Integration of plug-in electric vehicles into power grid

Nima Harsamizadeh Tehrani

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INTEGRATION OF PLUG-IN ELECTRIC VEHICLES INTO POWER GRID

NIMA HARSAMIZADEH TEHRANI

School of Electrical and Electronic Engineering

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Abstract

Plug-in Electric Vehicles (PEVs) are increasingly being seen as a sustainable mode of transport by countries worldwide. However, PEVs will add significant new load to the existing power distribution system and it will be a challenge to meet the new demand. On the other hand, the energy storage capability and charging flexibility of PEVs create an opportunity for being as ancillary service providers to improve performance of grid.

In this study, stochastic modeling has been presented to estimate the system-wide PEV charging load within domestic grids. US National Household Travel Survey (NHTS) data set has been utilized in several ways to probabilistically quantify the PEVs status. The results indicate that the PEVs can contribute to increase the load demand at certain hours, although the charging demand is very limited most of the time. The most suitable methodology for the uncertain nature of the problem in modelling is the use of Monte Carlo simulation. Due to the existence of complex interdependencies between the system inputs, the problem definition leads to a multivariate uncertainty analysis problem.

From the significant levels of vehicles' state of charge (SOC) observed, it can be foreseen that PEVs should be able to provide a notable amount of reserve capability. The operation of a distributed charging infrastructure is characterized. Then, the charging and discharging pattern is optimized according to day-ahead price variations to maximize the objective function that is the social benefit of the participation in the electricity market. Furthermore, Vehicle-to-Grid (V2G) provides the potential for the system operator to call on the PEV as a distributed energy resource and offers financial benefits to vehicle owner when supplying ancillary services.

Using a stochastic model, a two-settlement market and fleet aggregator behavior has presented and showed that the problem of determining optimal contract offering for an aggregator can be solved using convex programming and coherent approaches to risk in optimization under uncertainty. The study provides decision-making tools for aggregator that allow making informed decisions within a short and medium term planning horizon while explicitly considering uncertain prices and demands. The main contribution is the formulation of the short-term trading problem of an aggregator as a stochastic programming problem with recourse, which, in addition, includes the modelling of the risk aversion using the Conditional Value-at-Risk (CVaR).

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List of Acronyms

BEV	Battery Electric Vehicle
BSS	Battery Storage System
CD	Charging Demand
CDF	Cumulative Density Function
CSP	Charging Service Provider
DoD	Depth of Discharge
EDV	Electric Drive Vehicle
EV	Electric Vehicle
EPRI	Electric Power Research Institute
ESS	Energy Storage System
FCV	Fuel Cell Vehicle
GHG	Green House Gas
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
MCP	Market Clearing Price
NERC	North American Electric Reliability Corporation
NHTS	National Household Travel Survey
PDF	Probability Density Function
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
RV	Random Variable
RES	Renewable Energy Source
SOC	State of Charge
V2G	Vehicle to Grid

List of Symbols

Chapter 3:

α	Confidence level
λ	Mean rate of vehicles' arrival
ρ	Rank correlation matrix
ϵ	Battery charging constant
d	Daily distance
d_{max}	Maximum mileage with a fully charged battery
E_0	Initial SOC of the battery
E_c	Instantaneous energy status of PEV battery
E_{max}	Maximum Energy level of storage battery
f_{SOC}	Probability density function of initial SOC
f_{ami}	Probability density function of daily mileage
f_{arr}	Probability density function of arrival time
G	Cumulative function of servicing time RV
$m(t)$	Congestion measure at time t
P_{max}	Maximum battery power
P_c	Instantaneous power absorbed from the grid
pr	Plug-in probability
S	Service time RV
t_{c_i}	Time for i^{th} PEV to absorb power
T_{max}	Maximum charging time
T_{min}	Minimum charging time

Chapter 4:

π	Market electricity price
η_{bat}	Battery efficiency
η_{chg}	Charger efficiency
η	Conversion efficiency
η_{rnd}	Round-trip efficiency
A	Plug accessibility vector
$\bar{e}$	Maximum energy level of storage battery
e	Energy level of storage battery
$\underline{e}$	Minimum energy level of storage battery
h	Duration of time period [hr]
E_{cn}	Aggregated energy consumption of PEV fleet
E_{dsp}	Total energy dispatched over the contract period
E_{up}	Energy available for up regulation
E_{dn}	Energy available for down regulation
P_c	Power absorbed from the grid

P_d	Power supplied to the grid
P_{lim}	Connection power limitation
P_{cnt}	Contracted capacity
P_{up}	Up regulation power
P_{dn}	Down regulation power
pr	Plug access probability
ps	Number of parked PEVs
r_c	Charging rate of storage battery unit
R_{d-c}	Dispatch to contract ratio
R	Reliability index
ΔE	Net stored energy
SOC_{min}	Minimum state of charge
t_{cnt}	Contract duration between ISO/RTO and Aggregator
t_{dsp}	Energy dispatched duration
t_{day}	Plug-in time per day

Chapter 5:

t	Subscript for time period
$W(\omega)$	Set (index) of all scenarios
P_t^{DA}	Power offered by a fleet aggregator (FA) in the day-ahead market [MW]
Δ_t^+	Positive deviation of energy incurred by an FA [MWh]
Δ_t^-	Negative deviation of energy incurred by an FA [MWh]
Δ_t	Total deviation of energy incurred by an FA [MWh]
ξ	Auxiliary variable used to compute the $CVaR$ [\$]
δ_ω	Auxiliary variable in scenario ω used to compute the $CVaR$ [\$]
β	$CVaR$ weighting factor
A_t	Plug accessibility
π_t^{DA}	Day-ahead market price at period t [\$/MWh]
π_t^R	Price for regulation resulting from the balancing market [\$/MWh]
ρ	Reserve to day-ahead price ratio
α	Confidence level
π_t^+	Positive imbalance price [\$/MWh]
π_t^-	Negative imbalance price [\$/MWh]
λ_t^+	Positive imbalance penalty
λ_t^-	Negative imbalance penalty
r_t^+	Normalized up regulation signal
r_t^-	Normalized down regulation signal
R_t	Delivered regulation power [MW]
P_t	Charging power realization [MW]
Q_t	Estimated Charging requirement [MWh]
P_t^{up}	Upward reserve bid [MW]

P_t^{dn}	Downward reserve bid [MW]
h	Duration of time period [hr]
P^{max}	Maximum aggregated charging power capacity [MW]
$B_{t\omega}$	Aggregated energy capacity of FA [MWh]
B^{max}	Upper limit of aggregator energy capacity [MWh]
B^{min}	Lower limit of aggregator energy capacity [MWh]
C	FA contact portfolio
e	Energy level of storage battery
P_c	Charging power
P_d	Discharging power
η	Charging/discharging efficiency
$\bar{P}$	Connection power limitation
$\mathcal{D}$	FA decision vector

Parameters if augmented with subscripts t and ω , represent their realizations in time period t and scenario ω respectively.

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Chapter 1. Introduction

1.1 Linking Electricity to Transportation

The electrical power and energy industry represents a major portion as contributor to global emission. It is responsible for 40% of the global CO₂ production, followed by the transportation industry (24%) [1]. Current transportation system is heavily dependent on fossil fuels and is at the mercy of oil prices. Electric-drive vehicles (EDVs) can potentially reduce the dependency on foreign oil imports and produce little or no emissions [2]. The main characteristic of EDVs is that the torque is supplied to the wheels by an electric motor that is powered either solely by a battery or in combination with an internal combustion engine. This covers hybrid electric vehicles (HEVs), battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), photovoltaic electric vehicles (PVEVs) and fuel cell vehicles (FCVs) [3].

BEVs and PHEVs have larger battery capacity compared to HEVs and are capable of being recharged from or discharged to the electric grid and they are called plug-in electric vehicles (PEVs) in this study. PEVs reduce emissions, energy use and petroleum consumption more than HEVs. PEVs are powered by multi-source generated electricity so they represent a change of paradigm within the transport sector. Their contribution to lower greenhouse gas (GHG) emissions increases especially if they are charged with electricity generated by renewable sources, where the carbon footprint is zero. Even in an alternative energy disadvantaged country like Singapore, which is powered mainly by natural gas, it is estimated that land transport sector's carbon emissions can reduce up to 4% by 2020 with just a 2% PEV penetration rate [4].

The International Energy Agency (IEA) EV/PHEV roadmap vision is to reduce annual CO₂ emissions by 2050 to half that of 2005 levels. In order to provide significant reductions in GHG emissions and oil use, widespread adoption use of PEVs worldwide must be achieved by 2050 as shown in the Figure 1 whereby PEVs contribute approximately a 30% reduction in light-duty vehicle CO₂ emissions [2].

Figure 1. Annual light-duty vehicle (LDV)¹ sales by technology type, BLUE Map scenario [2]

In the U.S. about 15.4 million barrels (where 1 barrel is equal to 42 U.S. gallons) of oil are used each day, and 2/3 of these are refined into automobile fuel. Light-duty vehicle travel accounts for 92% of the high way vehicle miles travelled, 76% of the energy consumed by highway travel modes and 74% of the CO₂ emissions from on-board sources. The government pledged to reduce greenhouse gas emissions by approximately 17% by 2020. According to the annual report from Energy Information Administration in 2010, the transportation sector alone takes up to 33.1% of all energy-related emissions and is the largest producer of carbon dioxide emission in U.S. This presents the needs for the transportation sector to act on emissions abatement. California Air Resources Board studies show that battery electric vehicles emit at least 67% lowers GHG than gasoline cars [5-7].

Major automakers have attempted to commercialize electric vehicles in the past with limited success, for example the EV1 produced by General Motors in the early 1990's. However, increasing environmental concerns, rising gasoline prices and the desire to reduce oil consumption in developed countries are key drivers in the current effort to commercialize PEVs. Although they cost more than conventional cars and require higher capital costs, there appear to be substantial market shares for PEVs within a few years and the market will experience a major accelerated growth. Many manufacturers have announced plans to begin

¹ The fleet of light-duty vehicles consists of cars and light trucks, including minivans, sport utility vehicles (SUVs), and trucks with gross vehicle weight less than 8500 pounds. These vehicles account for over 93% of the total fleet

serious production within the next few years and some models have already demonstrated in low-volume production. There are several examples of ambitious national targets for PEVs, e.g. goals of 1 million EVs in Germany by 2020 [8], 2 million EVs in France by 2020 [9], and 1 million PHEVs in the United States by 2015 [10]. As of early 2011 the market penetration is approaching 2% in the U.S. and 9% in Japan. Over the past decade, over 2.5 million HEV/PHEV/EV vehicles have been sold worldwide.

The notation "PHEV_{xx}" is commonly used to specify the PHEVs all-electric range (AER). For instance a PHEV40 corresponds to a PHEV with a 40 km electric range. Typical PHEVs AER are in the range 20-80 kilometer. Worldwide, a significant share of daily driving distance can be satisfied by this AER. For example in the United Kingdom, 97% of trips are estimated to be less than 80 km. In Europe, 80% of trips are less than 25 km. in the U.S. about 60% of vehicles are driven less than 50 km daily, and about 85% are driven less than 100 km [2].

Important advantages of PEVs are their efficient operation with up to three times over conventional ICE vehicles as shown in Table 1 and relatively low cost electric motor with a very low noise. At typical retail electricity price, the fuel cost per kilometer for PEVs can be far below that of ICE vehicles. Based on U.S. average of \$/kWh 0.11, a full charging of Nissan Leaf will cost about \$ 2.75 compared to \$/gallon 3.7 gasoline price. It could be even less if Time-of-Use (TOU) rates are available and owners charge at off-peak hours. The benefits increase directly with increased electric range [11, 12].

Table 1. Efficiency comparison based on average vehicles

	Efficiency (%)	CO ₂ Emission (g/km)	km/L
ICE-Gasoline	12-15	216	10.9
ICE- Diesel	15-20	194	13.8
HEV	18-30	127	18.5
PHEV	18-44	83	35
EV	60-90	zero / 40-60 (Conversion production)	128

On the other hand, electric power system and automobile fleet can be quite complementary. The electric grid has high capital cost and low production costs. When it comes to vehicle fleet, it is other way around. Electric generators are in use 57% of the time while automobiles only 4% time of the day (and in rest of the time, parked at homes and offices) [13]. The electric grid has no storage while the PEVs are introduced as an energy buffer used to store excess energy produced at off-peak hours. Concurrently, they can potentially benefit the consumers by offering cheaper charging while facilitating a higher share of renewable energy sources in the power system. Unlike transportation sector, the fuel type in electric power sector is much more diverse. The average price of electricity is stable. Moreover, the network is fully built up through the country. Because of these features and their continuous development, PEVs are seen as one of the most promising ways to improve the sustainability of the transportation and energy sectors [14].

Lack of charging infrastructures and high vehicle price are the main drawbacks of the PEVs today. Low volume production and battery technology which are still undergoing R&D are the main reasons for PEV high price. Moreover, the batteries have low energy and power densities compared to liquid fuels. It is possible to meet the driving requirement for one day or more with a fully charged 16 kWh battery of Chevy Volt or 24 kWh battery of Nissan Leaf but combined with the lack of infrastructure, the restrictions on the driving range seems to be a barrier for common use of PEVs. The recent MEC Intelligence report [15] which highlights the implications and opportunities for PEV in light of Danish test fleet indicates that charging time and driving range are among the most important factors influencing the purchase decision.

1.2 Vehicle-to-Grid

The mechanism of interaction between vehicles and grid, also known as Vehicle-to-Grid (V2G), is one of the key features of Smart Grid in future. V2G is the concept of having intelligent control over PEV battery power flow. PEVs are mobile distributed storage that can act as both a controllable load and source of energy. When prices are low, or there is excess power in the system, the PEVs will charge and if prices are sufficiently high, or the system is in need of power, then they will discharge. In this way, the idle battery is used to provide services to the grid [16].

The electricity market clearing price (MCP) is commonly known as the spot price. The spot electricity market is actually a day-ahead market since the independent system operator (ISO) / regional transmission organization (RTO) needs advanced notice to verify that the schedule is feasible and lies within transmission constraints. For very short time horizons before delivery the ISO/RTO operates the so-called balancing (or real-time) market. The ISO/RTO needs to be able to call in extra production at very short notice, since the deviations in supply and demand from spot or long-term contracts must be corrected in a matter of minutes or even seconds to ensure physical delivery and to keep the system in balance. Spot and balancing markets serve different purposes and are complementary. The balancing market is not the only technical market. To minimize reaction time in case of deviations in supply and demand the system operator runs the ancillary services which typically includes the up and down regulation service, the spinning and non-spinning reserve services, the responsive reserve service, black start and reactive services [17].

Use of storage to perform ancillary services in place of central generation has gotten a lot of attention in the power industry. Reference [18] explored the use of energy storage for fast regulation. The study used dynamic simulations of CAISO, NYISO, and PJM including automatic generation control (AGC) and real time markets to determine the effects of using storage for regulation. The CAISO issued a white paper in May of 2008 discussing the integration of storage technologies into the grid [19]. The paper studied the interconnection of storage assets at various levels of the power system in terms of present interconnection requirements, services they could provide, and asset ownership.

