last step is to demonstrate the risk indices in the GIS map and use different colors to indicate the severity of the customer cost impact.

1) Studied Network:

The distribution network data used is part of the Storm Vulnerability Assessment tutorial from Esri [128]. Data layer for distribution network primary overhead feeders was extracted. The layer is presented in Figure 33. The network consists of 20 feeders containing single, double and three phase primary overhead lines. The network is located in Fort Pierce, Florida.

In Figure 34 population count for different areas of the network is presented. Each area represents part of the distribution network connected to one feeder. In Figure 35 locations of customer types of interest are presented. Different points of interest

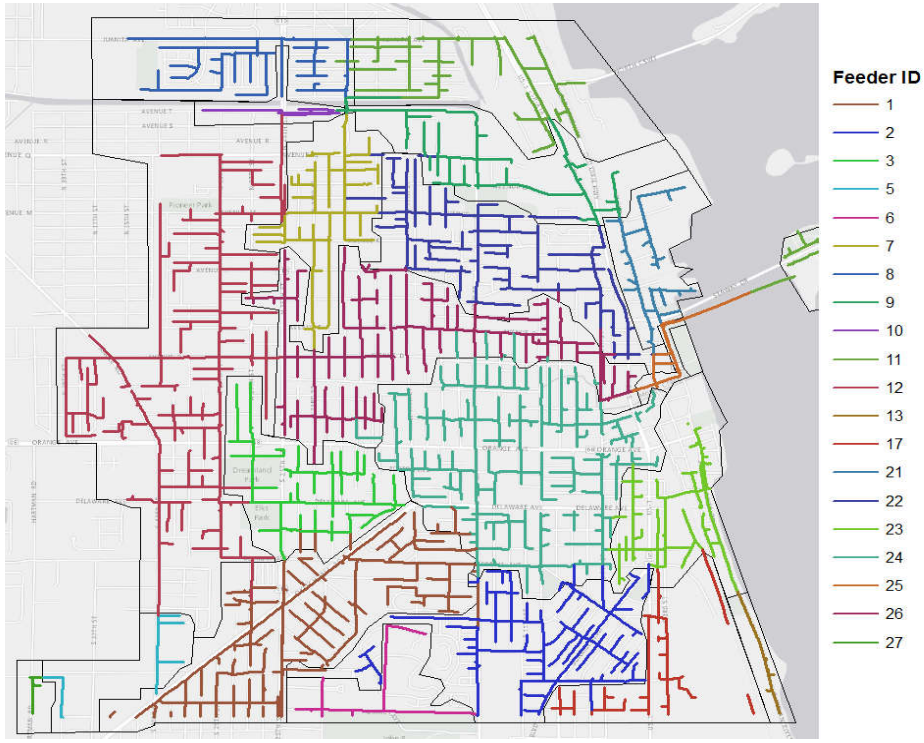


Figure 33: Distribution Network in Fort Pierce

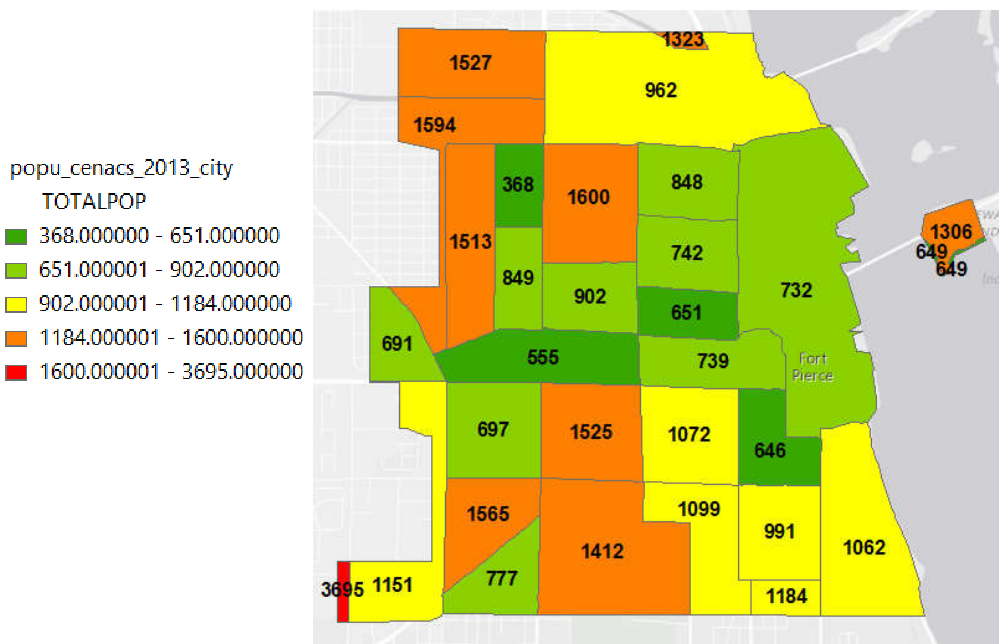


Figure 34: Population Map in Fort Pierce

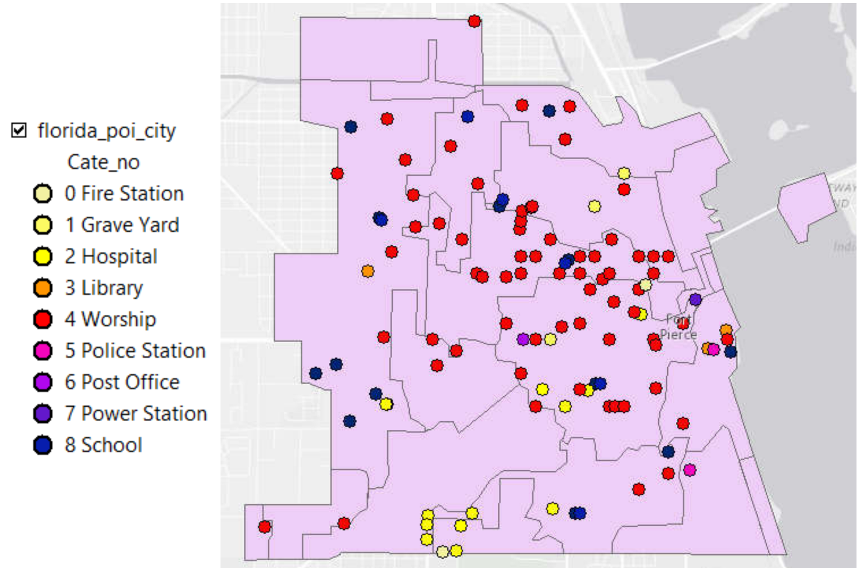


Figure 35: Points of Interest Map in Fort Pierce

will affect risk factor differently, for example area with hospital will have higher risk factor compared to the area without a hospital that is experiencing same weather conditions.

2) Test Scenarios:

Historical outage data is obtained for three years, starting from Jan.1st of 2012 and ending with Dec. 31st of 2014. Historical weather data is prepared to correlate with each historical outage event. The customer population data obtained from national census report and the location of facilities, which also indicate the customer categories are demonstrated in map as Figure 34 and Figure 35. An example of a normal weather scenario and an upcoming bad weather scenario is assumed based on the historical weather conditions in Fort Pierce area. For each weather condition, the risk indices of all the feeder areas are calculated accordingly and shown in the map with successive colors indicating the severity of risk.

3) Study Results:

For each feeder area, risk value was calculated, assigned, and presented on a map as shown in Figure 36, with a) showing the results under normal weather scenario and b) showing the results under expected bad weather scenario. The values of risk indices are presented as a percentage, where 100% is assigned to the feeder area with highest risk for the severe weather scenario. It can also be defined according to utility's standard of risk acceptance. The severity of the customer impact risk increases from the areas with green color to the areas with red color. After viewing the result map, utilities can judge whether to send pre-warning notifications to their serving customers or to take some actions to avoid such customer loss. Compared with a sudden unexpected power outage, a pre-notified power outage may significantly decrease the customer loss.

6.4.3 Use Case Study 2: Harris County Network

1) Test Scenarios:

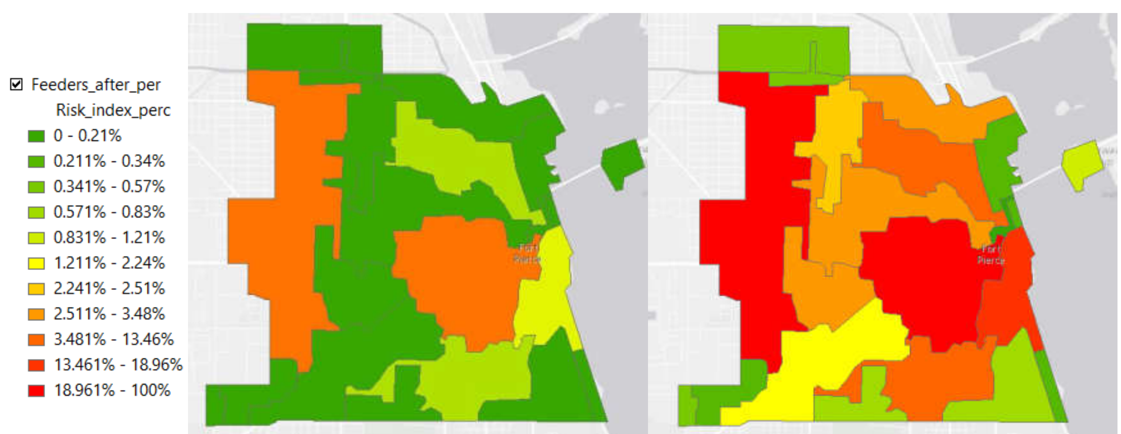


Figure 36: Predicted Risk for Two Weather Scenarios: a) normal weather conditions; b) expected severe weather conditions

The use case study is implemented in Harris county using part of the network that is operated by CenterPoint Energy [129]. The historical blackout data has been collected from [16] (data from 2012/1/1 to 2014/12/31), correlated with historical weather conditions obtained from [114] and geo-located in the GIS map. The customer information such as population distribution [126] customer category, facility locations [127], is gathered and visualized in the same map. The forecasted weather data from NDFD [116] has been used. For comparison purpose, two case studies are implemented, one with normal weather scenario (scenario 1) and one with severe weather scenario (scenario 2). The network is split into small polygon areas grouped with the same hazard value based on the forecasted weather distribution scenario. The customer data in each area is analyzed and imported to the customer cost model, together with the historical outage data and forecasted weather data. Figure 37 shows the hazard distribution map in scenario 2 with the points indicating the historical outage locations (indicating vulnerable locations in the area). Partial historical outage data is stated in Table 4. In Figure 38, the population distribution is presented as colors and health care-critical locations are shown as points. They are both under scenario 2. Based on the risk assessment theory, the corresponding risk index values are calculated and presented in the GIS map.

2) Study Results:

The severity of the risk is indicated by using successive colors from green to red in Figure 39 where a) shows the results under scenario 1 and b) under scenario 2. Percentages are used to present the value of risk indices, where the maximum value in

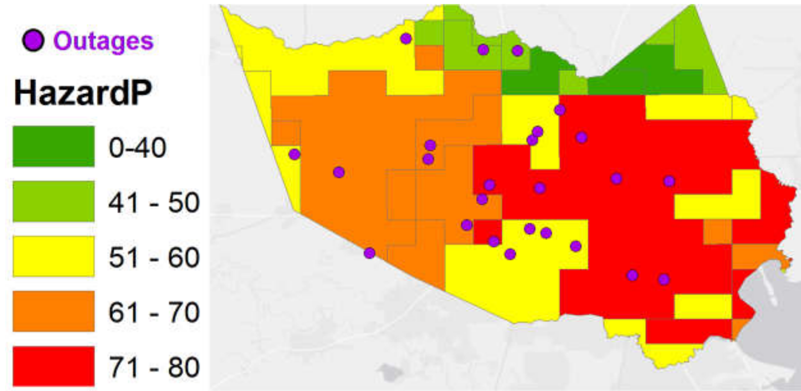


Figure 37: The Hazard Distribution Map in Harris County

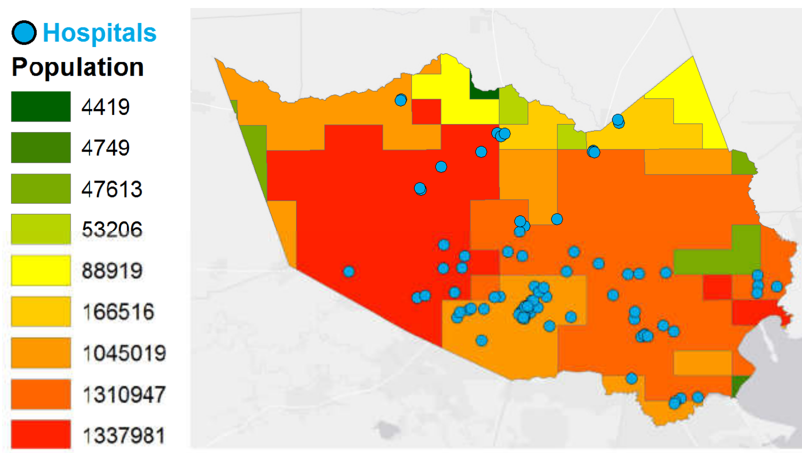
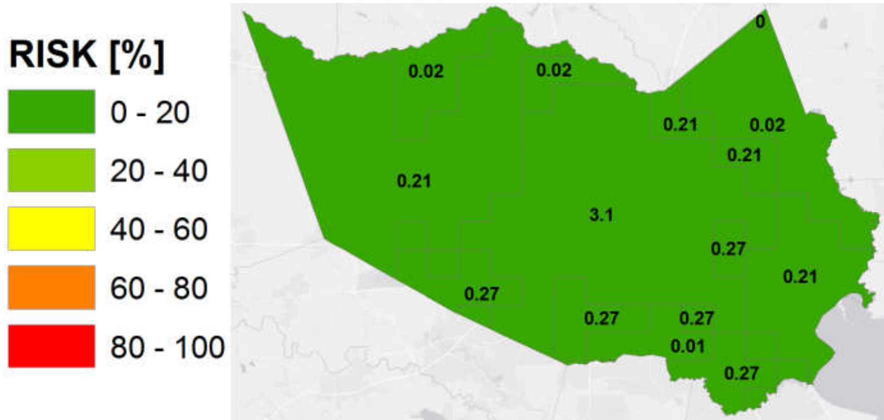


Figure 38: Population Distribution Map in Harris County

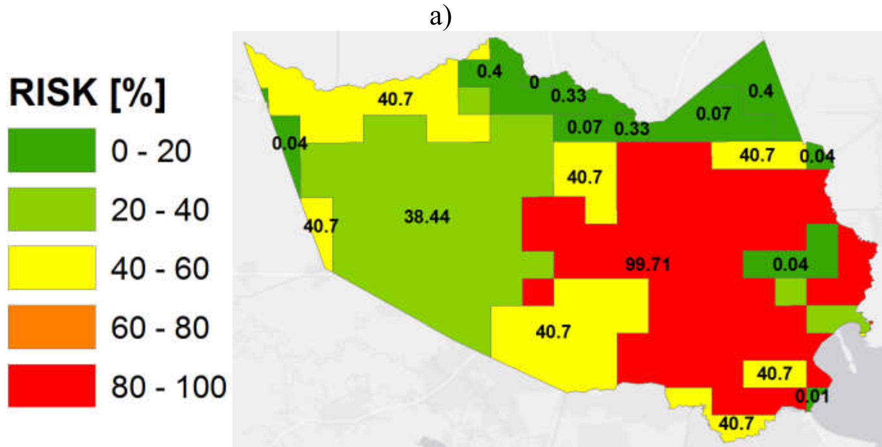
Table 4: Partial Historical Outage Events in One Area

Date	*Begin Time*	*Duration*	*Affected people*	*Event*
1/9/2012	10:07	70 min	19716	Flash Flood
8/16/2013	16:57	110 min	103000	Thunderstorm Wind
8/1/2014	4:00	55 min	26000	Flash Flood

scenario 2 is regarded as the denominator. The utilities can define the denominator based on their standard of risk acceptance. According to the resulting map, utilities can make decisions on whether it is necessary to send pre-warning notifications to their customers



a)



b)

Figure 39: Risk Maps for: a) normal weather conditions, b) severe weather conditions

or if just mitigation actions can be taken to avoid such potential customer loss. In most cases, the customer impact can be tremendously decreased if a possible power outage is pre-notified, instead of a sudden unexpected power interruption.

6.5 Conclusion

This chapter described a risk assessment methodology that estimates the impact of weather parameters on hazard, weather-caused outage vulnerability and weather-related customer losses, which fits the “Weather-Impact Risk Assessment” term under “Multiple IEVCS” branch, as shown in Figure 1. Chapter VII will use this risk assessment methodology to establish the optimal scheduling algorithm in order to alleviate the negative weather impact. In order to validate hypothesis #3, in this study,

- The probability of outage in each location is determined based on the real historical outage events and prevailing weather condition, which allows formulation of customer risk indices based on weather-caused outages, as described in Chapter 6.3.1.
- Weather factors are considered in the evaluation of Customer Interruption Cost for different customer categories, as described in detail in Chapter 6.2.3 and it is shown that the impact of different weather factors varies mainly based on customer categories in both case studies.
- The obtained risk map can provide the areas where the risk of customer impact under the impending weather condition is comparably higher than other areas. Thus, distribution system operators can benefit from the customer risk assessment results by being aware of the impending risk allowing them to take preventive countermeasures to avoid potential customer losses.
- The obtained risk map can provide customers whether their place has high risk of losing power supply under the impending weather condition. Thus, utility customers can benefit from the outage risk assessment results by being pre-warned of the potential blackout and being provided the time to make preparedness plans to mitigate potential loss.

VII. UTILITY APPLICATIONS*

7.1 Framework

After establishing the weather-related risk assessment in Chapter VI, the integration of PEV mobile battery storage and stationary energy storage (BESS) with PV generation, how such system supports the supply of electricity to the customers under the inclement weather impacts, and how the risk map will be changed after the participation of the integrated system are studied in this chapter. The Use case to validate the last hypothesis scenario that the IEVCS can contribute as preventive countermeasures to help mitigate the weather impact and support several utility applications is studied.

To predict weather impacts, first a risk assessment methodology and associated indices need to be determined. Customer Interruption Cost (CIC) index can be used as the cost consequence [23, 76, 130]. In this chapter, the CIC index formula is improved based on the algorithm described in Chapter VI and risk assessment is implemented for both potential power outage and demand fluctuation caused by weather change. Based on the risk assessment result, the energy dispatch of PEVs, BESS and PV generation in different locations is optimized to support DSM and OM respectively.