The potential of PEV fleet to provide electric power is substantial. 25% PEV penetration level of the LDVs in U.S. will have more generation power than the electric generation system with a power price comparable with peak load prices [14]. PEVs will not generate bulk power which is limited by their technical characteristics. Calculated per kWh cost of energy from vehicles is also higher than bulk electricity from centralized generators. The role as an energy buffer, predominantly used for delayed charging can be used for ancillary service markets to help grid stabilization at critical periods, e.g. by providing near instant up and down regulation. Negative/down regulation is when power is absorbed from the grid and charged into the battery and positive/up regulation is when power is withdrawn from the vehicle and supplied to the grid in a controlled manner at certain times.

Studies show that PEVs are most competitive within the low energy demanding services such as reserve and regulation and less competitive in more energy demanding markets such as providing peak power [20]. Besides, their response time is in order of milliseconds which is well suited to provide some ancillary services. Fleet of PEVs is able to respond more quickly to load reference set point changes than large generators [14]. It is acknowledged that in different countries and markets, different ancillary services can obtain the greatest benefits which require different levels of equipment and control. In [21] services that are less certain in their feasibility have been identified. In most of the studies greatest benefits can be obtained in the regulation power market because the duration of supply is short (order of minutes) and it is the highest priced ancillary service on the market. This offers greater financial return for vehicle owners. The deployment of PEVs for regulation service may not necessarily involve the supply of energy but simply the use of the capacity they provide as the pricing mechanism of regulation is based on the available power capacity, not the generation cost. Besides, it minimally stresses the vehicle power storage system. There are also several possibilities for PEVs to contribute to load management at the system level [22].

Furthermore, with the intense focus on climate challenges, renewable energy becomes an important tool for reducing emissions from fossil fuels. In Denmark, the government has set the target of 50% wind power in the electricity system by 2020. When wind power capacity is expanded, more regulating power will likely be needed due to the limited or imperfect predictability of wind power. Reference [23] describes the structure of prognoses error in wind power forecasts. It was found that the largest errors occur when medium wind speeds are expected. More wind power is expected to increase the need for regulating power, and thus, more focus will be in the regulating power market.

If small consumption, as in the case of PEVs, should be activated in the regulating power market, then the preconditions involving the minimum bid size and the requirement of real time measurement should be carefully investigated. In May of 2010, the Danish TSO, Energinet.dk, with that purpose in mind, introduced draft thoughts of how small consumption units can be activated in the regulating power market. They suggest publishing a regulating price in the hour of operation to be used only for small consumption. The published price will be the price of the last taken bid from the bidding list (from the more

individual PEVs to participate in the current regulating power market [26]. Furthermore, there are some challenges in connection with imbalances related to PEVs in the regulating market, since regulating power from PEVs work fundamentally different from other sources as there is no fuel input and only energy storage. Providing down regulation would normally result in a plant lowering production, whereas the PEVs will start charging more or discharge less. Since the PEVs will also have to supply the needed driving consumption, their deviation from the original plan of charging/discharging would be limited which is more evident when providing up regulation. A power plant providing up regulation will use some extra fuel, but the PEVs will need to discharge more energy to provide up regulation. The energy used for up regulating should either be in excess or should be recharged before reuse. Therefore, the recharging will affect the charging pattern and also the ability to provide regulating power. Introducing a fleet operator to aggregate the consumption of a number of PEVs and handle their interaction with the electricity market as one unit can solve these challenges.

Several organizations are guiding the development of communications standards and standards necessary for PEV connection to the grid. In addition the University of Delaware (UD) and the University of Michigan currently have V2G research programs in place. The program at UD has focused primarily on determining the economic payback that may be possible when using PEV to supply ancillary services. In 2008 UD studied the use of V2G as a regulation resource which can be dispatched by PJM [27]. V2G provides the potential for the system operator to call on the vehicle as a distributed energy resource. Therefore, it is important to review standards for interconnection of distributed resources with electric power system like IEEE Std 1547™.

To evaluate the potential of V2G operation mode, there are several issues which need to be considered:

- Resource aggregation techniques
- Load aggregation techniques
- Intelligent system availability for smart charging
- Whether advent of PEVs will affect daily travel pattern and lifestyles
- V2G operation be convenient enough for owners (No extra trouble or cost)
- Economic incentives for owners

- The better the driving pattern is known, the more V2G services can be available
- Battery loss consideration
- Wear on batteries for additional discharging (dependent on charging rate and SOC)

The ultimate goals of V2G are: (1) Enhance the reliability and efficiency of existing electric grid by load shifting methods (peak shaving, valley filling, load smoothing). V2G cars can reduce over loaded distribution feeders and congestion costs when energy demands are high by acting as spinning reserves or meeting load demand locally, (2) Provide regulation power and reduce the cost of supplying ancillary services at critical hours in the power system with high level penetration of renewable generation resources, and (3) provide electrical storage to encourage adoption of distributed and intermittent power generation such as wind power.

V2G is technically a feasible option to balance electricity. Research shows that there exists a significant return on investment in PEVs that can perform ancillary grid services which further encourage their adoption [27-31]. Although feeding back electricity to the grid is not found to be promising options due to the costs in terms of battery degradation [29, 32], most publications agree that V2G is underway and the technique to control battery power flow can make PEVs a valuable distributed asset for future power system.

1.3 Singapore's PEV Test-bed Project

Singapore embarked on a national PEV test-bedding programme. The programme was launched in May 2009 to provide an open platform for all auto manufacturers and technology companies to examine the infrastructure requirements of an PEV system, to test the performance of PEVs under local road conditions and in the tropical environment, and to identify related industry and R&D opportunities. A total of S\$20 million has been set aside for this programme to support infrastructure development and test-bed EVs. This test-bed will run for five years, starting from 2010 and will be driven by a multiagency Taskforce, co-chaired by the Energy Market Authority (EMA) and the Land Transport Authority (LTA). PEV Test-Bed was set up to evaluate 4 key issues:

1. PEVs could potentially become a huge market, potentially reshaping the automotive supply chain. Singapore has the capability to succeed in sizeable niches mainly in R&D and services.

2. Evaluate sustainability of the EVs for fleet and private use in terms of range, capabilities, required infrastructures and economics.
3. Measure impact on Singapore in terms of pollution reduction (including additional electricity required) and benefits (Gencos earnings, R&D capabilities, industry development, skills, carbon tax savings) vs. costs (infrastructures, inefficiencies).
4. Test PEV charging system adapted to Singapore context, including back end settlement mechanisms for the payment and obtain data on usage patterns and infrastructures to make recommendations on deployment.

Compact urban environment and short average driving distances make Singapore an ideal place to launch such a test-bed [33]. Average passenger vehicle mileage estimated to be less than 55 km per day which is well within the typical driving range of a fully charged PEV. Robust power grid and ICT networks make it a perfect location to deploy charging infrastructure to support PEVs easily.

EMA is also interested in the concept of V2G power to allow PEVs draw power from the grid during off-peak periods and sell power to the grid during peak periods. This will make load leveling possible and allow for a more efficient operation of the power system [34]. For a start, the charging stations will cater to the first batch of Mitsubishi i-MiEVs being brought in for the test-bed. Bosch has been appointed the first Charging Service Provider (CSP) for Singapore's PEV test-bed. It will design, develop, deploy, operate and maintain up to 60 normal charging stations and quick charging stations by the end of 2011. The normal charging stations will comprise both outdoor models manufactured by Bosch and indoor models supplied by Bosch's subcontractor Green lots. Most PEV users will rely on "normal charging", which will take about 7-8 hours for a full charge. The normal charging stations will be distributed on a 1:1 ratio to be sited either near the users' home or office location. For certain users such as taxi fleets, faster charging options will be required. Two types of charging_infrastructure have been suggested to deploy in Singapore: normal and quick charging.

The current test-bed is essential to gain real-life experience and build credibility in the PEV space and will have to be carefully designed to test key assumptions: vehicles operability, cost, charging infrastructure requirements, suitability of the business model,

driving experience and barriers to adoption. The main challenge in getting the test-bed going is in getting users to take up PEVs when the price of PEVs is currently much higher than their equivalent ICEs. For purposes of the test-bed, the Taskforce is trying to bring down the cost of PEVs. The first batch of PEVs will be essential in understanding consumers' acceptance of Singapore, the level of penetration of PEVs at current and proposed level of incentives as well as the level of infrastructure deployment required to meet the expected demand from PEVs in the coming years [4].

1.4 Motivation and Objectives

The integration of PEVs presents many unique opportunities and challenges in power grid operations. Currently, standard and academic organizations are collaborating on PEV infrastructure plan to facilitate the interconnection of these new sources along with transmission and distribution system improvements and consumer services. Addition of a two-way communications system from the control center to every part of the power grid allows assets at certain levels of the system to be monitored and controlled. In addition, digital electronics and distributed processors enable large-scale computational capabilities throughout the system leading to a smart grid.

Transitioning to a smart grid provides increased opportunities for advanced communications, automation, and intelligent appliance control. These will enable increased efficiency throughout the system and better integration of distributed energy resources (DER) with the goals of a more secure, intelligent, and sustainable system. The capability for two-way energy flow and two-way communications between PEVs and the grid known as V2G is one of the features that can be achieved in a smart grid environment. Furthermore, Researchers have proposed that distributed energy storage devices could be used to perform ancillary services for the power grid and accrue revenue.

PEVs are realistic starting point for the distributed energy storage discussion in today's power system due to their near-term large scale deployment. Using characteristics of PEV currently being developed allows considering practical constraints. These results can be readily extended to any type of storage. In light of the fact that specific standards for communications and interconnection will continue to develop and evolve, it is assumed that price-based controlled charging of the vehicle are available and dynamic pricing scheme is

fully functional. The 2009 U.S. NHTS transportation dataset are utilized to obtain important parameters like aggregated energy consumption, share of parked cars and plug accessibility to solve the optimization problems throughout the report.

This study aims to address topics relating to PEV charging load demand and their operation as distributed energy storage which can provide ancillary services.

The problem has been studied with the following in mind:

- In chapter 3 the attempt is to study system-wide effects of PEVs. Therefore, it is particularly useful for systems operating in an islanding mode like Micro Grids.
- Two-settlement market structure (day-ahead and real-time power market) has been considered in this study. PEVs are assumed to be price takers i.e., their interaction with the grid will not change the market price.
- User incentives are provided and potential customers are fully motivated to interact with the system.
- It is assumed that V2G capable cars are available and two-way power flow will be handled. It is beyond the scope of this thesis to study the impacts of the additional power flows in the system. The location of charging or supplying power in the grid is not considered or if that could cause local problems with congestion etc.
- This study will focus on the reserve and regulation services provided by PEVs and estimate energy available for system services from PEVs. Considering Data from Heffner's international survey of loads providing ancillary services [35] indicates that 50% of PJM's operating reserves derived from regulation and instantaneous spinning reserves and that 75% of ERCOT's operating reserves derived from regulation and spinning reserves.

1.5 Contributions

The main contributions of this work can be summarized as follows:

1. New models, namely copula theory is presented for the multivariate modelling of dependent random variable to model the uncertainty nature of PEVs to analyze demand characteristics of PEV charging.

2. Charging and discharging pattern of PEVs is optimized based on day-ahead price variation which shows the reserve capacity of PEV integration.
3. Using a stochastic model, a two-settlement market and fleet aggregator behavior has presented and showed that the problem of determining optimal contract offering for an aggregator can be solved using convex programming and coherent approaches to risk in optimization under uncertainty.
4. Optimal PEV aggregator scheduling strategies is formulated as a stochastic programming problem with recourse, which, in addition, includes the modelling of the risk aversion using the Conditional Value-at-Risk (CVaR). The formulation is a linear program so optimality is assured.

1.6 Organization of the thesis

This study contains six chapters. After the introduction, Chapter two reviews basic components of PEV infrastructures. In chapter three, a probabilistic approach is used to find the appropriate amount of load which will contribute to bulk system based on realistic PEV movement data. Chapter four characterizes the aggregate PEV power potential based on limits on charge rates and customer behavior. Chapter five contains analytical analysis of optimal contract offering for an aggregator and simulations on stochastic bidding strategy with coherent approaches to risk while chapter six includes the conclusion of the study and the suggested future works.

Chapter 2. PEV Infrastructure

PEV infrastructure is defined as structures, machinery, and equipment necessary and integral to support a PEV. It consists of energy storage, charger(on-board or off-board), EV supply equipment, advanced meters, local network, parking lots, communication architecture, information technology, aggregation algorithm, distributed generation/storage and renewable generation. Infrastructure must meet or exceed any applicable standards, codes, and regulations.

2.1 Battery Storage System (BSS)

A summary to the terminology that are generally used to describe, classify, and compare batteries is provided in the following [36].

State of Charge (SOC) (%) – An expression of the present battery capacity as a percentage of maximum capacity. SOC is generally calculated using current integration to determine the change in battery capacity over time.

Depth of Discharge (DOD) (%) – The percentage of battery capacity that has been discharged expressed as a percentage of maximum capacity. A discharge to at least 80 % DOD is referred to as a deep discharge.

C- and E- rates – In describing batteries, charge current is often expressed as a C-rate in order to normalize against battery capacity, which is often very different between batteries. A C-rate is a measure of the rate at which a battery is charged relative to its maximum capacity. A 1C rate means that the charge current will charge the entire battery in 1 hour. For a battery with a capacity of 100 Amp-hrs, this equates to a charge current of 100 Amps. A 5C rate for this battery would be 500 amps, and a C/2 rate would be 50 Amps. Similarly, an E-rate describes the charge power. A 1E rate is the charge power to charge the entire battery in 1 hour.

Capacity or Nominal Capacity (Ah for a specific C-rate) – The coulometric capacity, the total Amp-hours available when the battery is discharged at a certain discharge current (specified as a C-rate) from 100% state-of-charge to the cut-off voltage. Capacity is

calculated by multiplying the discharge current (in Amps) by the discharge time (in hours) and decreases with increasing C-rate.

Energy or Nominal Energy (Wh (for a specific C-rate)) – The “energy capacity” of the battery, the total Watt-hours available when the battery is discharged at a certain discharge current (specified as a C-rate) from 100% state-of-charge to the cut-off voltage. Energy is calculated by multiplying the discharge power (in Watts) by the discharge time (in hours). Like capacity, energy decreases with increasing C-rate.

Cycle Life (number for a specific DOD) – The number of discharge-charge cycles the battery can experience before it fails to meet specific performance criteria. Cycle life is estimated for specific charge and discharge conditions. The actual operating life of the battery is affected by the rate and depth of cycles and by other conditions such as temperature and humidity. The higher the DOD, the lower the cycle life will be.

Specific Energy (Wh/kg) – The nominal battery energy per unit mass, sometimes referred to as the gravimetric energy density. Specific energy is a characteristic of the battery chemistry and packaging. Along with the energy consumption of the vehicle, it determines the battery weight required to achieve a given electric range.