The framework of the proposed algorithm is shown in Figure 40. The proposed method is in accordance with the sequence of "predictive – preventive – corrective" actions. The PV generation, PEV (mobile) and local (stationary) BESS are integrated to

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support the grid. First, for predictive purpose, utility operators conduct the risk assessment and create risk map, which provides predictive results of the evaluation of potential weather impact. Based on the prediction results, the preventive stage will decide the optimal participation of PEV/local BESS and the output of PV generation. Demand response providers participate in the day-ahead reserve market with the aggregated resources from customers, which preventively reserves some capacity in face of the predicted weather impact. Then, DSM and OM, are conducted by utility operators as the predicted weather impact unfolds in real time, with the consideration of PV generation and PEV owners' participation in utilizing their generation resources and discharging their PEV batteries respectively. The benefit of the grid integration of PEVs with mobile battery storage, PVs and fixed BESS and their participation in DSM and OM to correctively mitigate the weather-caused risk for customers are studied. Last, the risk assessment is conducted again considering the participation of the PEV/local BESS and PV generation to predictively evaluate the impact of the corrective action.

7.2 Methodology

- Risk Assessment

The framework of risk assessment estimating the weather impact on electricity customers is described in detail in Chapter VI. The risk index is presented as the product of three elements: *hazard*, *vulnerability* and *worth of loss*. (38) can be extended as,

$$Risk = Hazard \times Vulnerability \times Worth\ of\ Loss \tag{45}$$

$$= pr_{w_0} \times pr_{CL/w_0} \times Loss_{w_0} + \sum_{w_i \in W_i} pr_{w_i} \times pr_{CL/w_i} \times Loss_{w_i}$$

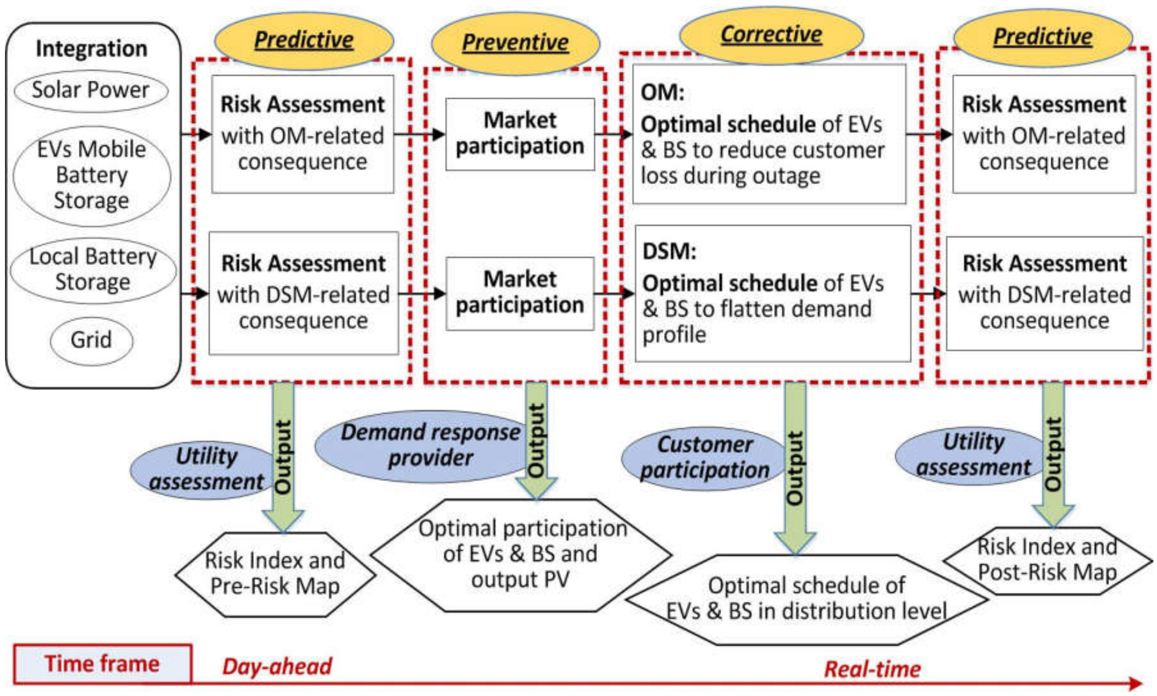

Figure 40: Framework of the Proposed Optimization Algorithm

Where w_0 refers to deterministic scenario and w_i refers to probabilistic scenarios. *Hazard* is mainly based on the accuracy of weather forecast, and *vulnerability* is determined by historical weather-caused outage data. The modeling of worth of loss, which is the estimation of customer interruption losses in case of the weather-caused power outage (OM is needed to recover the power outage as soon as possible) or the customer losses in case of the weather-caused power demand change (DSM is needed to optimally balance the demand change) are investigated. When estimating the customer losses, the targeted distribution network where the customers are located, and the basic information about the customers, e.g. population, customer type (residential, industrial, commercial, medical), expected power consumption, etc., are taken into consideration and analyzed.

Based on (39)-(44), the customer interruption losses used in the risk assessment for potential outage are formulated as follows,

$$Loss_{i,w}^{FA=k} = \sum_{\substack{ct(x)=1 \\ x\in FA}}^{CT(k)} \begin{bmatrix} CDF_{i,w,OM}^{FA=k}\left(q\big(ct(x)\big)\right) + EL_{i,w,OM}^{FA=k}\left(q\big(ct(x)\big)\right) \\ +HL_{i,w,OM}^{FA=k}\left(q\big(ct(x)\big)\right) \end{bmatrix} \tag{46}$$

$$CDF_{i,w,OM}^{FA=k} = \sum_{\substack{lp=1 \\ lp\in FA}}^{L} \left[CL_{w}^{lp}\left(dr,s,d,wk,cf,q\big(ct(x)\big)\right) \cdot EENS_{i}^{lp}\right] \tag{47}$$

$$EL_{i,w,OM}^{FA=k} = \sum_{\substack{lp=1 \\ lp\epsilon FA}}^{L} \{ACL_{x}^{lp}\left(dr,s,d,wk,cf,q\big(ct(x)\big)\right) \cdot AE_{EF,i}^{lp} + O_{EF,i,w}^{lp}\} \tag{48}$$

$$HL_{i,w,OM}^{FA=k} = \sum_{\substack{lp=1 \\ lp\epsilon FA}}^{L} f_{cf,x}^{lp}\left(tp,hu,st,ws,pr,ot,q\big(ct(x)\big)\right) \tag{49}$$

The loss at time *i* for each feeder area (FA) consists of customer damage function (CDF) (including cost of expected energy not supplied (EENS)), function of additional loss (EL) caused by environment elements, and function of health loss (HL), for each customer *x.* A customer can be a residential household, hospital, industry site, community, school, etc. Assume customer type *ct(x)*=1 for medical facility, 2 for industry, 3 for school, 4 for commercial facility, 5 for residential household, etc. *CT* is the total number of customer types. *q(ct(x))* represents the percentage of interrupted energy not supplied for each customer type. The detailed explanation for the parameters is given in Chapter 6.3.

Instead of (46), (48) and (49), the customer losses used in the risk assessment for demand change are formulated with new notation as,

$$Loss_{i,w}^{FA=k} = \sum_{\substack{ct(x)=1 \\ x \in FA}}^{CT(k)} \begin{bmatrix} CI^{ct(x)} \cdot EENS_{i,w}^{x} + EL_{i,w,DSM}^{FA=k}\left(p\big(ct(x)\big)\right) \\ +HL_{i,w,DSM}^{FA}\left(p\big(ct(x)\big)\right) \end{bmatrix} \tag{50}$$

$$EL_{i,w,DSM}^{FA=k} = \sum_{\substack{lp=1 \\ lp \epsilon FA}}^{L} \{ACL_{x}^{lp}\left(dr, s, d, w, cf, p\big(ct(x)\big)\right) \cdot AE_{EF,i}^{lp} + O_{EF,i,w}^{lp}\} \tag{51}$$

$$HL_{i,w,DSM}^{FA=k} = \sum_{\substack{lp=1 \\ lp \epsilon FA}}^{L} f_{cf,x}^{lp}\left(tp, hu, st, ws, pr, ot, p\big(ct(x)\big)\right) \tag{52}$$

where *CI* represents the cost index used to indicate the value of expected energy not supplied (*EENS*) for each customer type. *p(ct(x))* represents the percentage of the demand change that are not supplied for each customer type.

- Market Participation

The wholesale market operators use ancillary services to better handle the imbalance of supply and demand, which might be caused by the weather. The demand response providers can participate in the ancillary service and offer bids with the aggregated capacities from customers in response to market dispatch schedules [131].

To preventively alleviate the potential negative weather impact, demand response providers can schedule the available capacity of energy storage and PV generation to participate in the day-ahead contingency reserve service (CRS) market based on the day-ahead prediction results from the risk assessment, so that certain amount of capacity can be reserved in advance to deal with the potential negative weather impact. In this research, the proposed bidding strategy considers not only the stochastic nature, but also the purpose of alleviating the weather impact based on the risk prediction results.