Specific Power (W/kg) – The maximum available power per unit mass. Specific power is a characteristic of the battery chemistry and packaging. It determines the battery weight required to achieve a given performance target.

Energy Density (Wh/L) – The nominal battery energy per unit volume, sometimes referred to as the volumetric energy density. Specific energy is a characteristic of the battery chemistry and packaging. Along with the energy consumption of the vehicle, it determines the battery size required to achieve a given electric range.

Power Density (W/L) – The maximum available power per unit volume. Specific power is a characteristic of the battery chemistry and packaging. It determines the battery size required to achieve a given performance target.

The energy requirements per mile for selected light duty vehicle classes adopted from Electric Power Research Institute’s (EPRI’s) Hybrid Electric Working Group [37] are listed in Tables 2 and 3.

Table 2. Energy requirements per mile

Vehicle class	Specific Energy Requirements [kWh/mile]	Size of Battery for PHEV33 [kWh]
Compact sedan	0.26	8.6
Mid-size sedan	0.30	9.9
Mid-size SUV	0.38	12.5
Full-size SUV	0.46	15.2

Table 3. EV & PHEV battery requirements (for high efficiency medium-size cars)

Vehicle Type	Specific Energy(Wh/kg)	Specific Power(W/kg)	Deep Cycle Life (80% ΔSOC)	Shallow Cycle Life (+/- 50Wh)	Specific Cost (\$)
EV	> 100-120	> 300-400	> 1000-1500	>300000	<100-150
PHEV	> 60-30	> 400-800	> 2000-3000	>300000	<200-400
<p>For vehicles of comparable weight, performance and cost.</p> <p>High efficiency : 4 miles/kWh.</p> <p>First number in range applies to 60 miles and second to 20 miles all electric range (AER).</p>					

PEV requires greater energy density than current hybrid batteries, medium-to-high power density and maximum possible deep cycle life. Energy density is usually the defining characteristic of BSS and life cycle cost significantly influenced by battery durability. The main trade-off in battery development is between power and energy: batteries can be either high-power or high-energy. Most attention has been given to Nickel Metal Hydride (NiMH) and Lithium-ion (Li-ion) chemistries. As it is clear from Figure 3 among battery technologies, Li-ion have a clear edge over others when optimized for both energy and power density and it is likely energy storage candidate for near-term vehicle. These batteries are lightweight and powerful when compared to others and with the right charger are capable of recharging in approximately 10 min to 95% of full capacity [38].

Figure 3. Specific energy and specific power of different battery types adopted from [2]

Usually Li-ion batteries should have charge rates lower than 1C especially to prolong battery lifetime. As it is obvious from Figure 4 the charge rate is not constant and depends on the SOC. But the point is for vehicle-grid interaction, the connection will be the limitation rather than the battery specifications. Therefore, it is assumed that the battery charge rate is 0.5 C. In fact, setting this value higher will give a more realistic estimate of the V2G services. Furthermore, it is assumed that maximum charge and discharge rates are the same.

Figure 4. Typical Li-ion charging characteristics [39]

As mentioned earlier the biggest problem nowadays in PEV industry is battery cost and performance. Energy storage is an enabler of electrification of transportation. According to a 2010 study by the U.S. National Research Council, currently the cost of a lithium-ion battery pack is about USD 1,700/kWh of usable energy. Based on Table 2 it requires about 0.3 kWh/mile. The manufacturer cost of the battery pack for a PHEV-20 is more than \$10,200 and it can go up to \$30,600 for a PHEV-60. However, with technology improvement, it is believed that the cost could drop to as little as \$420 per kWh by 2015 with better performance. Additionally, LDVs have an average vehicle life of 15 years, as opposed to 28 years for heavy duty vehicle. It should be noted that the battery wear cost is not included in ancillary service provision in this study. Since many factors affect battery cycling ability such as DOD, charge/discharge rate, temperature and humidity, estimation of average cycling ability is very difficult and is beyond the scope of this study.

2.2 Charging Levels

Currently, the charging levels in the United States are governed by a specification published by the Society of Automotive Engineers (SAE), a standards development organization that is responsible for the engineering of powered vehicles of all kinds, including cars, trucks, boats, aircraft, and others. The specification, entitled J1772, defines levels of charging as well as the interface between the vehicle and the electric vehicle supply equipment [40].

AC level 1 uses a standard 120V, single phase power, comes with 15A of branch circuit breaker rating and 12A of continuous maximum current or 20A of branch circuit breaker rating and 16A of continuous maximum current. This method uses the lowest common voltage level which can be found both in residential and commercial buildings, allows a PEV to be connected to the traditional home plug. Because only a small amount of power can be provided as for AC level 1 charging (maximum of 1.44/1.92 kW), the charging time can extend up to 8- 15 hours depending on the size of the battery. AC level 1 is an entry level voltage charging during the introduction of battery electric vehicles and not the ultimate charging solution. The importance of this charging level is due to the availability of 120 VAC outlets, charging is still accessible during emergency situations. In most typical configuration, the AC level 1 charger is installed on the vehicle and the 120V power is

brought through a plug and cord set. Although Level 1 appears to be very popular, a new dedicated 15 or 20A circuit is highly recommended to supply the PHEV charging demand. The new circuit will provide overload protection while preventing future charging disturbances from other household appliances connected in series upstream. Many household circuits have multiple outlets in series served by a single breaker, which appears to be a common problem when Level 1 charging is exercised.

AC level 2 specifies 240V, single-phase power, and charging current of 12A up to 80A. The voltage it applied can be found in many homes for electric clothes driers, electric ovens, or pool pumps. Thus, AC level 2 is considered as the preferred option for a PEV charger at home. Because AC level 2 works on a higher voltage, a dedicated electric vehicle supply equipment to provide a high level of safety is required. Although the maximum current for AC level 2 is 80 A, most vehicles are being designed to accept a Level 2 charge at no more than 30 A, due to the smaller on-board charging system in the car. The on-board charger in the vehicle converts power from 120V or 240V AC to the DC voltage that actually controls the charging rate. This limits the level 2 charging a maximum power of 7.2kW. SAE establishes the standard connector for AC level 2 in SAE J1772 in January 14, 2010. It specifies five pins; The function of each pin of the connector are: 2 pins for AC power (line 1 and line 2), 1 pin for ground, 1 pin for signals related to the amount of current allowed for the particular vehicle model being charged (control pilot), and 1 pin for preventing the car from being moved while charging is under way (proximity detection).

AC level 3 is known as the 'fast charging' option. This method will be used for commercial and public applications. Level 3 charging uses an off-board charging system, which is powered by a three phase 480VAC circuit. The equipment sizes range from 60kW to 150kW and is believed to provide an approximate 50% charge within 10-15 minutes.

Conclusively, each charging level has its own designated utilization: level 1 charging is merely for emergency situations; level 2 is the solution to hour-lasting overnight home charging; the fast level 3 charging is designed for public charging.

DC fast charging is designated to have the similar performance as a commercial gasoline filling station. It requires very high levels of voltage and current, thus bring a very high speed of charging. There are many challenges regarding DC fast charging such as reliability,

losses, thermal management and high switching frequency but the main concern is about the load handling capability. The fast charging will also have an off board charger system, but it should be supply a DC current directly feeding to the PEV high voltage battery bus. Actual charge rate is limited by battery chemistry, infrastructure and some other factors.

Table 4. Summary of different charging levels based on SAE J1772 Standard

Classification	AC Level 1	AC Level 2	AC Level 3
Nominal Supply Voltage	120 V AC	208 or 240 V AC	208 - 600 V AC
Phases	1-phase	1-phase or 3-phase	3-phase
Branch Circuit Breaker Rating	15 A	40 A	As required
Maximum Continuous Current	12 A	32 A	As required
Maximum Power Rating	1.4 kW	7.7 kW	25-160 kW
Charger Location (AC/DC Converter)	On-board	On-board	Off-board
Energy Supply/Interface	Charge coupler to NEMA 5-15R grounded receptacle	Dedicated Electric Vehicle Supply Equipment (EVSE)	Dedicated EVSE
Energy Supply Location	Home or any appropriate electrical outlet	Private or public	Private or public

2.3 Types of Charging

Based on the research carried out by Frost & Sullivan to analyze the growth potential of PEV charging infrastructure in the total European market [41], cumulative number of various charging level points expected to be in the range of 1.9 to 2 million by 2017. Home charging and fast charging captures around 97% of charging infrastructure in 2017. Home charging with semi-public will cater to bulk of the charging requirements. DC fast charging will mostly fulfill the requirement of extended range vehicles. In general, four different infrastructures according to the type of charging can be defined:

2.3.1 Fast charging

Long duration (3-8 hours) required to charge PEV batteries with the level 1 and 2 charging along with mass production of PEVs capable of traveling longer distances, results in a need for electric service stations that can satisfy the requirements for a significant

amount of power provided in time duration similar to that of filling a conventional ICE-based car. Fast charging stations are capable of reducing the charging time to 10-15 minutes [42]. Public charging options are needed to add more flexibility, better fuel economy as well as to increase consumer confidence. The U.S. Department of Energy's grant to companies to deploy public charging site in several regions shows the importance of the situation. Fast charging units are like fuelling stations we know today but instead of petroleum, vehicles will be fuelled by a high power connection to the grid. Moreover, fast charging has flexibility with usage locations. It should be noted that the charging station must have its own electrical transformer for distribution line to supply the massive energy demand from the fast charging PEVs.

2.3.2 Distributed charging

In future when PEVs represent a substantial percentage of personal cars on the roads- the electricity demand and consumption will rise accordingly, wide access to charging stations will play a critical role in surpassing the need for sudden change in PEV charging load profile. Besides, charging stations are relatively expensive to implement which restricts mass penetration of PEVs and are not capable of providing ancillary services. This justifies the distributed charging infrastructure concept which enables vehicles to be plugged-in at all times when parked.

Distributed charging stations divided in two main groups: home and outdoor public applications like workplaces, retailers, municipalities and parking services. These charging stations deliver controlled power to effectively charge electric vehicles. All stations should be network-enabled, capable of reporting energy usage in addition to [43]:

- Providing open access for all drivers using any standards based card
- Generating revenue to offset electricity, capital equipment and maintenance costs
- Sending SMS or email notifications to the driver for charging complete or interruptions in charging
- Controlling access to eliminate energy theft and to enhance safety
- Integrating with the utility Smart Grid for demand side management and preferred pricing

The main advantage is that the implementation of this infrastructure requires minimal changes in the current power grid and it does not need any significant initial investment.

2.3.3 Battery swapping

In battery swapping station the vehicle owner will get a fully charged battery as replacement for the battery in the vehicle, when it is in need of charging. This means that the owner probably will not own the battery in the PEV, since it is exchanged often. Extensive standardization is needed to make the battery swapping infrastructure common for all vehicles i.e., all PEVs can have the battery swapped at the same station, but on the other hand battery swapping stations have the potential to decouple battery costs from vehicle purchase costs; thus, enable PEVs to be sold at more competitive prices in the market.

2.3.4 Inductive charging

In inductive energy transmission or wireless charging, the station is connected to the grid with a primary coil that resides underground. A secondary coil attached to the car receives an electric current induced by the magnetic field caused by the primary coil and the current would recharge the battery. An example is the Korean “On-Line Electric Vehicle (OLEV)” project. Vehicle gets its energy from cables underneath the surface of the road by magnetic induction. Well-known companies like Qualcomm, Siemens and BMW currently conducting researches and trials to prove the applicability of this concept. Considering losses in the inductive charging, the advantage is having smaller batteries and lighter vehicles.

2.4 PEV Standards

Currently available standards regarding PEVs deployment and integration that can be divided to four parts:

- Device Standards
- Installation Standards
- Communication Standards
- Interconnection Standards : Currently IEEE Std 1547™ Standard for Distributed Resources Interconnected with Electric Power Systems is being developed by Standards Coordinating Committee 21 on Fuel Cells, Photovoltaic, Dispersed Generation, and Energy.

This standard provides technical and testing requirements for the interconnection of distributed resources with an aggregate capacity of 10 MVA or less. Charging infrastructure specifications and features are summarized in Table 1 in appendix A which adapted from [41].

2.5 Charging Control

Similar daily pattern of energy consumption puts a lot of strain on the electrical grid at certain peak hours. Moreover, during off-peak hours generating units (running at minimum capacity) sometimes have to sell off excess energy with a profit loss. The difficulty arises because the charging load of PEVs and the potential capacity depend completely on the usage pattern. These functions will also depend on the actual infrastructure developed. Significant penetration of PEVs is likely to play a major role in the power grid soon and introduces two important issues:

1. PEV charging profile prediction based on vehicle usage data
2. PEV battery capacities utilization to support the power grid.

As will show in the following, the aggregated PEV battery has large energy storage capacity. This combined capacity can have both negative and positive effects on the electric grid. Negative effects rise when PEVs start charging during peak hours which cause tension on the grid as well as leading to higher energy prices. It is foreseen that if charging cars occurs in an uncontrolled manner, even overnight, it will cause the transformer station to overload [44]. In addition, serving as a buffer or a source of energy (V2G operation), increase the volatility in the power distribution network. Therefore, they require a significant change in the management of the electricity generation and consumption. Non-intelligent charging will not utilize the storing capacity of the batteries and will add on to peak loads and increase pressure on the electric grid. PJM/Better Place study finds unmanaged charging of 1 million electric cars could add \$750M in annual wholesale energy costs [45]. Intelligent power grid management (Smart Grid) like one that is depicted in Figure 5 is necessary if the PEVs are supposed to have a positive effect on the power system and to manage power distribution for charging and discharging. This scenario could potentially even out the energy consumption curve, leading to better prices, lower losses and resource utilization improvements.

Figure 5. Smart integration of PEV into the Power Grid

Reduced rates help improve vehicle performance in terms of operating cost. The intelligent charging requires some level of communication with the system and this communication opens possibilities for further interactions with the power system, in which the PEVs also supply power to the grid [46-49].

The most prevalent strategies currently being pursued to implement intelligent charging are labeled as delayed charging, valley filling, critical peak pricing, Time-of-Use (TOU) rates, real-time price charging, and Fleet Aggregator (FA) based charging. Four different dominant charging scenarios can be defined based on [50,51]:

- ***Uncontrolled Charging:*** Plug in and charge
- ***Delayed Charging:*** The starting time of charging is shifted from peak load hours by a timer
- ***Price Based Charging:*** Each individual PEV owner receives a price signal and he/she governs the vehicle charging and is responsible to ensure sufficient charge to cover driving needs.
- ***Direct Charging Control:*** Aggregator is capable of bundling PEVs and selling services to the grid and responsible to ensure sufficient charge at a specified time.

Chapter 3. PEV Charging Load Profile

3.1 Literature Review

Recently, the study of PEVs in a power system framework has been an active research topic. Due to the expected high penetration of PEVs in near future, it is important to estimate the load they impose on the electrical grid. Several studies during last few years investigated this topic at both national and regional scales [47, 48, 52, 53]. They usually represent situations unlikely to occur. In [47] all PEVs begin charging simultaneously at 5 p.m. or 10 p.m. In [54], off-peak electricity is consumed by the entire vehicle fleet. In uncontrolled charging scenario of [54] all vehicles leave home evenly between 8 and 9 a.m. and return home between 6 and 9 p.m. The electric energy consumption is often estimated without considering vehicle travel patterns. For example in [46, 47, 53, 54] all vehicles return home with the entire usable energy exhausted which leads to an overestimation of energy consumption. It is assumed in [50] that charging start time and initial SOC are random variables and probability distribution of daily distance driven follows a normal distribution.

In 2006 a study [46] showed that the U.S. national power grid has the technical potential to support charging of 73% of LDVs. Therefore, sufficient generating capacity exists to charge large number of PEVs in the near future. However, it should recognize that PEVs are usually connected to local residential areas which are often heavily loaded. Therefore, reliable models for the behavior of electric vehicle are needed. In [64] a probabilistic constrained load flow is proposed considering both wind power generation and electric vehicles. In [88] and [89] the impact of charging electric vehicles in the distribution grid is analyzed. The power consumption of electric vehicles is estimated in [90]. In [91], two different algorithms are proposed to control the charge of electric vehicles in deregulated electricity markets. Reference [92] presents a mid-term operation model to analyze the impact of PEVs in the Spanish power system. The recent paper [93] presents a robust optimization model to analyze the effect of including vehicle-to-grid facilities in small electric energy systems.

In fact, the power demand of PEV charging load depend on the number of vehicles, initial SOC, charging start time and its duration that will always have an element of randomness

but, first of all, the parameters and general pattern related to mobility behavior of vehicles can be extracted from traffic habits.

3.2 Transportation Dataset

The most comprehensive reference for transportation data is the National Household Travel Survey (NHTS) sponsored by the US Department of Transportation [55]. The NHTS website includes detailed transportation data from 1995 to 2009. The NHTS provides information to assist transportation planners and others who need comprehensive data on travel and transportation patterns in the United States. Few papers like [56] have used the travel patterns in the U.S. obtained from NHTS. This study also utilizes the NHTS data set for probabilistic modeling of PEVs charging load. It is assumed that the advent of PEVs will not affect daily travel pattern and lifestyles in general; therefore, the driving behaviour of PEV owners will remain similar to the behaviour of drivers of conventional vehicles. With these assumptions the parameters introduced will be valid for real-world travel patterns. The 2009 NHTS dataset contains data for 294,408 light-duty vehicles and 150,147 completed households in which at least 50% of the adults (age 18+) were interviewed. It consists of four large databases including household, person, vehicle and daily (travel day) trip level data. The 2009 NHTS was carried out by telephone interviews, and sampling was based on random digit dialing list of telephone numbers. This large pool of data is geographically distributed across the U.S. and reflect daily trip in a 24-hour period. For the purpose of PEV studies, this paper primarily considered data related to vehicle and daily trips. Therefore, two MS Excel files of the 2009 NHTS: VEHV2PUB and DAYV2PUB are utilized to extract useful information. 2009 NHTS codebook defines the attributes in all four datasets. Each household, person and vehicle in the 2009 NHTS has a unique ID number. These IDs are appropriate for linking any two data files [57].

Vehicle trips in District of Columbia and the 13 eastern states of U.S. which are covered by PJM Interconnection have been considered. Those who reported no day travel trip are eliminated. Thus, the relevant data sets of the 2009 NHTS are filtered out for this study from a large number of vehicle trips (more than 260,000). As the data pool is distributed over a broad enough portion of the U.S., it can be used for developing stochastic analyses that will be explained in details in section 3.3.1.

It is possible to extract the trips in progress by time of the day and day of the week from NHTS dataset, as required. The number of trips is found to have a peak in the morning when people leave their home and another peak in the afternoon which is mainly representative of education related trips and getting-back home trips. The latter is found to be more spread out than the morning peak. The average proportion of parked cars for weekdays and weekends can be obtained from this procedure, which is shown in Figure 6. The share of parked cars seems very high in general. High share of parked cars comes because many vehicles do not drive at all during a day. About 12 percent of the 60,282 persons in useable households in the 2009 NHTS reported no day travel trips [57].

Figure 6. Average proportion of parked cars

3.3 Stochastic Model for PEV Demand

Until the time that we have an active control over the period at which each vehicle starts to charge its battery, it is assumed that only the uncontrolled domestic charging scenario is available, i.e., charging starts at the moment when the PEVs plugged in as they get back home. Suppose that required infrastructure for grid connection is available.

Mobility model which pictures the driving and parking behaviour of private cars is defined alongside the time axis of weekday. The departure time, arrival time and trip distance for a set of trips are randomly generated based on the NHTS data which will be explained in

the following. The time step was set to one hour according to the discretization of the mobility patterns.

PEVs are modeled as customers arriving in a queue to receive energy [58]. To model the dynamics of the population; $M_t/G/\infty$ queue was used which has a non-homogeneous Poisson arrival process with deterministic time-dependent arrival-rate function λ (assuming that the arrival rate equals the departure rate), and service times that are independent of arrival process, and infinitely many servers. Poisson arrivals mean that the arrival time of one PEV carries no information of the arrival times of other PEVs. Having infinitely many servers means that PEVs do not interfere with each other which are correct and reasonable assumptions under the scenario of uncontrolled domestic charging.

3.3.1 Dependence Structure via Copula Approach

In most power system statistical studies, joint normal distribution is used to model dependency between normally distributed RVs but in some cases the marginal distribution of RVs do not have necessarily normal distribution. In order to model dependency of correlated non-normal distributions we should utilize a general method to find stochastic dependency of RVs. The mathematical function named copulas can be adopted to model the stochastic dependency of two measured data and obtain joint probability distribution of them. Marginal distribution of RVs can be coupled (or jointed) to their multivariate distribution using copulas [59].

Copulas are functions that characterize dependencies among variables and can be used to create distributions that model correlated multivariate data. Copulas model dependency of correlated non-normal distributions by coupling multivariate distribution functions to their one-dimensional marginal. Alternatively, copulas are multivariate distribution functions whose one-dimensional marginal are uniform on the interval $[0,1]$ [60].

According to Sklar's theorem [61] for a given joint distribution function F_{XY} of two RVs X and Y with marginal distribution F_X and F_Y (i.e, CDF of X and Y respectively), there exists a function C namely a copula such that

$$F_{XY}(x, y) = C(F_X(x), F_Y(y)) \quad (3 - 1)$$

If F_X and F_Y are invertible, then for $F_X = u$ and $F_Y = v$ one can write

$$C_{UV}(u, v) = F_{XY}(F_X^{-1}(u), F_Y^{-1}(v)) \quad (3 - 2)$$

It should be noted that F_X and F_Y are CDFs of X and Y . Equation (3-2) can be used to find the joint distribution of X and Y . Copula method is used to develop a set of random variables with similar stochastic behavior of the empirical data but joint to each other with particular correlation.

Copula method couples two or more variables to produce another distribution function. To obtain the set joint random variables using copula, the level of dependency between them should be measured. The strength of the dependency between RVs can be measured using product-moment correlation or linear correlation ρ . The linear correlation in actual domain fails to measure accurate level of dependency for non-normal distribution. In order to avoid the effect of marginal distribution on dependency structure, the RVs X and Y in actual domain are transferred to their rank domain using CDF transform. The transferred RVs to rank domain retain the dependence structure of the original variables. The product moment correlation for the respective ranks is calculated.

Suppose $U = F_X(x)$ and $V = F_Y(y)$ are corresponding rank of X and Y respectively. The rank correlation ρ_r between two RVs X and Y is defined as linear correlation between respective ranks of these X, Y (i.e. U, V), so one can write:

$$\rho_r(X, Y) = \rho(F_X(X), F_Y(Y)) \quad (3 - 3)$$

Then, the measured rank correlation is used as input of copula function. The copula function is utilized to generate a set of stochastic variables in rank domain which are correlated to each other by measured rank correlation. The developed variables using copula are transformed back into their original domain by applying the inverse-CDF transformation of RVs. In the present context, Copulas will be adopted to find the joint probability of home arrival time, daily travelled distance and home departure time. In order to generate the required random samples, the aforementioned RVs are modeled by probability density functions fitted to them which will be explained in details in the following.

BESTMILE developed by Oak Ridge National Lab, gives out the best estimate of annual miles driven by each vehicle. This study calculates daily mileage by dividing *BESTMILE* by 365. Histogram of daily mileage is shown in Figure 7, where the average daily mileage

is found to be 29 km which is consistent with the formerly reported 33 km average miles driven in major U.S. metropolitan areas [21]. In practice there is always some charge left in the vehicles' batteries when they get back home which is directly related to their daily traveled distance. In order to estimate the SOC upon PEV arrival, the daily mileage data from NHTS dataset is employed, which is found to fit Weibull distribution as follows

$$f_{dmi}(d|a,b) = ba^{-b}d^{b-1}e^{-\left(\frac{d}{a}\right)^b} I_{(0,\infty)}(d) \quad (3 - 4)$$

The assessment whether the mileage data fits a Weibull distribution is conducted graphically and is depicted in Figures 8 and 9.

Figure 7. Histogram of daily mileage

Through maximum likelihood estimation [62] with confidence degree $1 - \alpha = 95\%$, Weibull distribution with $mean = 29.9273$, $Variance = 594.305$ and estimated parameter $a = 32.039$, $b = 1.23451$ is found to fit best with the data. The fit between the actual data and Weibull distribution is shown in Figure 9. In order to validate the above hypothesis, a two-sample Kolmogrov-Smirnov goodness-of-fit test (K-S test) [63] is performed to compare the distribution of the values in the two data vectors. The result accept the null hypothesis which confirms that two samples are from the same continuous distribution at the 5% significance level.

Figure 8. Probability density function of daily mileage

Figure 9. Test for Weibull distribution of daily mileage

Estimation of state of charge (SOC) when a PEV arrives is carried out as in [50]. It is assumed that the SOC of a PEV drops linearly with the distance of travel and adopt the idea of fully charged battery at $t = 0$, if a fully charged PEV drives d_{max} mile on electricity, then the residual battery charge of a vehicle after being driven d miles would be:

$$E_0 = 100. \left(1 - d/d_{max}\right) \quad (3 - 5)$$

Figure 10. Probability density distribution of initial battery SOC

The probability distribution of initial battery SOC at the end of the day is derived using the daily mileage data, and is shown in Figure 10. Obviously it follows the similar trend shown as Figure 7. Based on derived densities formula, the pdf of initial SOC is found. Suppose $d_{max} = 100$, then

$$f_{soc}(E_0) = b a^{-b} (100 - E_0)^{b-1} \exp\left(\left(\frac{E_0 - 100}{a}\right)^b\right) \quad (3 - 6)$$

Same procedure is applied to find the marginal distribution for departure and arrival time. Weibull PDF is found to be the most appropriate function to be fitted to home departure time RV. Generalized expected value pdf with shape parameter k , scale parameter σ , and location parameter μ , is fitted to the home arrival time as follows

$$f_{arr}(t) = \frac{1}{\sigma} \left(1 + k \frac{(t - \mu)}{\sigma}\right)^{-\left(1 + \frac{1}{k}\right)} e^{-\left(1 + k \frac{(t - \mu)}{\sigma}\right)^{-\left(\frac{1}{k}\right)}} \quad (3 - 7)$$

When modeling dependent random variables using copula function, the following steps should be followed:

- 1) Find the most appropriate function to be fitted for each of the RVs
- 2) Transform datasets to the corresponding uniform space
- 3) Transform unified data via adopted copula family such as normal copula, t -copula and Archimedean copula family (e.g. Frank copula, Gumbel and Clayton). The best

fit which can model more accurately stochastic characteristics of RVs can be found by comparing the original data distribution and simulated results using K-S test. The most promising copula function is then selected.

- 4) Obtain correlation matrix of the mentioned datasets
- 5) Finally, the extracted copula can be utilized to generate correlated samples.

3.3.2 The $M_t/G/\infty$ Model

Consider the queuing model shown in Figure 11. Assume that the $M_t/G/\infty$ system started empty in the distant past, i.e., at $t = -\infty$ and let S be a generic service-time Random Variable (RV) and let G be its cumulative density function (cdf). Let S_e be a RV with the associated stationary excess CDF:

$$G_e(t) \equiv pr(S_e \leq t) \equiv \frac{1}{E[S]} \int_0^t (1 - G(u)) du, t \geq 0 \quad (3-8)$$

Let $N(t)$ represent the number of busy servers (EVs charging from the grid) at time t and let $m(t) = E[N(t)]$. The main $M_t/G/\infty$ result is that $N(t)$ has a Poisson distribution with mean

$$\begin{aligned} m(t) &= \int_0^\infty (1 - G(u)) \lambda(t - u) du = E \left[\int_{t-S}^t \lambda(u) du \right] \\ &= E[\lambda(t - S_e)]E[S] \quad (3-9) \end{aligned}$$

Note that the time-dependent mean $m(t)$ is related to the instantaneous offered load $\lambda(t)E[\mu]$. From (3-9), the congestion as described by $m(t)$ lags behind $\lambda(t)$ (the peak of m will come after the peak of λ). $\int_{t-S}^t \lambda(u) du$ describes the cumulative arrival rate during a service period before time t . The expectation is then the expected number of arrivals during a random service period before t .

Figure 11. Congestion measure as a response of the queuing model

In [58] various polynomial approximations for $m(t)$ were introduced which are based on assuming that the arrival rate function λ is a polynomial or can be approximated by a polynomial. Based on Taylor series expansion for λ ,

$$R_n(t) = (-1)^{n+1} E[\lambda^{(n+1)}(t - S_e^{(n+2)})] \frac{E[S^{n+2}]}{(n+2)!},$$

$$m(t) = \sum_{j=0}^n (-1)^j \frac{\lambda^{(j)}(t) E[S^{j+1}]}{(j+1)!} + R_n(t), \quad n \geq 0 \quad (3-10)$$

Equation (3-10) gives an explicit probabilistic expression for the congestion measure and remainder term. The probability of charging k vehicles at the same time in an $M_t/G/\infty$ queue, denoted as $pr(k)$, is given by:

$$pr(k) \approx \frac{1/n!}{\sum_{i=0}^{n-1} \left(\frac{1}{i!}\right) + \frac{1}{(1-\frac{1}{n})^{n!}}} \quad k = 0, 1, 2, \dots, n \quad (3-11)$$

where n is the maximum number of vehicles. The charging time for vehicle i to absorb power follows the exponential distribution with mean t_μ but truncated within a certain range $[T_{min}, T_{max}]$:

$$t_{c_i} = \begin{cases} T_{min} & t_{c_i} \leq T_{min} \\ -t_\mu \cdot \ln(U) & T_{min} \leq t_{c_i} \leq T_{max} \\ T_{max} & t_{c_i} \geq T_{max} \end{cases} \quad (3-12)$$

where U is a random number between 0 and 1. Based on the trips in progress the normalized arrival rate function of vehicles at each hour is found and the associated polynomial fit is used in the above equation.