Deterministic scenario and all the probabilistic scenarios are considered. Different scenarios are generated according to the previous assessment on weather's impact, and pr_{w_i} is the probability of the occurrence of some negative weather impact, i.e. outage, peak load, etc.

$$\min \sum_{i\in T_1} pr_{w_0}\left[\begin{array}{c}\overbrace{r_{G,i}^{w_0}p_{G,i}}^{\text{cost of purchased power}}+\overbrace{\sigma_{EV,i}^{w_0}f_{EV,i}^{w_0}S_{EV,i}}^{\text{cost of PEV discharge}}-\overbrace{r_{EV,i}^{w_0}p_{EV,i}^{w_0}}^{\text{earn from PEV charge}}-\overbrace{r_{R,i}^{w_0}S_{EV,i}}^{\text{benefit from reserved power}}-\overbrace{\theta_{PV}p_{PV,i}^{g,w_0}}^{\text{benefit of PV power sold to grid}}\\ +\overbrace{\tau pr_{CL/w_0}\Delta Loss_{w_0}}^{\text{cost of customer impact}}+\overbrace{\lambda_1 f_{EV,i}^{w_0}S_{EV,i}}^{\text{penalty term for PEV discharge}}+\overbrace{\lambda_2\left|p_{BS,i}^{w_0}\right|}^{\text{penalty term for battery storage}}\end{array}\right] \tag{53}$$

$$+\sum_{i\in T_2}\sum_{w_i\in W_i} pr_{w_i}\left[\begin{array}{c}\overbrace{r_{G,i}^{w_i}p_{G,i}}^{\text{cost of purchased power}}+\overbrace{\sigma_{EV,i}^{w_i}f_{EV,i}^{w_i}S_{EV,i}}^{\text{cost of PEV discharge}}-\overbrace{r_{EV,i}^{w_i}p_{EV,i}^{w_i}}^{\text{earn from PEV charge}}-\overbrace{r_{R,i}^{w_i}S_{EV,i}}^{\text{benefit from reserved power}}-\\ \overbrace{\theta_{PV}p_{PV,i}^{g,w_i}}^{\text{benefit of PV power sold to grid}}+\overbrace{\tau pr_{CL/w_i}\Delta Loss_{w_i}}^{\text{cost of customer impact}}+\overbrace{\lambda_1 f_{EV,i}^{w_i}S_{EV,i}}^{\text{penalty term for PEV discharge}}+\overbrace{\lambda_2\left|p_{BS,i}^{w_i}\right|}^{\text{penalty term for battery storage}}\end{array}\right]$$

Where

$$\Delta Loss_w = Ld_i^w + p_{EV,i}^w + p_{BS,i}^w - p_{G,i} - P_{PV,i} + p_{PV,i}^{g,w} - f_{EV,i}^w S_{EV,i} \quad , i\in T_1\cup T_2, w\in\{w_0\}\cup W_i \tag{54}$$

$$\text{s.t. } Ld_i^w + p_{EV,i}^w + p_{BS,i}^w \geq p_{G,i} + P_{PV,i} - p_{PV,i}^{g,w} + f_{EV,i}^w S_{EV,i} \quad , i\in T_1\cup T_2, w\in\{w_0\}\cup W_i \tag{55.a}$$

$$p_{PV,i}^{g,w} + p_{PV,i}^{l,w} = P_{PV,i}, i\in T_1\cup T_2, w\in\{w_0\}\cup W_i \tag{55.b}$$

$$0 \leq p_{PV,i}^{g,w} \leq P_{PV,i}, i\in T_1\cup T_2, w\in\{w_0\}\cup W_i \tag{55.c}$$

$$0 \leq p_{EV,i}^{w} \leq p_{EV+,i}^{\max}, i\in T_1\cup T_2, w\in\{w_0\}\cup W_i \tag{55.d}$$

$$0 \le S_{EV,i} \le n_{R,EV} p_{EV-,i}^{\max}, i \in T_1 \cup T_2 \quad (55.e)$$

$$0 \le f_{EV,i}^{w} \le 1, i \in T_1 \cup T_2, w \in \{w_0\} \cup W_i \quad (55.f)$$

$$0 \le p_{EV,i}^{w} + f_{EV,i}^{w} S_{EV,i} \le p_{EV,i}^{\max}, i \in T_1 \cup T_2, w \in \{w_0\} \cup W_i \quad (55.g)$$

$$p_{EV,i}^{w} - p_{EV,i}^{g,w} \le \begin{cases} P_{PV,i} - p_{PV,i}^{g,w}, & \text{if } p_{BS,i}^{w} \ge 0 \\ P_{PV,i} - p_{PV,i}^{g,w} - p_{BS,i}^{w}, & \text{if } p_{BS,i}^{w} < 0 \end{cases} \quad (55.h)$$

$$, i \in T_1 \cup T_2, w \in \{w_0\} \cup W_i$$

$$E_{EV,i-1}^{w} - E_{EV,i}^{w} = \left(\frac{1}{\eta^{-}} f_{EV,i}^{w} S_{EV,i} - \eta^{+} p_{EV,i}^{w}\right) \Delta T, i \in T_1 \cup T_2, w \quad (55.i)$$

$$\in \{w_0\} \cup W_i$$

$$E_{EV,req} \le E_{EV,i}^{w} \le E_{EV,max}, i \in T_1 \cup T_2, w \in \{w_0\} \cup W_i \quad (55.j)$$

$$\begin{cases} 0 \le p_{BS,i}^{w} \le p_{BS+,i}^{\max}, \text{if } p_{BS,i}^{w} \ge 0 \\ 0 \le -p_{BS,i}^{w} \le p_{BS-,i}^{\max}, \text{if } p_{BS,i}^{w} < 0 \end{cases}, i \in T_1 \cup T_2, w \in \{w_0\} \cup W_i \quad (55.k)$$

$$E_{BS,i-1}^{w} - E_{BS,i}^{w} = \begin{cases} \eta^{+} p_{BS,i}^{w} \Delta T, & \text{if } p_{BS,i}^{w} \ge 0 \\ \dfrac{1}{\eta^{-}} p_{BS,i}^{w} \Delta T, & \text{if } p_{BS,i}^{w} < 0 \end{cases}, i \in T_1 \cup T_2, w \quad (55.l)$$

$$\in \{w_0\} \cup W_i$$

$$E_{BS,req} \le E_{BS,i}^{w} \le E_{BS,max}, i \in T_1 \cup T_2, w \in \{w_0\} \cup W_i \quad (55.m)$$

The objective function is to minimize the total cost while considering the worth of loss change in the risk assessment. The total cost includes the cost of purchased power from power grid, cost of PEV discharging, cost of customer impact if customers are affected, penalty cost for PEV discharging and BESS discharging. The total profit includes the earning from PEV charging, benefit from reserved power, and benefit of PV power sold to the grid. The constraint (55.a) describes the power balance; (55.a)**)**.b) and (55.a) indicate the limit for PV generation energy bidding, while constraints for PEV charging and discharging is presented in (55.a) - (55.a); (55.a) – (55.a) denote additional constraints for PEV charging related to other elements in the integrated system, where (55.a) guarantees that BESS should be considered supplying PEV charging first if needed instead of selling to grid, (55.a) is PEVs' energy dynamic equation, and (55.a) meets the energy requirement for PEV batteries; similar to PEV batteries, constraints for BESS is presented in (55.a) – (55.a).

7.3 Outage Management (OM)

Power supply outage may take place if power delivery infrastructure is damaged or fault is caused by the severe weather conditions. The role of OM (when fault happens) to mitigate the negative weather impacts on the customers is explored. OM needs to be implemented to restore the power supply as soon as possible and alleviate the impact of the power interruption. If a bad weather condition is predicted one day ahead, the risk of customer impact caused by potential power interruptions can be evaluated based on the predicted weather information and customer information in that region. In the day-ahead market, the energy of the participating PEV with mobile battery storage, BESS and PV generation to be reserved is calculated. According to the reserved energy, the distributed PEVs with mobile battery storage, BESS and PV generation in the distribution network can be coordinated to provide electricity to the interrupted customers if power outage happens at the predicted time. The priority order of the power supply restoration is assigned based on the importance of the customers.

The optimization function for obtaining the total participant energy by PEV and PV generation for each feeder area is

$$\min_{E_{EV,i}^{FA=k}} \sum_{k=1}^{N_{FA}} \begin{cases} w_D(FA=k)\cdot p_{G,i}^{FA=k} + w\left(pr_{CL/w,k}\right)\cdot\left(P_{PV,i}^{k} - p_{PV,i}^{FA=k,l}\right) \\ +a\cdot pr_{CL/w,k}\cdot p_{EVd,i}^{FA=k} + b\cdot pr_{CL/w,k}\cdot p_{EVc,i}^{FA=k} \\ +a\cdot pr_{CL/w,k}\cdot\left(Ld_i^k + p_{EVc,i}^{FA=k} + p_{BS,i}^{FA=k} - p_{G,i}^{FA=k} - p_{PV,i}^{FA=k,l} - p_{EVd,i}^{FA=k}\right. \end{cases} \tag{56}$$

$$\text{Where } a = \sum\nolimits_{j=1}^{CT(k)}\left(w_d(ct=j)\cdot\sum_{x\in FA=k} D^i(ct(x)=j)\right), \tag{57.1}$$

$$\mathrm{b} = \sum\nolimits_{j=1}^{CT(k)}\left(w_c(ct=j)\cdot\sum_{x\in FA=k} D^i(ct(x)=j)\right)$$

$$\text{s.t. } \sum\nolimits_{k=1}^{N_{FA}} p_{EVd,i}^{FA=k} = f_{EV,i}S_{EV,i} \tag{58.a}$$

$$\sum\nolimits_{k=1}^{N_{FA}} p_{EVc,i}^{FA=k} = p_{EV,i} \tag{58.b}$$

$$\sum\nolimits_{k=1}^{N_{FA}} p_{PV,i}^{FA=k,l} = p_{PV,i}^{l} \tag{58.c}$$

$$\sum\nolimits_{k=1}^{N_{FA}} p_{G,i}^{FA=k} = p_{G,i} \tag{58.d}$$

$$\sum\nolimits_{k=1}^{N_{FA}} p_{BS,i}^{FA=k} = p_{BS,i} \tag{58.e}$$

$$0 \le p_{PV,i}^{FA=k,l} \le P_{PV,i}^{FA=k}, \qquad k = 1,2,\ldots,N_{FA} \tag{58.f}$$

$$\begin{cases} 0 \le p_{EVc,i}^{FA=k} \le p_{EV+,i}^{FA=k,max} \\ 0 \le p_{EVd,i}^{FA=k} \le p_{EV-,i}^{FA=k,max} \\ 0 \le p_{EVc,i}^{FA=k} + p_{EVd,i}^{FA=k} \le p_{EV,i}^{FA=k,max} \end{cases}, \qquad k = 1,2,\ldots,N_{FA} \tag{58.g}$$

$$\begin{cases} 0 \le p_{BS,i}^{FA=k} \le p_{BS+,i}^{FA=k,\max}, \text{if } p_{BS,i}^{w} \ge 0 \\ 0 \le -p_{BS,i}^{FA=k} \le p_{BS-,i}^{FA=k,\max}, \text{if } p_{BS,i}^{w} < 0 \end{cases}, \qquad k = 1,2,\ldots,N_{FA} \tag{58.h}$$

Where $E_{EV,i}^{FA=k}$ represents the energy provided by PEV battery for the k-th feeder area at time i; $p_{PV,i}^{FA=k,l}$ is determined by the availability of PV generation in feeder area k. $f_{EV,i}S_{EV,i}$, $p_{EV,i}$, $p_{PV,i}^{l}$, $p_{G,i}$, and $p_{BS,i}$ are the total participant energy of PEV discharging/ charging and PV generation obtained, energy purchased from grid, and energy scheduled for BESS, from the ancillary market, respectively. This objective function (56) is used to schedule participating PEV energy for each feeder area in order to support more vulnerable customers. Constraints (58.a) – (58.e) are sum equations and (58.f) – (58.h) shows the limits of the schedulable energy from PV generation, PEV battery and BESS.

After obtaining the participant energy for each feeder area, how to coordinate the power supply for each customer type are optimized by

$$\min_{p_{ct=j,i}^{FA=k}} \sum_{j=1}^{CT(k)} Loss_{ct=j,i}^{FA=k}\left(p_{ct=j,i}^{FA=k}\right), \qquad k = 1,2,\dots,N_{FA} \tag{59}$$

$$\text{s.t.} \sum_{j=1}^{CT(k)} p_{ct=j,i}^{FA=k} = p_{G,i}^{k} + p_{PV,i}^{k,l} + p_{EVd,i}^{k} - p_{EVc,i}^{k} - p_{BS,i}^{k}, \tag{60.a}$$

$$k = 1,2,\dots,N_{FA}$$

$$0 \le p_{ct=j,i}^{FA=k} \le D^{i}(ct(x) = j), \qquad k = 1,2,\dots,N_{FA} \tag{60.b}$$

OM:

$$0 \le q\left(ct(x)\right) \le 1, \qquad x \in FA = k \tag{60.c1}$$

$$q\left(ct(x)\right) = \frac{D^{i}(ct(x) = j) - p_{ct=j,i}^{FA=k}}{D^{i}(ct(x) = j)}, \qquad j = 1,2,\dots,m_k \tag{60.d1}$$

$$q(b) > 0, \text{if } q(a) > 0, \forall b > a \tag{60.e1}$$

Where $Loss_{ct=j,i}^{FA=k}$ is calculated according to (46). This objective function (59) is to minimize the total cost for each feeder area. Constraints (60.a)-(60.e1) show the relation between $p_{ct=j,i}^{FA=k}$ and $q\big(ct(x)\big)$ used in (46). (60.a) indicates the priority of the customer types.

When the predicted power interruption does happen, OM is conducted considering the reserved available resources at that time in the market to cover the potential power loss. Based on the severity in terms of the outage impact on the various customer types covered by the feeder areas, the available PV generation, and the required stored energy reserve participating in the market, the participant PEVs, BESS are assigned to provide electricity back to the customers.

7.4 Demand Side Management (DSM)

Even when the weather condition is not so severe and the system is under normal operation, the weather change can still cause the imbalance of supply and demand. In this case, the role of programs for DSM (in daily operation) to mitigate the negative weather impacts on the customers is explored. DSM needs to be implemented to handle the imbalance and alleviate the impact of sudden demand change. The risk of customer impact caused by potential demand change can be evaluated. According to the stored energy reserve participating in the ancillary market, the distributed PEVs with mobile battery storage, BESS and PV generation in the distribution network can be coordinated to provide electricity to balance the demand difference.

Compared with OM, (57.1) will be replaced by (57.2):

$$\text{Where } a = \sum_{j=1}^{CT(k)} \left(w_d(ct = j) \cdot \sum_{x \in FA = k} DC^i(ct(x) = j) \right), \tag{57.2}$$

$$\mathrm{b} = \sum_{j=1}^{CT(k)} \left(w_c(ct = j) \cdot \sum_{x \in FA = k} DC^i(ct(x) = j) \right)$$

Where DC^i is the expected demand change at time i.

In addition, the $Loss_{ct=j,i}^{FA=k}$ in (59) is calculated according to (50). (60.c1) - (60.e1) will be replaced by (60.c2) - (60.e2):

$$0 \leq p\big(ct(x)\big) \leq 1, \qquad x \in FA = k \tag{60.c2}$$

$$p\big(ct(x)\big) = \frac{DC^i(ct(x) = j) - p_{ct=j,i}^{FA=k}}{DC^i(ct(x) = j)}, \qquad j = 1,2, \dots, m_k \tag{60.d2}$$

$$p(b) > 0, \text{if } p(a) > 0, \forall b > a \tag{60.e2}$$

Suppose that the load peak does happen the next day, DSM has to be called to shave the peak. PEVs and BESS are assigned to provide electricity back to the customers.

7.5 Use Case Study

In order to implement risk assessment to support utility applications, such as DSM and OM, the same distribution network can be used to demonstrate both applications for comparison purpose. In this use case study, a distribution network with 20 feeders [128] and 47,000 customers with the participation of 15,000 PEVs and 140 MW PV generation capacity is used. Both historical weather data obtained from weather stations and forecasted weather data obtained from the National Digital Forecast Database (NDFD) are used to assign weather element values. The risk analysis is implemented and visualized in time and space using ArcGIS software. The proposed approach is tested under two scenarios, OM and DSM, in which the cases with and without PEV energy storage, BESS and PV generation are compared and analyzed. To be more specific, two cases are studied: case 1- no PEV energy storage, PV generation and BESS are available; case 2- with PEV energy storage, PV generation and BESS participated. The simulation is implemented in MATLAB environment.

For OM, numerical experiments are implemented to illustrate the impact of PV generation, fixed BESS, and PEVs' ability to charge/discharge the stored energy on supporting demand of the interrupted load. The scenario considers the possible power interruptions caused by the weather change and estimates the consequent impact on the customers. In the use case study, a severe weather condition is predicted to happen the next day around 12:00 pm. Based on the severity of the customer types covered by the feeder areas, the available PV generation, and the required reserved energy, the participant PEVs with mobile battery storage are assigned to provide electricity back to the customers.

For DSM, numerical experiments are implemented to illustrate the impact of PV generation, fixed BESS, and PEVs' ability to charge/discharge the stored energy on the flexibility of the electricity customer demand. The scenario investigates the possible load peak that may lead to the imbalance of supply and demand due to the weather change. The weather change and demand change are predicted to happen around 12:00 pm. Suppose that the load peak does happen the next day, DSM has to be called to shave the peak. Based on the severity of the customer types covered by the feeder areas, PEVs with mobile battery storage and BESS are assigned to provide electricity back to the customers.

7.5.1 Predictive

Predictive risk results are needed to evaluate the potential weather impact and provide risk map to guide development of the preventive actions, which is the next stage.

- Use Case Study for OM

In this use case study, the risk map for case 1 is illustrated in Figure 41 (Figure 42 shows the feeder areas numbering and potential outage location). Different colors indicate value of various risk indices with the monetary value in dollars. The weather impact on customers in some areas is significant because either a large number of people are affected or some critical customers are located there.