The details of PEV battery charging process is shown in Figure 12. As it is depicted in the figure, charging process of PEV battery is exponential function over time. Instantaneous charging status of PEV is simulated by the following exponential formula [64];

$$E_c(t_c) = E_{max} \left(1 - e^{-\epsilon t_c / t_{max}} \right) + E_0 \quad (3-13)$$

Accordingly, the power demand of a PEV at any instant of charging is:

$$P_c = P_{max} \cdot \epsilon / t_{max} \cdot e^{-\epsilon t_c / t_{max}} \quad (3-14)$$

Figure 12. Schematic graph of Li-ion battery charging [65]

For a linear approximation of PEV charging demand, the same procedure as [52] is followed for recharging cycle. According to the current PEVs on the market shown in Table 5, the average battery size is assumed to be 24 kWh with a consumption of 0.23kWh/mi.

Table 5. PEVs with battery type, driving range and consumption

Plug-in Electric vehicle	Battery	Range advertised	Charge times	Range in real world	Consumption [kWh/km]
BMW Mini E	35 kWh, air cooled; 18650 cells; NMC 355V, 96s53p	250 km, 156 miles	26 h at 115VAC; 4.5 h at 230V, 32A	153 km, 96 miles; 112 km, 70 miles below freezing	0.26
Chevy Volt	16 kWh, liquid cooled Li-manganese, 181kg (400lb)	64 km, 40 miles	10 h at 115VAC; 4 h at 230VAC	45 km, 28 miles; 149hp electric & 1.4 liter IC engine	0.36
Mitsubishi iMiEV	16 kWh; 88 cells, 4-cell modules; Li-ion; 109Wh/kg; 330V	128 km, 80 miles	13 h at 115VAC; 7h at 230VAC	88 km, 55 miles; highway speed, mountain pass	0.18
Nissan LEAF	24 kWh; Li-manganese, 192 cells; 80Wh/kg, air cooled; 272kg (600lb)	160 km, 100 miles	8 h at 230VAC; 30 min high ampere	100 km, 62 miles at highway speed with heater on	0.24

Tesla Roadster	56 kWh, 6,831 Li-cobalt computer cells; liquid cooled	352 km, 220 miles	3.5 h at 230VAC 70A	224km, 140 miles; 172km, 108 miles driven sports car	0.28
Think City	24.5 kWh, Li-ion or sodium-based	160 km, 100 miles	8 h at 115VAC	N/A. Sodium-type has few problems	0.15
Smart Fortwo ED	16.5 kWh; cylindrical Li-ion (computer cells), made by Tesla Motors	136 km, 85 miles	8 h at 115VAC 3.5 h at 230VAC	Less than predicted	0.12

The energy demand of each vehicle to be fully charged is

$$E_c = E_c(t_c) - E_0 = E_{max} \left(1 - e^{-\epsilon t_c / T_{max}} \right) \quad (3 - 15)$$

If there is $n_c (= m(t))$ charged vehicles at time t :

$$Q_c = n_c \cdot P_{max} \cdot \epsilon / T_{max} \cdot e^{-\epsilon t_c / T_{max}} \quad (3 - 16)$$

3.4 Simulation & Analysis

First of all, using copula functions the population size of the input data is increased by generating correlated samples. The parameters of the fitted PDFs to all three random variables are given in Table 6.

Table 6. The parameters of the fitted pdfs

Random Variable	Fitted Distribution	Parameters
Departure time	Weibull	$a = 7.67$ $b = 21.83$
Travelled distance	Weibull	$a = 32.04$ $b = 1.23$
Arrival time	Generalized extreme value	$k = -0.06$ $\mu = 17.3$ $\sigma = 0.85$

In the following, the results are depicted which shows the scatter plots of initial dataset in Figure 13 and their associated in uniform space in Figure 14.

Figure 13. Initial scatter plot between (a) departure time and travelled distance, (b) departure time and arrival time, (c) arrival time and travelled distance

Figure 14. Scatter plot in uniform space between (a) departure time and travelled distance, (b) departure time and arrival time, (c) arrival time and travelled distance

Normal copula is a common choice for modeling the dependence structure between variables but due to the fact that the t -copula presents more observations in the tails than the Normal copula, it is more suitable for modeling. Correlation matrix of the mentioned datasets employed in this study is obtained as follows:

$$\rho = \begin{bmatrix} 1 & 0.38 & 0.29 \\ 0.38 & 1 & -0.02 \\ 0.29 & -0.02 & 1 \end{bmatrix}$$

Therefore, the final scatter plot with marginal histogram between departure and arrival time is shown as an example in Figure 15.

Figure 15. Final Scatter plot between departure time and arrival time in actual domain

The initial and final 3D scatter plots of random variables are shown in Figures 16(a) and 16(b) respectively.

Figure 16. (a) Initial 3D scatter plot of three random variables in actual domain, (b) Final 3D scatter plot of three random variables in actual domain

Having estimated the PEV arrival for charging and the power demand at different instants of charging process, the power demand for the charging can be readily estimated. It should be noted that each charging PEV will be drawing power for the maximum period of T_{max} . For this example, a full charge of the $24kWh$ battery system with $T_{max} = 8 h$ and $3 kW$ average capacity is adopted.

Li-ion batteries currently used does usually not tolerate charge rate above 1C. A charge rate of 1C means charging at a rate equivalent of full capacity reached within an hour. Li-ion batteries should have lower charge rates, especially to prolong battery lifetime, but here the restriction is the capacity limit set by the domestic power connection. Thus, the maximum power is $P_{max} = 3 kW$ and the constant parameter ϵ is calculated at a value of 10.5197, assuming that a full battery system of PEV absorbs 97% of maximum power capacity approximately in the third part of the maximum charging time. The penetration of PEVs is certainly the most uncertain aspect of the charging model. It is common to assume the number of electric vehicles penetration and to work on different scenarios. For example, in [30, 47, 48] penetration factors between 0% and 100% are treated. In this study the simulation is performed for 1000 PEVs. It is assumed that charging starts upon arrival of the PEV and the battery is fully charged upon departure.

The flow chart for the complete simulation procedure for each time-frame is shown in Figure 17.

Random simulation is applied to calculate charging load at each time/iteration. The procedure of this random simulation is outlined as follows:

1. Set k the lowest value such that $U > pr(k)$ according to (3-11)
2. Randomly generate PEV driven mile and the corresponding SOC according to (3-4) and (3-6);
3. Calculate required recharge energy;
4. Randomly generate charging time according to (3-12);
5. Calculate charging demand according to (3-15);
6. Accumulate total charging demand

Figure 17. Flow chart illustrating the procedure for the whole day

3.4.1 Analytical Estimation of PEV Charging Demand Scenarios

Assume that the plug-in probability of all the vehicles are identical and equal to p . In this case, probability distribution of the number of the plugged-in vehicles is a binomial random variable

$$pr(k) = \binom{n}{k} p^k (1-p)^{n-k} \quad k = 0, 1, \dots, n \quad (3-17)$$

where k is the number of plugged-in vehicles and n is the number of electric vehicles.

When n is sufficiently large, a good approximation can be given by normal distribution as

$$N(np, np(1-p)) \quad (3-18)$$

Meanwhile, normality is preserved by linear transformation, i.e. if X is a normal random variable with mean μ and variance σ^2 , and if a, b are scalars, then the random variable $Y = aX + b$ is also normal, with mean and variance $E[Y] = a\mu + b$, $var(Y) = a^2\mu^2$. For and identical power capacity P_{max} , the probability distribution of charging demand (CD) can be obtained as follows:

$$CD \sim N(P_{max}np, P_{max}^2np(1-p)) \quad (3-19)$$

The cumulative distribution function (CDF) of (3-18) is given as

$$F(x) = 1/2 \left[1 + \operatorname{erf} \left(\frac{x - P_{\max}np}{P_{\max}\sqrt{2np(1-p)}} \right) \right] \quad (3-20)$$

where $\operatorname{erf}(\cdot)$ is the *Gauss error function* and is twice the integral of the Gaussian distribution with 0 mean and variance of 1/2. Thus, the probability that the CD is larger than a certain amount x is

$$\operatorname{pr}(CD \geq x) = 1 - F(x) = 1/2 \left[1 - \operatorname{erf} \left(\frac{x - P_{\max}np}{P_{\max}\sqrt{2np(1-p)}} \right) \right] \quad (3-21)$$

In practice, vehicles would have different plug-in probabilities and power capacities but still by clustering the vehicles into groups with similar specific plug-in probability and power capacity and considering the fact that the summation of two independent normal random variables is also normally distributed as follows

$$X_1 + X_2 \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2) \quad (3-22)$$

The overall probability distribution of CD can be estimated by summation of each group. Therefore, it is expected that the pdf of charging demand within each hour follows a normal distribution which can be used to generate scenarios of PEV fleet demand required by the system planners. It should be noted that the obtained distribution is only valid for a specific time instance and CD is varying gradually as the time goes on as shown in Figure 18.

Figure 18. Probability distribution at each time unit

3.4.2 Numerical Simulation

By estimating hourly PDF of charging load demands, planners are able to produce as many as demand samples and then can be efficiently applied in a probabilistic distribution system planning procedure. As an example, Figures 19 (a)-(c) demonstrates demand distributions during three hours for a fleet of 1000 PEVs in addition to the normal PDFs fitted to them.

(a)

(b)

Figure 19. Samples of the distributions of PEVs demand power along with the fitted PDFs at (a) h=17, (b) h=18 and (c) h=19

Table 7 shows the characteristics of fitted normal distribution to estimated charging demand from hour 17 to midnight.

Table 7. Characteristics of normal distribution fit to estimated charging demand

Hour	μ (Estimate)	σ (Estimate)	μ (Std. Err.)	σ (Std. Err.)	Log likelihood
17 o'clock	2885.1	51.8404	3.66567	2.6018	-1072.92
18 o'clock	2493.9	121.435	8.58677	6.09466	-1243.16
19 o'clock	1818.6	149.519	10.5726	7.50412	-1284.77
20 o'clock	1105.05	142.494	10.0758	7.15157	-1275.15
21 o'clock	570.6	110.338	7.80209	5.53771	-1224
22 o'clock	263.25	87.7063	6.20177	4.40185	-1178.09
23 o'clock	109.5	61.691	4.36221	3.09618	-1107.72
24 o'clock	40.35	36.1651	2.55726	1.81508	-1000.91

Figure 20 shows how the charging demand is varying gradually as the time goes on.

Figure 20. Probability distribution of charging demand from h=17 to h=24

Normal probability plots are used to assess whether data comes from a normal distribution. Many statistical procedures make the assumption that an underlying distribution is normal, so normal probability plots can provide some assurance that the assumption is justified, or else provide a warning of problems with the assumption.

Figure 21. Normal probability plot of charging demand from h=17 to h=24

To model the superposition of the demand caused by the PEVs at each hour t , it should be noted that the power demand at any instant is the sum total of the power drawn by PEVs which started charging in the previous hours following the flow chart illustrated in Figure 17. To calculate charging power demand, the initial SOC of the arriving PEVs is incorporated by mapping the SOC distribution and the appropriate charging process at that level of SOC. the probability of number of vehicles for a specific SOC at each hour is known. Thus, the power drawn at each instant of charging and the duration to full charge will depend on the level of SOC. Both these quantities will decrease for higher levels of SOC at the time of arrival.

Figure 22 demonstrates 50 load scenarios for 1000 PEVs generated regarding the extracted PDFs besides their average scenario. Although, the charging load varied from simulation to simulation, it is found that they stay within a narrow band, which reflects steady driving and charging patterns. The peak charging demand is observed in the evening hours when the PEV arrival rate is also highest and it is going to contribute to the daily peak of the load. The maximum charging demand is found to lie between 3.32 MW and 2.66 MW.

Figure 22. Uncontrolled domestic charging power demand for 1000 PEVs

3.5 Concluding Remarks

Integration of the vehicular loads into the probabilistic distribution system planning problems has been addressed in this chapter. A stochastic modeling framework has been thoroughly elaborated that can be efficiently employed in order to take into account the uncertainty attributes of the plug-in electric vehicles. Stochastic approach based on queuing theory is presented to estimate the system wide battery charging power demand of PEV fleet. The exponential charging profile of the battery has been used to extract the power demand at different instances of the charging period. NHTS data set has been utilized in several ways to probabilistically quantify the PEVs status in terms of whether it is 'parked' or it is 'on the move'. The daily mileage data was also used for multiple purposes. The driving data was also utilized for the arrival rates of PEVs for charging at different hours of the day.

This chapter presented a Monte Carlo simulation approach for the derivation of the system load due to EVs based on a model representing real commuting patterns. Since the model variables are characterized by a stochastic behavior and are correlated, a multivariate distribution function was built by means of copula function and the respective marginal empirical distributions, which in turn allowed the computation of the hourly system load. The results indicate that in the fixed electricity rate environment, PEVs can contribute to significant increase the load demand at certain hours, although the charging demand is very limited most of the time. However, these high charging demands is found to decrease significantly when we consider the limited or short commuting mileage leading to significant levels of SOC on the PEV batteries when arriving for charging.

Chapter 4. Aggregator & PEV Fleet Potential Assessment

In aggregated command architecture, Fleet Aggregator (FA) is the actor that serves as the link between the individual PEVs and the market. FA aggregates individual vehicles to make a single controllable power resource. It receives the appropriate signals from both PEVs like current and desired SOC and ISO/RTO which may include a contribution of MCP, ancillary services requirements, grid congestion etc. FA issues power commands to contracted vehicles that are both available and willing to perform the required services. Under the aggregative architecture, the FA can contract with the system operator at any time. While in decentralized architecture there exists a direct line of communication between the ISO/RTO and the vehicle so that each vehicle can be treated as a deterministic resource to be commanded by the system operator.

While it is conceptually simple; there are some drawbacks of such architecture. Firstly, it cannot use the conventional control signals that are currently used for control and ancillary services contracting because the size and geographically distributed nature of each individual vehicle is incompatible with the existing contracting frameworks. Besides, in current markets for many system services, a certain amount must be bid into the market. For instance the PJM regulation market eligibility is a minimum bid of 50 MW and the RTO regulation requirements are 1% of forecasted peak RTO load for on-peak period and 1% of forecasted valley RTO load for off-peak period. This means that several PEVs will have to pool together into larger groups to provide the services needed. This is often referred to as a Virtual Power Plant (VPP). Secondly, in the long term as millions of vehicles connect to and disconnect from the grid, monitoring and controlling all of the vehicles in the power control region will be an overwhelming communications and control task for the system operator [66].

In the following, the importance of aggregated architecture is highlighted from availability and reliability perspectives.

4.1.1 Availability Assessment

Availability factor (AF) is a North American Electric Reliability Corporation (NERC) reported metric of the ability of an individual generation resource to enter into a contract

with the system operator. According to NERC definition, an available unit is in a state in which it is capable of providing service, whether or not it is actually in service, regardless of the capacity level that can be provided. For example, The NERC reports an AF of 92.3% for gas turbine plants in operation from 2005-2009 [67]. Gas turbine plants are commonly used for ancillary service provision due to their short response time. Generating availability based on NERC report is presented in Table 1 in Appendix B.