- Use Case Study for DSM

In this use case study, the severity of risk that the demand change may not be balanced in case 1 is illustrated in Figure 43. It is noted that the risk index values for

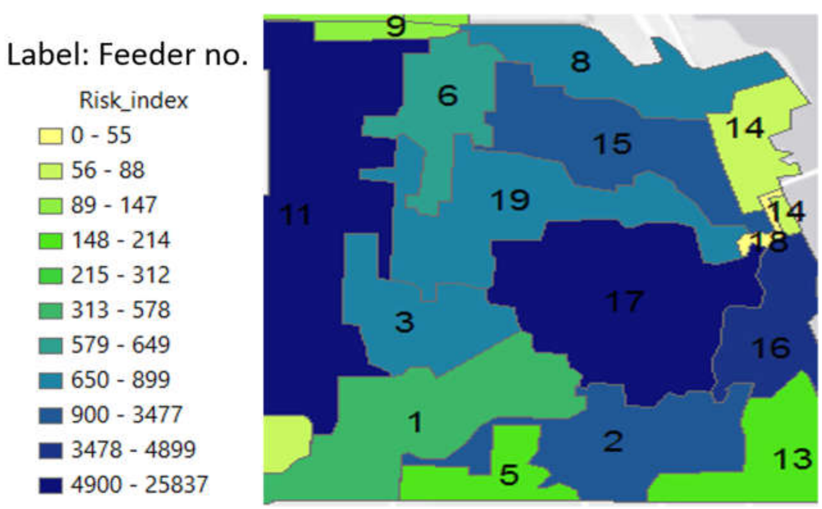

Figure 41: Prediction of Risk Map before Correction- OM

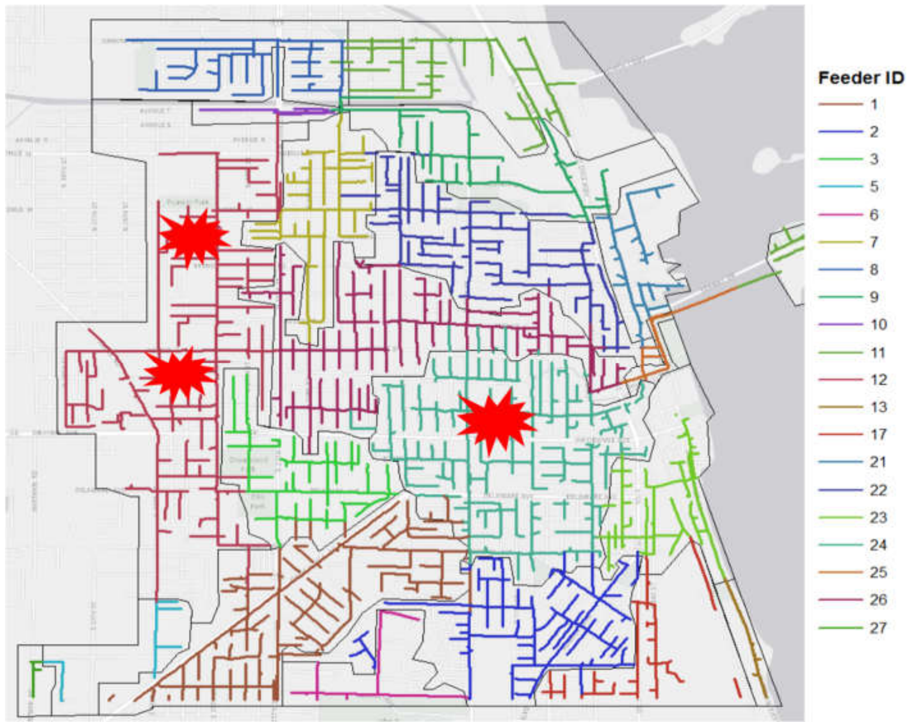

Figure 42: Feeder Areas and Potential Outage Location- OM

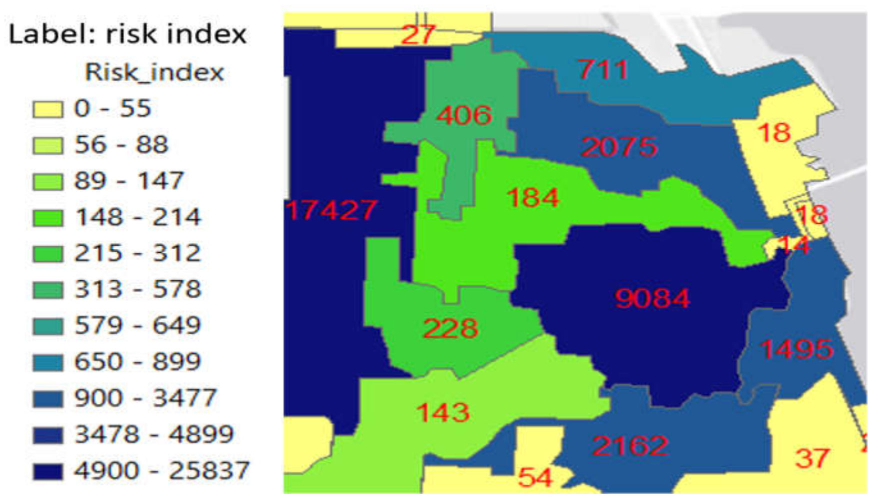

Figure 43: Prediction of Risk Map before Correction- DSM

feeder area 11 and 17 are comparably higher since the number of significant customers whose demand may be affected by the weather change are higher.

7.5.2 Preventive

Based on the prediction results, we will decide the optimal participation of PEV/local BESS and the output of PV generation to be reserved.

- Use Case Study for OM

When a severe weather condition happens at 12:00 pm, it is assumed to cause an outage, which means the power supply from grid is decreased to 0. In addition, the PV generation power is assumed to be decreased by 50 MW. After simulation, the participating PEV energy storage, BESS and PV generation in the ancillary services and the schedule of purchased energy from grid and BESS in use case 2 are shown in Figure 44. We can observe that they preventively tend to offer more capacity to serve as a reserve from PEV discharging and BESS discharging during the predicted outage.

Moreover, PEV batteries and BESS are charged and store energy during the off-peak hours, and discharged during the peak hours. During the hour with predicted outage, PEV energy storage, and fixed BESS, together with PV energy, serves as the back-up generation to alleviate the negative weather impact. The collaboration between PV, BESS and PEVs enables PV energy to be stored to some extent in face of the potential outage and load peak.

- Use Case Study for DSM

When a weather change happens at 12:00 pm, it is assumed to cause unbalance between supply and demand. In this use case study, the load demand is assumed to increase by 5 MW, while PV generation power is assumed to decrease by 5 MW. After simulation, the participation of PEV energy storage, BESS and PV generation in

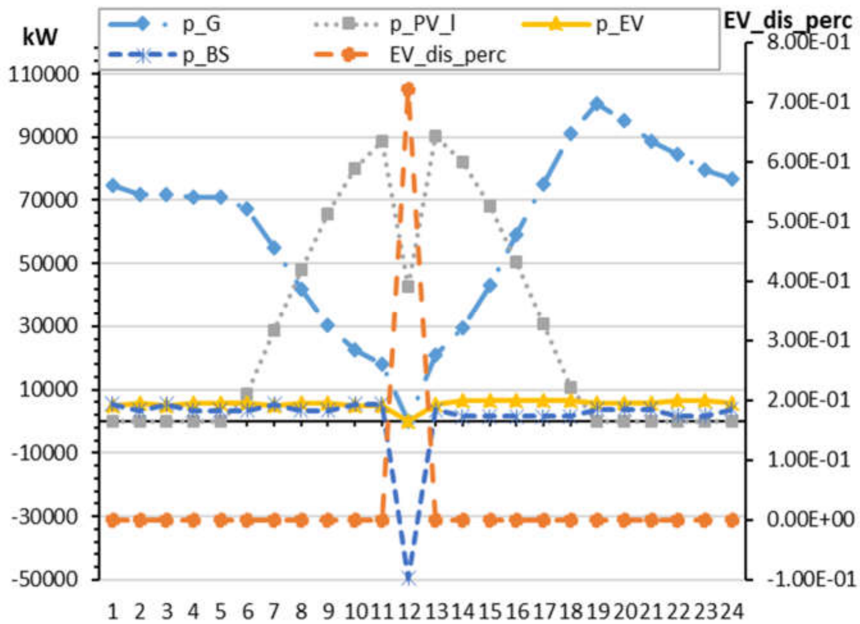

Figure 44: Participation of PEV Energy Storage, BESS and PV Generation in the Ancilliary Services- OM

the ancillary services and the schedule of purchased energy from grid and BESS in use case 2 is shown in Figure 45. The bidding strategy takes advantage of the load flexibility to purchase more energy during the off-peak, so that less energy needed to be purchased during the peak hour. We can observe that because of the sudden weather change, the optimal schedule has obvious change even after the predicted weather change. Compared with OM scenario, the PEV discharging and BESS discharging do not occur during the predicted weather change. Because of that, the electricity price is changing from time to time, and the demand change is not that significant in this case.

7.5.3 Corrective

Based on the reserved energy in the preventive stage, the utility operators can benefit from the integration of PEVs, PVs and BESS by taking measures to correctively mitigate the potential weather-caused risk for customers.

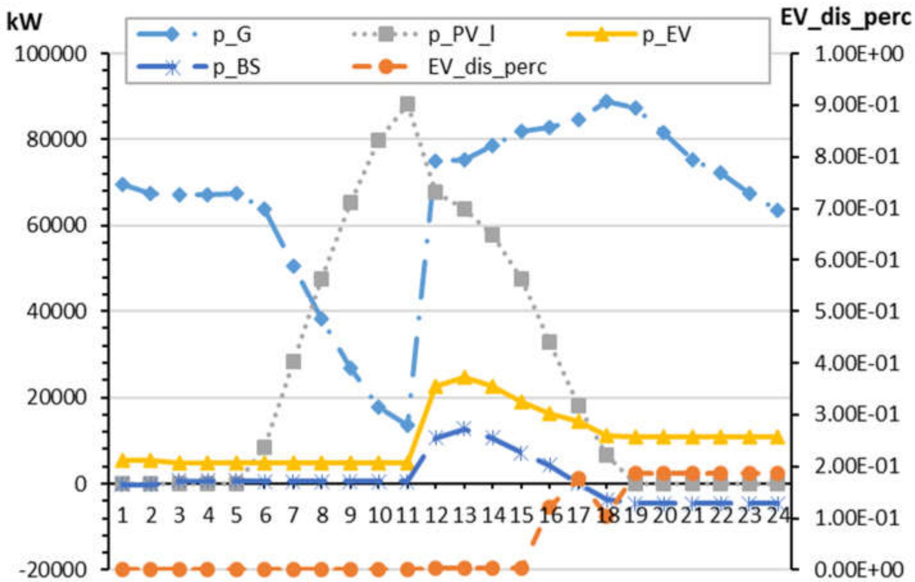

Figure 45: Participation of PEV Energy Storage, BESS and PV Generation in the Ancilliary Services- DSM

- Use Case Study for OM

When the predicted power interruption does happen, OM procedures are conducted based on the available resources at that time. Table 5 shows partial results of the energy provided by the participating PEVs, BESS and PV generation. Compared with feeder area 7 that has only residential customers, the PEVs, BESS, and PV participation in feeder area 17 is much higher since there are 6 hospitals, 5 communities, 1 industry and 3 schools in that area. It is shown in the fourth column of Table 5 that in this case about 99.9% of the power demand at the occurrence of weather change can be supported by PEV energy storage, BESS and PV generation. In some feeder areas, the participation of PEV energy storage, BESS and PV generation is lower than the load demand in that feeder area. It is because that the weather change is impacting the availability of PV generation and the charger numbers in each PEV charging station are limited. The remaining load can be supplied by neighbor areas, which makes the overall load demand completely covered. Figure 46 shows the participation of PEV energy storage, BESS and PV generation, the load demand, and the predicted output power from PV generation in each feeder. Note that in this case, PEVs and BESS are coordinated to discharge their batteries to support the potential power outage.

Table 5: Energy Provided by the Participant PEVs, BESS and PV Generation- OM

Feeder No.	Load (kW)	PV + PEV +BESS power (kW)	% of load supplied by PV + PEV + BESS
1	6359	9847	155%
2	8402	8637	103%
6	5259	5327	101%
7	828	2163	261%
14	4677	3903	83%
17	15415	6045	39%

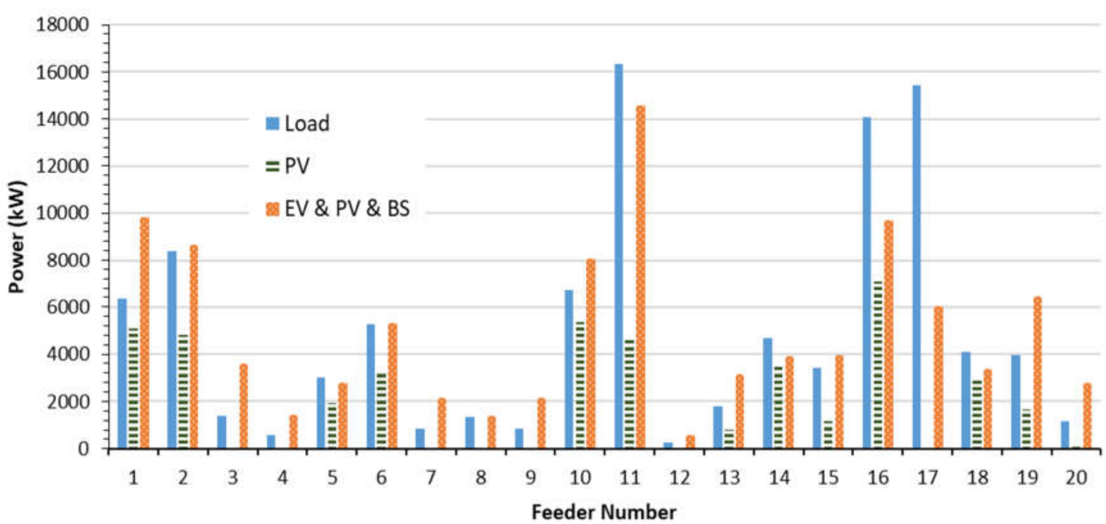

Figure 46: Participation of PEV Energy Storage and PV Generation in Each Feeder- OM

- Use Case Study for DSM

PEVs, BESS are assigned to provide electricity back to the customers. Table 6 shows partial results of the energy provided by the participating PEVs, BESS and PV generation. Figure 47 shows the participation of PEV energy storage, BESS and PV generation, the increased load demand, and the predicted output power from PV generation in each feeder. Note that in this case, the power grid is still supplying power to the load and the components in the IEVCS are coordinated to help balance the increased power demand and the decreased PV generation power caused by the weather change.

Compared with the results in OM scenario, the power supply from the PV generation is different because of different weather conditions. In addition, the extra power supply from PV generation are scheduled to be sold to the grid. The overall participation of PEVs, BESS and PV generation is less since the power supply in need during outage is much more than what is needed to meet the demand fluctuation. It can also be seen from the fourth column of Table 6 that lower percentage (average of 28.5%) of the power demand at the occurrence of weather change are supported by PEV battery energy, BESS and PV generation.

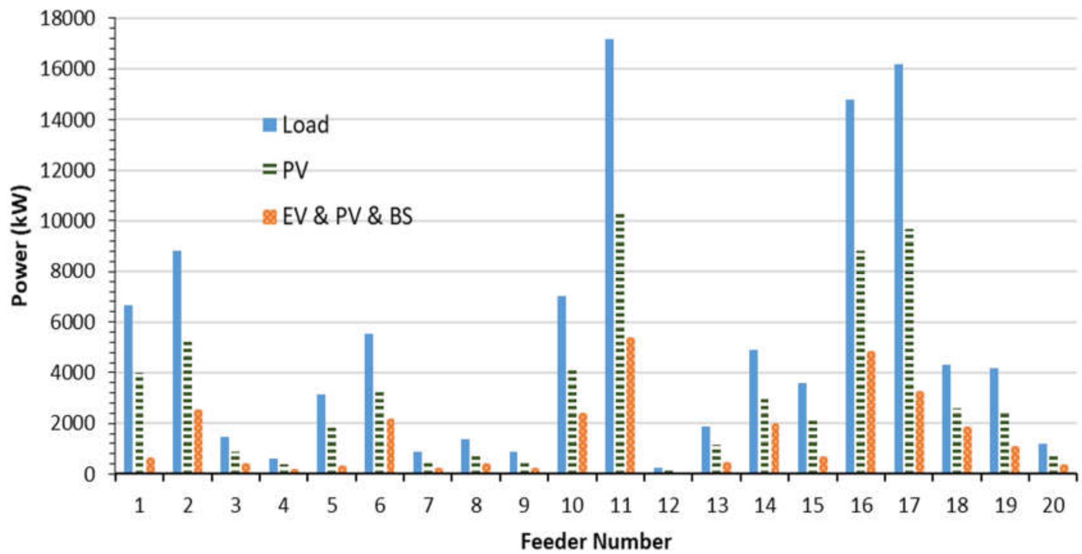

Figure 47: Participation of PEV Energy Storage, BESS and PV Generation in Each Feeder- DSM

Table 6: Energy Provided by the Participant PEVs, BESS and PV Generation- DSM

Feeder No.	Load (kW)	PV + PEV +BESS power (kW)	% of load supplied by PV + PEV + BESS
1	6677	669	10%
2	8823	2543	29%
6	5523	2210	40%
7	870	248	28%
14	4911	2001	41%
17	16186	3252	20%

7.5.4 Predictive after Corrective

In order to evaluate the effect of the corrective actions, risk assessment is implemented again considering the obtained results in the corrective stage.

- Use Case Study for OM

The risk assessment is implemented again after the scheduling of PV generation output power, PEV energy storage, and local BESS are determined for OM described in the previous chapter. The purpose is to evaluate the effect of the schedules on the risk results. The worth of loss is different from the risk assessment in second phase since the PEV battery storage, BESS and PV power can reduce the potential customer impact. Figure 48 compares the estimated customer cost results for partial feeder areas for case 1 (no PEVs, BESS & PVs) and case 2 (with PEVs, BESS & PVs). It turns out that, OM actions together with the available capacity reserved by the integration of PEVs, BESS and PVs can help reduce 73% of the estimated customer cost caused by possible outage due to the weather impact. Although the load can be almost completely covered by the participation of PEVs, BESS and PVs, there is still risk that the availability of PV generation and the load demand may be further affected by the weather change.

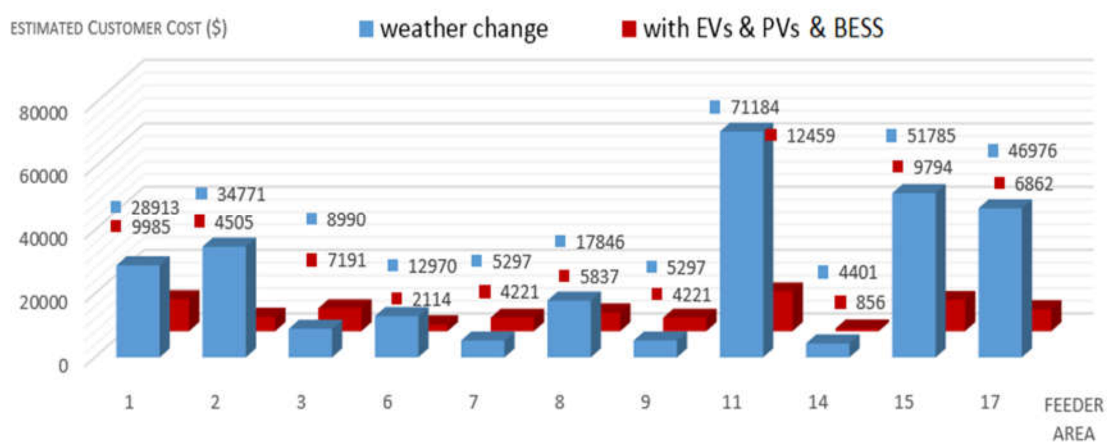

Figure 48: The Estimated Customer Cost in Case 1 & 2- OM

- Use Case Study for DSM

The risk assessment is implemented again after the scheduling of PV generation output power, PEV energy storage, and local BESS are determined for OM described in the previous chapter. The purpose is to evaluate the effect of the schedules on the risk results. The worth of loss is different from the pre-risk assessment since the PEV battery storage, BESS and PV generation can reduce the potential customer impact. Figure 49 compares the estimated customer cost results for partial feeder areas for case 1 and case 2. It turns out that, DSM together with the available capacity reserved by the integration of PEVs, BESS and PVs can help reduce 94% of the estimated customer cost caused by demand change due to the weather impact.