In best case scenario, assume that distributed charging infrastructure is deployed. Obviously, the availability of V2G enabled cars depends on the presence of cars. Based on NHTS dataset and as explained in chapter 3, the percentage of parked cars at each hour in weekdays and weekends is extracted. Another unknown that should be explored is *Plug accessibility* vector. Plug accessibility (A_t) estimates how likely an EV will be able to plug in when parked either at home or at public locations. Therefore, aggregator is not limited to control EV charging during a fixed period. It is calculated by allocating a constant probability of an available plug to each type of location during the day as shown in Table 8. The plug accessibility in a given hour can be determined from multiplying plug access probability with share of the cars parked for the ten different purposes as shown in (4-1).

$$A_t = \sum_{j=1}^{10} \frac{ps_{tj} \times pr_j}{\sum_j ps_{tj}} \quad t = 1, 2, \dots, 24 \quad (4-1)$$

Table 8. Trip purpose summary with plug probability based on NHTS 2009

j	Location	Probability
1	Home	1
2	Work	0.5
3	School/Daycare/Religious activity	0.3
4	Medical/Dental services	0.3
5	Shopping/Errands	0.3
6	Social/Recreational	0.3
7	Family/personal/business/Obligations	0.1
8	Transport someone	0.1
9	Meals	0.1
10	Other locations	0.1

ps_{tj} is the number of parked EV at time period t and location j and pr_j is the plug access probability of location j . The average plug accessibility percentage for each hour during the period of 12 months are calculated and shown in Figure 23 for weekdays. For a specific hour, each bar represents the average plug accessibility percentage over weekdays of each month which clearly follows a similar trend. The vehicles are assumed to be plugged in when they are not used for driving. Considering the above assumption, the availability of the vehicle to perform ancillary services is equal to the average fraction of a day that the vehicle is present at a V2G charging station. Note that plug accessibility pattern on weekdays is quite similar and different from weekends. Therefore, for simulation purposes the average value on weekdays is considered.

Figure 23. Plug accessibility percentage on weekdays

The average plug accessibility vectors for both weekdays and weekends are shown in Figure 24.

Figure 24. Average plug accessibility vector

In the decentralized architecture, suppose that individual vehicles will be available to perform ancillary services whenever they are connected to the grid. Under these assumptions, the AF of the vehicle to perform ancillary services is equal to the average fraction of a day that the vehicle is present at a V2G charging station.

Figure 25. Availability of V2G enabled vehicles in decentralized architecture

As it is expected the availability of vehicles is very high early in the morning from 23:59-05:00. During the day, the availability of vehicles decreases as they drive to work or other locations. Between 8 am and mid-afternoon, more than 30% of vehicles are not available to perform V2G services. The minimum vehicle availability in weekdays is 62.44%, and the averaged vehicle availability equals 79.51%. These values for weekends decrease to 62.11% and 76.97% respectively. The AF of the decentralized architecture is lower than the NERC reported availability for gas turbine generators of 92.3%. In fact, it is outside the normal ranges of conventional power generation units according to Table 1 in the Appendix B.

On the other hand, since the FA can vary the size of its power contract with ISO/RTO and under the assumption that the aggregator does not have any outages, and that the communications connection between the aggregator and the system operator is completely reliable, the AF of the aggregative architecture is simply 100%. The aggregative architecture allows the aggregator to achieve industry standard availability, simplifying the interface between the system operator and the V2G grid services provider.

4.1.2 Reliability Assessment

According to NERC definition, total equivalent derated hours (EDH) is the product of derated hours and size of reduction divided by net maximum capacity. Subsequently, derated hours ratio (DHR) is defined as total equivalent derated hours divided by total period hours.

$$EDH = \frac{\text{Derated hours} \times \text{Size of reduction}}{\text{Net maximum capacity}} \quad (4 - 2)$$

$$DHR = \frac{EDH}{\text{Total period hours}} \quad (4 - 3)$$

DHR is the probability that generation system working in derated state. The reliability (R) of a system to provide the contracted ancillary services is $R = 1 - DHR$. For example, The NERC reports a reliability of 99.97% for gas turbine plants in operation from 2005-2009. Generating reliability based on NERC report is presented in Table 2 in Appendix B.

V2G regulation is a zero net energy service [28]. The energy removed from or added to the battery, will net to zero over both short and extended periods. These assumptions eliminate the finite energy capacity of batteries from consideration in V2G reliability evaluation. With a qualitative discussion and in comparison with the above values it is concluded that the decentralized architecture is unable to meet industry standards for reliability. It should be noted that the grid system operator cannot prevent the driver from disconnecting from the grid at any time, and the system has no foresight into the driver's intentions, it is not possible to calculate the reliability of decentralized architecture.

On the other hand, the aggregator can manage the fleet size and contract size to maintain industry standard reliability over the course of each hour, day, and year. It is intrinsically more reliable than the decentralized architecture because the reliability of this architecture is entirely dependent on the uncontrolled behavior of the vehicle owners.

In summary fleet aggregator aims to: 1) reduce the cost of its own electricity usage; 2) eliminate load spikes; 3) charge all vehicles by morning; and 4) charge commuter vehicles with charge spots before leaving work. This improves reliability and allows the aggregator to participate in the hourly ancillary services market and gain revenues. As such, this architecture solves the two primary problems with the decentralized architecture. The main goal of an aggregator is to maximize the payment from grid operator by providing the power

capacity for ancillary services. Therefore, the aggregator should provide as much power capacity as possible whenever the regulation price is expensive. Revenue of the aggregator could be maximized by performing a charging control so that each vehicle remains idle whenever the regulation price is expensive. But since system services are naturally unpredictable and cannot be considered before the optimization process, only charging and discharging can be included in the optimization. This is because the power consumption can be predicted very accurately and the prices are determined on the day ahead market. Therefore the actions of the PEVs can be optimized by aggregator with buying cheap power from the grid for the vehicle battery charging. Detailed discussion is provided in next section.

4.2 Price Based PEV Charging/Discharging

Smart charging of PEVs is a subcategory of demand response (DR) programs. According to US Department of Energy, DR is “a tariff or program established to motivate changes in electric use by end-use customers in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized” [94]. Based on the type of signal used to activate the DR program, these programs could be categorized as either emergency DR (reliability based) or economic DR (price based). Considering the transmission constraints dynamic pricing with enabling technology (refers to rate structures that offer customers time-varying electricity prices on a day-ahead or real-time basis with the appropriate technology to automate price-response behavior) reflects the marginal clearing price at each node. In another word, the correct price signal reflects the current situation of the grid in terms of congestion etc. That is the motivation behind the market based modeling in this thesis. As it is mentioned in chapter 2, price-based charging in one of the prevalent strategies currently being pursued to implement intelligent charging.

In the following sections, charging/discharging pattern of 100,000 PEVs is optimized in response to hourly electricity prices. Subsequently, V2G regulating power potential that aggregator could offer the ISO/RTO is estimated by a dynamic optimization approach. For the case study, the Elspot market data from Monday the 1st to Sunday the 7th of August 2011 has been used. In V2G terminology, whenever a vehicle become idle, it should be paid for

its available power capacity. If the vehicle starts charging, it should pay for its energy consumption. Thus, both market clearing price (MCP) and regulating market clearing price (RMCP) have to be reflected in the performance measure. By definition, regulation is a variable amount of generation energy under automatic control which is independent of economic cost signal and is obtainable within 5 minutes [71].

It was not possible to get data with better resolution than one hour from the publicly available market data. Obviously for regulating power potential analysis, data with much shorter time scales is required. Nord Pool market data is used in the simulations since it provides detailed regulating power data in its database. Besides, wind power constitute a high share of power generation in Nordic countries which directly affects power price and gives large imbalances that have to be corrected by regulating power. Nord Pool spot runs the leading power market in Europe and offers both day-ahead and intraday markets to its customers. 350 companies from 20 countries trade on the market. In 2011 the group had a total turnover of 316 TWh, which includes the auction volume in the UK market N2EX [68].

The distributed infrastructure is not constrained by low battery capacity and can choose the charging periods more freely. In previous sections, two suggested architectures for PEV integration into the electric power grid was compared and the advantages of aggregated over decentralized architecture was highlighted. Based on this, PEV fleet is treated as one aggregated battery from the power system viewpoint instead of having to consider each individual vehicle. On the other hand, to evaluate the PEV fleet potential, an aggregated battery capacity and an average driving range and consumption pattern is assumed for all the vehicles. Two average rated power connections 2.5 kW and 3.5 kW are assumed for the distributed grid to investigate the effect on the charging/discharging pattern and energy potential. Power flow is limited by connection rather than battery or power electronics limitations but we check this during to program and define the constant η_{lim} . η_{lim} is one unless the battery is the limiting factor.

In this study an important point to be kept in mind is that the PEVs are only price takers, i.e., they will not affect the market price when they are connected to the grid. When PEVs have significant influence on the power production curve, then the V2G interactions will

affect the power prices, which will again affect the level of V2G. This is not included in this study.

4.2.1 Input Data Description

Charging/discharging pattern is optimized economically, i.e., PEVs react on hourly price fluctuations. Optimizing the charging time of vehicles' batteries based on price variations is essential for the balancing of electric power, peak shaving and preventing negative impacts on the supply side during peak demand periods. In this way, some surplus energy can be effectively used due to correlation between power consumption and electricity price. Description of the assumptions made for determining the input parameters for the optimization program is provided. Other variables used in the simulation were discussed in previous chapters.

The average battery capacity and average energy consumption are assumed to be 25 kWh and 0.23 kWh/km respectively. Average driving distance is assumed to be 50km. The program determines a total driving consumption for a day, from the total number of PEVs, and distributes this consumption via driving pattern. It is assumed that the efficiencies of charger and battery (round-trip) are 95% [44] and 92% [69] respectively. Round-trip efficiency is the efficiency of charging and discharging the battery including all losses. Thus η and η_{rnd} can be obtained based on Figure 26.

$$\eta = \eta_{chg} \times \eta_{bat} = 0.95 \times 0.96 = 0.91 \quad (4 - 4)$$

$$\eta_{rnd} = \eta_{bat}^2 = 0.92 \quad (4 - 5)$$

Figure 26. Schematic illustration of energy flows to and from the battery storage unit

As explained in chapter 3 the driving data comes from NHTS 2009 to extract relevant vectors regarding PEVs mobility behavior. For regulation power potential the share of parked cars at each hour and the plug accessibility vector are the most important input data

for the program to estimate the probability of the PEV being plugged which were explained earlier in section 4.1. Although input parameters have been estimated conservatively, the potential for V2G indicated by this study could be overestimated because of the assumption of perfect forecasting of driving demand. It is important to note that the results presented in this chapter comes from data from the specified week, and this data will be different for other periods, which means that the results will also be different for other periods.

Figure 27 shows how the power prices change with the daily variation of demand. It also highlights the fact that the hourly electricity demand pattern is quite similar on weekdays and weekends. Figure 28 shows the MCP which is the basis for the optimization process along with the prices the PEVs pay for providing down regulation and receive for providing up regulation. There are hours when the spot price and the regulating prices are equal, and this is not necessarily hours with no regulation of that kind. This means that the battery and conversion losses can make it unfeasible to provide regulating power in some hours. Since taxes and tariffs constitute a large share of power price, they will have an impact on V2G operation. Additional discharging when power grid needed causes extra losses and battery wear; therefore, it is necessary for the PEV owner to be compensated when supplying power to the grid. This implies

$$\eta_{rnd} > \frac{\text{charging price}}{\text{discharging price}} \quad (4 - 6)$$

Figure 27. Consumption and MCP during first week of August 2011 in Western Denmark

V2G operation should be relieved of taxes in order to be able to compete in the market and provide enough incentive for owners to participate. Note that if a fixed value of tax per unit power is added to both charging and discharging price in the above inequality, making the price ratio higher and it will be less likely that the owners are willing to participate. In other words, if PEVs are supposed to participate in the market, the price fluctuations should be sufficiently high and if they want to support the renewable resources, then these resources should have a significant impact on power price.

Figure 28. MCP with Up and down regulation prices (first week of August 2011, Western Denmark)

Figure 29. PEV driving consumption

The driving consumption is calculated from the average daily driving distance, the number of PEVs and the driving pattern, which is determined from the parked pattern described in chapter 3. Figure 29 shows the driving consumption, for weekdays and weekends.

4.2.2 Optimization formulation

Optimization formulation will describe the basic principles used for Buy/Sell model. The definition of the energy being delivered at the grid side is important when efficiencies are included.

$$\text{Min} \quad Z = \sum_{t=1}^{168} \pi_t (P_{ct} - P_{dt}) \quad (4-7)$$

Such that

$$\partial e_t = \eta P_{ct} - \frac{P_{dt}}{\eta} - E_{cnt} \quad \text{for } t > 1 \quad (4-8)$$

$$e_t = \underline{e} + \eta P_{ct} - \frac{P_{dt}}{\eta} - E_{cnt} \quad \text{for } t = 1 \quad (4-9)$$

The constraints (4-8) and (4-9) keep track of energy consumed from and supplied to the battery, including the demand for driving purposes. Since this is a minimization problem the SOC will be at minimum at the last period in the optimization, therefore the initial value is set to be minimum charge as well.

$$\underline{e} \leq e_t \leq \bar{e} \quad (4-10)$$

The variable e_t is constrained to never exceed minimum or maximum values. $\underline{e}$ can be determined from minimum charge level.

$$\eta_{lim} P_{ct} \leq A_t r_c \quad (4-11)$$

$$\frac{P_{dt}}{\eta_{lim}} \leq A_t r_c \quad (4-12)$$

Constraints (4-11) and (4-12) make sure that the power absorbed by the batteries does not exceed the maximum. The constant η_{lim} is one unless the battery is the limiting factor. If so it makes sure that the conversion efficiency η is included. The vector A_t estimates the

availability of the aggregated battery. A similar rate constraint makes sure that the variable P_{dt} does not violate the same rates.

$$\eta P_{ct} \leq A_t(\bar{e} - e_t) \quad (4 - 13)$$

$$\frac{P_{dt}}{\eta} \leq A_t(e_t - \underline{e}) \quad (4 - 14)$$

Constraints (4-13) and (4-14) consider the fact that the plugged vehicles, cannot charge for the driving ones. It is important to try to limit this effect, as it can limit the applicability of the aggregated battery assumption. The constraint dictates that in any given hour the energy charged to the batteries cannot exceed the available capacity of the aggregated battery multiplied with the share of cars that are assumed parked and plugged. Again a similar constraint is constructed for the variable P_{dt} that assumes the energy available for discharging is the extractable energy from the aggregated battery multiplied with the vector A_t .

Energy balance equation is

$$\sum_t (\Delta E_t - E_{cnt}) = 0 \quad (4 - 15)$$

where

$$\Delta E_t = \eta P_{ct} - \frac{P_{dt}}{\eta} \quad (4 - 16)$$

The $\Delta E_{bat}(t)$ describes the net energy stored in the battery in hour t.