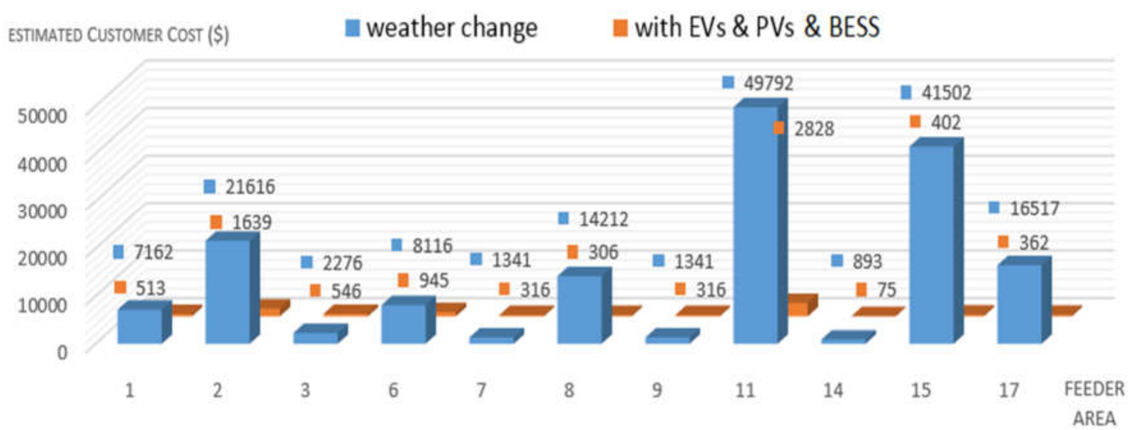

Figure 49: The Estimated Customer Cost in Case 1 & 2- DSM

7.6 Conclusion

This chapter fits the "Optimal Scheduling" term under "Multiple IEVCS" branch, as shown in Figure 1. The contributions of this chapter are summarized as follows:

- In order to consider the weather impact on customers, CIC index is improved. The improved CIC index is calculated considering probabilistic weather scenarios and risk maps are created to predict the weather impact on customers' electricity supply;
- Before dispatching the energy participation of PEVs, BESS and PV generation to each area, the preventive strategy is proposed to enable the

customer to offer energy from their PEV energy storage, BESS and rooftop PV generation in the day-ahead CRS market considering both the risk prediction and the stochastic nature of PEV and PV participation;

- The PEV energy storage, BESS and PV generation are evaluated in each area (feeder area or hazard areas based on predicted weather condition) based on their participation in day-ahead market for energy dispatch in the DSM and OM services, to correctively alleviate negative weather impact on reliability of customers' electricity supply;
- By implementing the above-mentioned methods in the Use case, numerical experiments are conducted to validate the contribution of PEV energy storage, BESS and PV generation in mitigating negative weather impacts on the power supply, and thus validate the last scenario under the hypothesis discussion.

VIII. CONTRIBUTION AND CONCLUSIONS

8.1 Contribution

To make full use of the energy stored in PEVs with mobile battery storage and fixed batteries (BESS) combined with PV generation, IEVCS with intelligent management system is developed to relax customers' dependency on the electric grid supply and improve electric grid performance. To evaluate the hypothesis stated in Chapter II, the following solutions are formulated:

1) **Integrated Simulation Models:** IEVCS components with statistical PEV consumption estimation, pricing algorithm, building load model, and renewable energy supply estimation are modeled and assessed through simulation. With the proposed models, the Use case for the corresponding Hypothesis scenario is validated.
2) **Optimization of Operational Cost and Related Control Algorithms:** Optimization and control management algorithms are established to intelligently coordinate the demand and supply balance in the IEVCS, at the same time minimize operational cost, which correspond to the Use Case where the corresponding hypothesis scenario is validated.
3) **Risk Assessment for Weather-related power interruptions**: The potential impact of loss of power supply on customer under predicted weather change is assessed through the risk model with particular consideration of customer satisfaction impact when utilizing the IEVCS. The distribution system

operators and utility customers can benefit from the assessment, which reflects a Use Case to validate the next validates Hypothesis scenario.

4) **Electricity Grid Support:** The algorithms apply risk assessment approach and provide an overall optimization of the impact of the IEVCS on several related utility applications such as DSM and OM to help improve electric grid performance. The use case study validates the last scenario mentioned under the Hypothesis discussion.

8.2 Conclusions

This dissertation proposes an intelligent management system for integrated PEV charging station (IMS-IEVCS), including PEVs with mobile battery storage connected via the PEV chargers, PV panels, fixed BESS, and the building load connected to the same bus.

The major accomplished work that validates the hypotheses are:

1) Establish stochastic model of PEV charging and derived the probabilistic description of the electricity needs from PEV charging. The output of the estimated electricity consumption of PEV charging is used in the optimization algorithm in Chapter V, which validates the first scenario in hypothesis that utilizing such models can help reduce the potential PEV charging impact on the power grid.
2) Develop a novel real-time multi-tiered electric pricing system and a new display board design for PEV charging stations. It aims to validate the first scenario in hypothesis that utilizing such pricing system can encourage

vehicle owners to adjust their charging time in return for reduced electricity bills.

3) Propose a four-stage optimization and control algorithm for the purpose of reducing the operational cost of the IEVCS. Such algorithm can provide more resilience for unpredictable conditions, provides more incentives for PEV users, and better reliably serve the customers while lessening the cost, which validate the second scenario in hypothesis that utilizing the proposed algorithm on the IEVCS can provide more resilience for the power grid facing unpredictable conditions, while benefiting both grid owner and IEVCS owner (customer).
4) Develop the risk assessment methodology that estimates the impact of weather parameters on hazard, weather-caused outage vulnerability, and weather-related customer losses. The comparison between the risk maps before and after the optimal scheduling validates the third scenario in hypothesis that the distribution system operators and utility customers can benefit from the risk assessment results.
5) Conduct risk assessment in the DSM and OM services to validate contribution of PEVs with mobiles energy storage, BESS and PV generation in mitigating negative weather impacts on the power supply, which validates the last scenario in hypothesis that the IEVCS can contribute as preventive countermeasures in mitigating weather impacts.

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APPENDIX A

AUTHOR'S PUBLICATIONS

Journals:

Q. Yan, B. Zhang, M. Kezunovic, "Optimized Operational Cost Reduction for an EV Charging Station Integrated with Battery Energy Storage and PV generation," in IEEE Transactions on Smart Grid, in press 2018.

Conferences:

J. Leite, J. Mantovani, T. Dokic, Q. Yan, P.-C. Chen, M. Kezunovic, "Resiliency Assessment in Distribution Networks Using GIS Based Predictive Risk Analytics," IEEE PES 2018 Transmission and Distribution Latin America (T&D LA), Lima, Peru, Sepember 18-21, 2018.

C. M. Affonso, Q. Yan, M. Kezunovic, "Risk Assessment of Transformer Loss-of-Life due to PEV Charging in a Parking Garage with PV Generation", IEEE PES General Meeting, Portland, OR, USA, August 4-10, 2018.

J. Leite, J. Mantovani, T. Dokic, Q. Yan, P.-C. Chen, M. Kezunovic, "Failure Probability Metric by Machine Learning for Online Risk Assessment in Distribution Networks," IEEE/PES Innovative Smart Grid Technologies Latin America (ISGT-LA), Quito, Ecuador, September 20-22, 2017.

Q. Yan, C. Qian, B. Zhang, M. Kezunovic, "Statistical Analysis and Modeling of Plug-in Electric Vehicle Charging Demand in Distribution Systems," International Conference on Intelligent Systems Applications to Power (ISAP), San Antonio, Texas, USA, September 17-21, 2017.

B. Zhang, Q. Yan, M. Kezunovic, "Placement of EV charging stations integrated with PV generation and battery storage," 2017 Twelfth International Conference on Ecological Vehicles and Renewable Energies (EVER), Monaco, April 11-13, 2017.

J. Leite, J. R. Mantovani, T. Dokic, Q. Yan, P.-C. Chen, M. Kezunovic, "The Impact of Time Series-based Interruption Cost on Online Risk Assessment in Distribution Networks," IEEE PES 2016 Transmission and Distribution Latin America (T&D LA), Morelia, Mexico, September 2016.

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Q. Yan, M. Kezunovic, "Impact Analysis of Electric Vehicle Charging on Distribution System," Proc. of the 43rd North American Power Symposium, Urbana-Champaign, MA, Sep. 9-11, 2012.