4.2.3 Simulation Results

The charge and discharge patterns determined by the optimization process for both of connections are shown in figures below. Charging power is shown by solid lines while the discharging power is shown by dashed line.

Figure 30. PEV charging and discharging pattern with 2.5 kW average connections

Stored energy in aggregated battery storage system increase in night and discharge during the day when the electricity prices rise.

Figure 31. Energy variations in aggregated PEV battery with 2.5 kW average connections

Energy level of the aggregated battery increases on the third day due to the decrease of discharging power. This is only because of market reasons as we seen lower prices both during night and day on the third day. As the connection power increases more discharging power is observed.

Figure 32. PEV charging and discharging pattern with 3.5 kW average connections

As night time electricity prices are lower than during the day, the aggregated battery mainly charges during night when most of the vehicles are parked and plugged. The aggregated battery can then supply the driving demand during the day. As the PEV determines the charge patterns from market clearing prices, there should in general be an increased PEV consumption when power production gets close to power overflow, the prices would become very low (could even become negative). It is clear that in the last day when the prices are lower because the wind power production is high which would provide a big incentive for the PEVs to charge in these hours. More details on charging/discharging pattern and the respective effect on energy level of the aggregated battery will be discussed in section 4.3.

Figure 33. Energy variations in aggregated PEV battery with 3.5 kW average connections

The power consumption curve in Figure 34 shows that PEVs in a distributed infrastructure have the potential to increase base load (valley filling) and decrease peak load. 2.12 % decrease in peak load and 15.17 % increase in valley load is observed. Including PEVs increase the capacity factor (CF) of power production curve from 74.67% to 78.35%.

Figure 34. PEV effect on consumption with 2.5 kW average connections

The peak shaving capability is directly related to the power connection. In the case of 3.5 kW connection 2.67 % decrease in peak load and 9.43 % increase in valley load is observed. Including PEVs increase the CF of power production curve from 74.67% to 78.93%. If the power prices are sufficiently high during peak load they are able to shave the conventional

peak production. In our case study it reflected clearly; the effect of price on peak load during weekends is clearly observed. From 3 to 5 pm of the last day when the prices decreased due to high wind generation we observe a higher increase in peak demand. It is only because of market reason as the power is sold back to the grid in the following hours. With intelligent charging in this case we are able to do peak shifting as it is depicted in Figures 34 and 35.

Figure 35. PEV effect on overall power production with 3.5 kW average connections

The increase in consumption caused by the PEVs is mainly located at night. But if the price does not encourage continuous charging during the night, the minimum production will still be about the same. This feature is directly related to the penetration level of PEVs.

4.3 V2G Service Potential

In this section, the procedure to estimate the potential to provide V2G system services is described. PEVs are simply mobile energy storages. As explained in section 1.2, since there is no fuel input like conventional power plants, the regulating power from PEVs works fundamentally different from other sources. Because the PEVs will have to supply the needed driving consumption, it is limited how much there can be deviated from the original plan of charging and discharging. A power plant providing up regulation will use some extra fuel and that would be it. But the PEVs will need to recharge the energy used for the up regulation. The energy used for up regulating should either be in excess or should be recharged before needed. Providing down regulation would normally result in a plant lowering production, whereas the PEVs will start charging or discharge less. This will affect

the charging/discharging pattern and therefore also the ability to provide regulating power. Therefore PEVs are best suited for system services that are not too energy intensive, such as frequency control [20]. Regulation provision is estimated in the hours when battery capacity is not fully utilized. Same as charging and discharging, regulation is defined on the grid side.

The estimated regulating potential will therefore be a theoretical potential that might not be realizable in real life with the same conditions or at least it is not certain that it is realizable in a given hour and this certainty is quite important when considering system services, as the ISO/RTO must be sure to have adequate reserves available. Still it is interesting to see the order of magnitude of this potential, to get an idea of to how large an extend the PEVs can provide system services considering the assumed number of parked and plugged cars, connection limits, aggregated consumption of vehicles based on average driving distance which explained earlier. Providing regulating power is not based on economic optimization. This means that providing the regulating power as described above is not necessarily economically feasible.

In the up regulation energy markets, it is assumed that the time between two dispatch events is sufficient to recharge the energy withdrawn. Where down regulation energy is concerned; the dispatch probability is taken into account additionally so as to avoid the battery being fully charged [20],

$$R_{d-c} = \frac{E_{dsp}}{P_{cnt} \times t_{cnt}} \quad (4 - 17)$$

The energy per vehicle which is available for delivery back into the grid is

$$E_{up} = \eta(e.DoD - E_{cn}) \quad (4 - 18)$$

The energy which can be delivered to the battery during charging period is

$$E_{dn} = \frac{E_{cn}}{\eta} \quad (4 - 19)$$

And the corresponding power will be

$$P_{up} = \min \left\{ \frac{E_{up}}{t_{dsp}}, P_{lim} \right\} \quad (4 - 20)$$

$$P_{dn} = \min \left\{ \frac{E_{dn}}{\max\{t_{dsp}, t_{day} \cdot R_{d-c}\}}, P_{lim} \right\} \quad (4 - 21)$$

Regulating power cannot be included in the optimization process because it is naturally unpredictable. The regulating power potential of the aggregated battery is estimated after the optimization. This is done by looking at the energy the battery can supply or absorb in each hour:

$$Up\ regulation : A_t / h (e_t - \bar{e} \cdot SOC_{min}) \quad (4 - 22)$$

$$Down\ regulation : A_t \frac{(\bar{e} - e_t)}{h \cdot \eta} \quad (4 - 23)$$

But there is another constraint than the energy. The batteries cannot supply more regulating power, than the grid connection allows and some of this connection may already be utilized for charging or discharging. On the other hand if the battery is charging, then lowering this charge can also be a way of supplying regulating power:

$$Up\ regulation : \left(A_t r_c - \frac{P_{dt}}{\eta_{lim}} \right) \cdot \eta_{lim} + P_{ct} \quad (4 - 24)$$

$$Down\ regulation : \frac{A_t r_c - P_{ct} \cdot \eta_{lim}}{\eta_{lim}} + P_{dt} \quad (4 - 25)$$

The potential to provide up regulation in each hour is the minimum of equation (4-22) and (4-24) and for down regulation it is the minimum of equation (4-23) and (4-25). This will be referred to as regulating potential, as it is the regulation the PEVs potentially can supply each hour. System services provided by PEVs have some special characteristics. If power is used then it will be missing from the PEVs, which means that it will have to be compensated at a later time. This means that the estimated potential is not what can actually be provided, because whenever some system service is provided, the power involved will have to be replenished. Therefore it is estimated how much regulating power can actually be provided.

An assumption done in this study is that the system services provided must be compensated in the next hour. Providing the system service will change PEVs' charging/discharging patterns determined by the optimization and in order to get back to the

pattern decided by the optimization, the PEVs will have to compensate in the next hour. However this compensation can also be used to provide regulating power in the next hour, which will then delay the compensation for the battery. If the PEV is charging in the given hour then by decreasing the charging, the PEV will effectively supply power to the grid by taking less. If there is energy available in the battery, then the PEV can start discharging to the grid if more power is needed than what the PEV was originally charging.

This results in a lack of energy in the battery to provide the needed services and the PEVs will therefore need to charge this missing energy at some point as soon as possible. This is the reason for the assumption of replenishing the power in the next hour. This assumption simplifies the program implementation but in practice when for example PEVs are providing down regulation i.e. absorbing power from the grid, it is only a good idea to discharge the power in the next hour if the prices are sufficiently high to provide revenue for owners. Therefore, in the last hour of simulation no regulation will be provided because its effect on charging/discharging cannot compensate.

The potential to provide regulating power is shown in Figure 39. It clearly shows that the distributed infrastructure has much more potential to provide balancing power than it is actually needed, although it is not able to provide power in every hour. Obviously it cannot supply down regulation when fully charging, but has a huge potential to provide up regulation. The same is true for up regulation and discharging. There are hours where no regulating power can be supplied. This means that other sources of regulating power must be available as well. This could be either power plant with fast ramp rates synchronized to the grid, or perhaps flexible demand.

Figure 36. Charging and discharging pattern including regulation provision with 2.5 kW average connections

Figure 37. Energy variations in aggregated PEV battery including regulation provision with 2.5 kW average connections

Ancillary service provision drawback as it is shown in Figure 38 is the negative effect on power consumption curve. The peak load not only decreases but also a 0.5% increase due to 124.3 MW charging occurs between 1:00 to 3:00 pm on second day is observed. Detailed comparison is provided in Table 9.

Figure 38. PEV effect on consumption including regulation provision with 2.5 kW average connections

Figure 39. PEVs potential to provide regulating power with 2.5 kW average connections

Figure 40. Charging and discharging pattern including regulation provision with 3.5 kW average connections

Figure 41. Energy variations in aggregated PEV battery including regulation provision with 3.5 kW average connections

Figure 42. PEV effect on consumption including regulation provision with 3.5 kW average connections

Figure 43. PEVs potential to provide regulating power with 3.5 kW average connections

Figures 39 and 43 reveal that the V2G enabled infrastructure are able to supply system services in all hours during the simulated week which cause revenues due to availability payment but on the other hand new peaks could be created which cause the need for additional peak generation capacity. It highlights the fact that purely price based control is not always favorable for the power system. On the other hand, providing ancillary services limits the ability to perform peak shaving.

Table 9. Comparison between infrastructures compare to the base load curve (CF=74.67%)

	2.5 kW	2.5 kW with V2G service provision	3.5 kW	3.5 kW with V2G service provision
Valley load	+15.17%	+1.5%	+9.43%	+6.9%
Peak load	-2.12%	+0.5%	-2.67%	+0.3%
Capacity factor	78.35%	76.27%	78.93%	76.61%

It is important to note that the above figure do not reveal how much regulating power can actually be provided. As explained earlier this is because PEVs function quite differently from other sources of regulating power. The regulating power provided must be compensated for later use. This poses the risk of the PEVs potentially moving the regulation demand to the hour when they need to be compensated. PEVs provide less regulating power

than the potential, because of the compensation of energy. Situations can arise where the PEVs are unable to supply the demand. Therefore additional regulating reserves are needed. The estimated regulating power is shown in Figure 44 along with the actual regulating demand. The results for both connections were the same which means as long as the regulation signal is not too energy intensive the ability to provide needed power is not affected by the grid connection.

Figure 44. Regulating power provided by PEVs

4.4 Economic Analysis

As it is uncertain how taxes would be included in a V2G scenario, there has been made no attempt to include these in the economy calculations for PEVs providing regulating power. But if taxes are added to the MCP and not to the regulating power prices, then it would be very favorable for the PEVs to provide down regulating power, as this power would be very cheap. This would however make it more unprofitable for the PEVs to provide up regulating power, unless the power provided can be recharged without taxes. The fact that the regulating power from the PEVs is not always available makes it difficult to determine whether or not the PEVs can supply all the regulating power as it is not known what hours the regulating power is needed.

In tables below total cost and profit of the distributed infrastructure with two different average connections has shown. This analysis does not consider the possibility of receiving availability payments.

Table 10. Cost and profit for the vehicle fleet with 2.5 kW average connections

	Daily optimization	Weekly optimization
Charging/discharging cost [€]	2.7428×10^5	2.7085×10^5
Total profits of providing down regulation[€]	1.0392×10^4	1.0837×10^4
Total profits of providing up regulation[€]	1.6135×10^4	1.2756×10^4
Total cost including regulation[€]	2.4776×10^5	2.4725×10^5

Table 11. Cost and profit for the vehicle fleet with 3.5 kW average connections

	Daily optimization	Weekly optimization
Charging/discharging cost[€]	2.3545×10^5	2.3412×10^5
Total profits of providing down regulation[€]	1.2675×10^4	1.2675×10^4
Total profits of providing up regulation[€]	8.1029×10^3	1.0019×10^4
Total cost including regulation[€]	2.1467×10^5	2.1143×10^5

According to [70], based on assumed and available input data on average in this study, the potential results of replacing gas-powered vehicles with PEVs equipped with V2G technology over the course of ten years in U.S. is shown in Table 12.

Table 12. Potential saving over ten years

year	Cash saved / year PEV to Conventional:
1	\$1,420
2	\$1,491
3	\$1,565
4	\$1,644
5	\$1,726
6	\$1,812
7	\$1,903
8	\$1,998
9	\$2,098
10	\$2,203

In the above calculation baseline data like costs of greenhouse gases emission, average annual energy inflation rate, battery replacement cost and maintenance cost are considered.

4.5 Concluding Remarks

The potential analysis of having PEVs provides system services has been implemented in order to get the possible power capacities for the proposed charging methods for PEV users. The important aspect is that the distributed infrastructure can be able to supply system services in all hours of the simulations. This opens the opportunity of receiving availability payments for the system services.

The possible power capacity from PEVs and the economic return for PEV owners by providing regulating power are obtained. A price based charging schedule scenario has been used to do the day-ahead charging schedule for all PEVs based on the predicted driving pattern. On top of the obtained charging schedule, the predicted PEV availability and the charging schedule are used to calculate the possible power capacity from PEVs for both up and down regulating power. The activated regulating power and regulating power prices in the Denmark West System have been used to calculate the economic return for PEV users if all the regulating power is provided by PEVs. The results show that the regulating power capacity from PEV grid integration are promising to meet the regulating power requirements in future power systems with high renewable energy penetration. In order to get more

accurate results of regulating power capacities, the transmission and distribution grid constraints have to be considered in the future work.

The results will be used to determine the impacts of PEVs charging load and how appropriate they are for providing ancillary services. All in all, the PEVs in the distributed infrastructure have the potential to charge during the night, but how effective it is done depends on the power price volatility. Regulations and incentives could be introduced to promote the best utilization of the PEVs.

Chapter 5. PEV Participation in Electricity Market

Vehicle-to-Grid (V2G) provides the potential for the system operator to call on the PEVs as distributed energy resources and offers financial benefits to vehicle owner when supplying system services. The idea is to control EV charging rate dynamically to absorb generation variability. FA aggregates individual vehicles to make a single controllable power resource. FA issues power commands to contracted vehicles that are both available and willing to perform the required services.

In PJM, load-serving entities can meet their obligation to provide regulation to the grid by using their own generation, by purchasing the required regulation under contract with another party or by buying it on the regulation market [71]. Systems with regulation market which provide MCP for regulation protect supplier by providing opportunity cost of energy and provides more incentive to provide regulation. On the other hand, failing to supply contracted amount will lead to financial penalties for service provider and may negatively affect reliable operation of system.

With this in mind, this chapter contains of two main sections. In the first part, using a stochastic model for the regulation signal, a model for the two-settlement market and proper formulation for aggregator profit function we show that the problem of determining optimal contract offering for a FA can be solved using convex programming in an analytical way with coherent approaches to risk in optimization under uncertainty. In the second part, stochastic-based optimal bidding strategy for an EV aggregator to participate in the day-ahead and reserve market is described. It is necessary to adopt stochastic approaches for aggregator optimal bidding problem due to uncertain nature of electricity market and fleet operation. FA decision process is modeled as a recourse stochastic problem. An optimal aggregator bidding strategy is proposed to maximize the total profit of FA with considering EV users driving requirements.

The proposed stochastic optimization approach supports the aggregator participation in day-ahead and reserve markets. A risk aversion criterion designated as conditional value at

risk ($CVaR$) is defined in the objective function to minimize trading risks. The simulation has been performed to illustrate the effectiveness of the proposed method.

5.1 Literature Review

Several publications have studied potential revenues from V2G. In [1, 95] unit commitment algorithms are developed which include charging and discharging PEVs for load leveling and peak shaving. Reference [1] focuses on reducing emissions of thermal units through V2G, balancing of wind and solar. Distribution feeder load leveling opportunities are explored in [96]. Optimal buying and selling of bulk energy in V2G is explored in [97, 98], though, none of these studies [1, 95-98] considered V2G ancillary services or aggregator bidding strategies and revenue structures. The necessity and participation of aggregators to V2G is more thoroughly explored in [25]. This proposes that aggregators would provide a link to the utility for participation in all types of energy markets.

References [72], [73] derived the optimal bidding strategies for FA by varying EV charging/discharging rate around the preferred operating point (POP). Bessa *et al.* [74] presented optimized bidding of an EV aggregator in the day-ahead and secondary reserve markets. The forecasted system deviation parameters were considered in the formulation. Pantos [75] focused on a day-ahead market and a provision of system regulation in an ancillary service market and propose the risk-based approach applying value at risk due to uncertainties. Han *et al.* [76] developed four profit functions with different penalty contract types for FA. In [77] the formulations include V2G services in optimal bidding of coordinated wind-thermal generation resources. An approach was proposed in [78] for integrating the EV aggregation function into simultaneous energy and reserve market clearing algorithm.

5.2 Market Framework

Based on the most current market structures, FA participates in the competitive electricity pool consists of two successive markets: a day-ahead market and a real-time balancing market. FA bids in the day-ahead market for energy and reserve regulation. Deviations from scheduled nominal charging designated as POP are within the reserve regulation limits. In

real-time, aggregator controls the charging of each single EV and minimizes variations of fleet power consumption around the POP. One hour power profile sample of a PEV on regulation is shown in Figure. 45.

Figure 45. Power profile sample of a PEV on regulation

Regulation services are shifting to EVs where the nominal power level is set at a negative value to provide power to replenish the battery energy consumed in driving. This also provides power to cover the expected losses of the battery/inverter system. Reserve regulation consists of down/up regulation. Down regulation actually representing increase in charging. To provide up regulation, FA decrease/cancel the charging power of vehicles.

Regulation services are contracted by the ISO/RTO on an hourly basis as needed throughout the day. The actual dispatch of the contracted regulation is normally a few minutes in one direction (up or down) at a time. Payment is typically made for the contracted amount of capacity for a given hour (\$/MW per hour) as well as energy actually delivered. This price is set hourly through the market clearing process. The ideal characteristics of a regulating market for vehicle provision are outlined in [32]. Some of the mentioned characteristics are as follow; energy and capacity payments, short contract times and small minimum bid sizes. FA should also be able to submit asymmetric power bids that is, up and down regulating power are tendered individually. The aggregator is assumed to be price-taker. Although the large scale integration of EVs in future will affect market prices but it should be borne in mind that, for minimizing expected charging cost ranking of the hourly

day-ahead electricity price is critical. EVs compete with each other for cheap electricity. It leads to increased marginal charging costs of adding more EVs and stable electricity prices at a high penetration level.

Regulation power signal dispatched from ISO can be modeled as a scalar-value discrete random variable (RV) $\{r_n | n \in \mathbb{N}\}$ so that $r_n \in [-1, 1]$. Generally, system operator distribute required regulation to generators in proportion to their power capacity and thus the ratio as it is shown in Fig. 1 would be the same for individual generator or in our case EV fleet aggregator. The y-axis represents a normalized ratio between the called and contracted power capacity. Usually, the energy management system in a grid tries to balance the amounts of up and down regulation so that the overall energy dispatched from the generator/battery sums to zero over short and long term.

For a fixed $n \in \mathbb{N}$, r_n is random variable with associated stationary excess cumulative density function (CDF) $\Psi(r, n) = \mathbb{P}\{r_n < r\}$. Assume that the hour where there is regulating demand is randomly distributed across the time interval $[t_0, t_f]$ of width $T = t_f - t_0$. The time averaged CDF on integer interval of length $N \in \mathbb{N}$ is defined as

$$\Psi(r) = \frac{1}{N} \sum_{n=1}^N \Psi(r, n) \quad (5-1)$$

The quantile function of the probability distribution of a RV specifies, for a given probability, the value at which the RV will be at or below with that probability. Define the c -quantile function $\mathcal{Q}: [-1, 1] \rightarrow [-1, 1]$ as the inverse of CDF Ψ as

$$\Psi(r) = \mathbb{P}\{r_n < r\} = c \quad (5-2)$$

$$\mathcal{Q}(c) = \inf \{x \in [-1, 1]: c \leq \Psi(x)\} \quad (5-3)$$

The real-time market is launched after the spot market and is cleared 5 to 15 minutes before the operating interval to ensure the balance of supply and demand. We define the settlement price $\pi \in \mathbb{R}_+$ (\$/MWh) in the day-ahead forward market and imbalance prices (π^-, π^+) during the real-time market which can take both positive and negative values depending on system condition. Negative and positive imbalance cost at price $\pi^- \in \mathbb{R}$ (\$/MWh) and $\pi^+ \in \mathbb{R}$ (\$/MWh) respectively. In this study the FA is only price taker i.e., it will not affect the market price therefore, forward price π is fixed and known while the

imbalance prices are modeled as RVs with expectations denoted by $\mu_{\pi^-} = \mathbb{E}[\pi^-]$ and $\mu_{\pi^+} = \mathbb{E}[\pi^+]$. The FA contract portfolio $\mathbf{C} \in \mathbb{R}_+^M$ is structured as a sequence of M power levels that are piecewise constant on intervals typically of one hour.

$$\mathbf{C} = [C^{(1)}, \dots, C^{(M)}] \quad (5-4)$$

The time interval corresponding to contract $C^{(m)}$ is defined as the integer interval

$$\mathcal{N}_m = \{N(m-1) + 1, N(m-1) + 2, \dots, Nm\} \quad (5-5)$$

5.2.1 Fleet Aggregator Model

FA is regarded as an aggregated storage from the power system viewpoint. A generic storage system can be modeled with a linear difference equation as follows [79]:

$$e_{n+1} = e_n + h \left[\eta P_{c,n} - \frac{1}{\eta} P_{d,n} \right] \quad (5-6)$$

Subject to the following constraints

$$0 \leq e_n \leq \bar{e} \quad (5-7)$$

$$0 \leq P_{c,n} \leq \bar{P} \quad (5-8)$$

$$0 \leq P_{d,n} \leq \bar{P} \quad (5-9)$$

The available energy at time n is denoted by e_n . The amount of power absorbed from and supplied to the grid at time n is denoted by $P_{c,n}$ and $P_{d,n}$ respectively. The parameters $\eta \in [0,1]$ model charging and discharging efficiencies. h is the discretization step size. We are interested in maximizing expected profit and minimizing energy mismatch at the same time but as the power contracts are offered *ex-ante*, deviations naturally occur between the offered contracts and the dispatched regulation signal from ISO. We want to analyze the problem of optimizing the offering contract from FA scheduled to be delivered within one hour before operating hour in real-time market and show that it is a convex problem.

5.3 Optimal Contract Offering

Define the FA decision vector $\mathcal{D}_n = [P_{c,n}, P_{d,n}]^T$ for a particular time n . All of the information from the past relevant to the future is contained in the current storage state e_n . An important point to be kept in mind is that the FA is basically large energy storage, the

decision of how much power to offer over any individual time interval is dependent of the decision for previous and later time interval. Hence, the problem couples with respect to contact intervals. Note that FA should cover the capacity payment for the vehicles. Therefore it is desired to optimally offer the size of available capacity so as to maximize the profit while meeting the contract requirements. On the other hand, penalties would be imposed if the aggregator procures less power capacity than the contract portfolio and fails to comply with the regulation command sent from system operator in consequence.

Han *et al.* [80] derive the optimal policy for V2G aggregator. As there is no holding cost associated with stored energy, especially in case of EV fleet, it is optimal to always charge the maximum allowed energy when there is a surplus in generation relative to offer contract. Similarly, if we assume there is no price arbitrage opportunities; i.e., the penalty price is time invariant when there is a shortfall in generation, relative to the offered contract, the optimal policy is to discharge the maximum allowable energy from the storage needed to cover the shortfall, in other words, if there is a contract shortfall,

$$\mathcal{D}_n^* = \begin{bmatrix} 0 \\ \min\{r_n - C^{(m)}, \frac{e_n \eta}{h}, \overline{P_d}\} \end{bmatrix} \quad (5 - 10)$$

And if there is a contract surplus,

$$\mathcal{D}_n^* = \begin{bmatrix} \min\{C^{(m)} - r_n, \frac{\bar{e} - e_n}{h \eta}, \overline{P_c}\} \\ 0 \end{bmatrix} \quad (5 - 11)$$

For a given contract portfolio $\mathcal{C}$ the profit acquired by the FA on the interval $\{1, \dots, NM\}$ is defined as

$$\begin{aligned} \Phi(\mathcal{C}, \mathcal{D}, r) = h \sum_{m=1}^M \sum_{n \in \mathcal{N}_m} & \pi C^{(m)} - \pi^- [r_n - C^{(m)} + P_{c,n} - P_{d,n}]^+ \\ & - \pi^+ [C^{(m)} - r_n - P_{c,n} + P_{d,n}]^+ \end{aligned} \quad (5 - 12)$$

where $x^+ := \max\{x, 0\}$

Obviously vehicles plug in or out regardless of the contract portfolio of their aggregator. This will cause continuous fluctuation of the available power capacity which may fails to procure the contract amount but yet it is possible to comply with the regulation signal as

long as it is less than the available power. Thus, penalties will be imposed only when the aggregator failed to comply with the regulation signal. Payment transactions would be postponed until the service delivery is completed to deduct the possible penalties. We are interested in the expected profit $J(\mathbf{C}, \mathcal{D})$:

$$J(\mathbf{C}, \mathcal{D}) = \mathbb{E}\Phi(\mathbf{C}, \mathcal{D}, r) \quad (5 - 13)$$

The profit maximizing contract portfolio $\mathbf{C}^*$ and storage operation policy $\mathcal{D}^*$ are given by

$$(\mathbf{C}^*, \mathcal{D}^*) = \arg \max J(\mathbf{C}, \mathcal{D}) \quad (5 - 14)$$

Considering set of all feasible operation policies $\mathcal{D}$ we first prove that the optimal value of $Z(\mathbf{C}, r) = \max \Phi(\mathbf{C}, \mathcal{D}, r)$ is concave in the parameters $(\mathbf{C}, r)$. Based on (5-12) two terms v_n and u_n for energy shortfall and surplus respectively is defined.

$$v_n = r_n - C^{(m)} + P_{c,n} - P_{d,n} \quad (5 - 15)$$

$$u_n = C^{(m)} - r_n - P_{c,n} + P_{d,n} \quad (5 - 16)$$

Without loss of generality, consider the following linear programming formulation

$$\mathcal{Y}(\mathbf{C}, r) = \max_{v, e, P_c, P_d} \sum_{n=1}^N phC - \gamma h v_n \quad (5 - 17)$$

Subject to

$$e_0 = 0$$

$$v_n \geq 0$$

$$v_n \geq r_n - C + P_{c,n} - P_{d,n} \quad \forall n \quad (5 - 18) - (5 - 20)$$

Showing the concavity of $Z(\mathbf{C}, r)$ in $(\mathbf{C}, r)$ is equivalent to showing that $\mathcal{Y}(\mathbf{C}, r)$ is concave.

Let $\sigma \in [0, 1]$ and define

$$C^\sigma = \sigma C^1 + (1 - \sigma)C^2 \quad (5 - 21)$$

$$r^\sigma = \sigma r^1 + (1 - \sigma)r^2 \quad (5 - 22)$$

where $C^1, C^2 \in [-1, 1]$ and $r^1, r^2 \in [-1, 1]^N$. Assume the set of vectors $\{v^*(C, r), P_c^*(C, r), P_d^*(C, r)\}$ are optimizers of (16) for particular C, r . A feasible point for problem (16) with parameters (C^σ, r^σ) is

$$\sigma \begin{bmatrix} v^*(C^1, r^1) \\ P_c^*(C^1, r^1) \\ P_d^*(C^1, r^1) \end{bmatrix} + (1 - \sigma) \begin{bmatrix} v^*(C^2, r^2) \\ P_c^*(C^2, r^2) \\ P_d^*(C^2, r^2) \end{bmatrix} \quad (5 - 23)$$

Since the parameters $(\mathbf{C}, r)$ enter linearly through the constraints in (16). Now, concavity of $\mathcal{Y}(\mathbf{C}, r)$ in $(\mathbf{C}, r)$ is proven as follows

$$\mathcal{Y}(C^\sigma, r^\sigma) = phNC^\sigma - \gamma h \sum_{n=1}^N v_n^*(C^\sigma, r^\sigma) \quad (5 - 24)$$

$$\begin{aligned} &\geq phNC^\sigma - \gamma h \sum_{n=1}^N [\sigma v_n^*(C^1, r^1) + (1 - \sigma) v_n^*(C^2, r^2)] = \sigma \mathcal{Y}(C^1, r^1) + (1 - \sigma) \mathcal{Y}(C^2, r^2) \end{aligned} \quad (5 - 25)$$

Clearly $(\mathbf{C}^*, \mathcal{D}^*) = \mathbb{E} \mathcal{Z}(\mathbf{C}, r)$ is concave in $\mathcal{C}$, because a convex combination of concave functions is concave. ■

So far we proved that the problem of computing optimal contract offering and the corresponding expected profit reduces to convex programming. Another important open point to address is investigating the trade-off between optimal expected profit and available power capacity of aggregator. An intuitive statement is the larger the number of vehicles pooled together at each instance, the higher the expected profit. Mathematically, we will prove that the optimal expected $J(\mathbf{C}^*, \mathcal{D}^*)$ is concave and monotonically non-decreasing in the maximum energy capacity $\bar{e}$. Assume $\epsilon > 0$. Let $J^*(\bar{e})$ denote the optimal expected profit corresponding to a system with storage capacity $\bar{e} \geq 0$. $J^*(\bar{e} + \epsilon) \geq J^*(\bar{e})$ as the set of feasible solutions for problem (5-14) with capacity parameter $\bar{e}$ is a subset of the feasible set corresponding to a capacity parameter $\bar{e} + \epsilon$. Due to linear programming formulation, concavity is proved similarly.

The marginal expected optimal profit $dJ^*/d\bar{e}$ for energy capacity $\bar{e}$ is quantified in closed-form. Consider contract portfolio $\mathbf{C} \in \mathbb{R}_+^M$ with individual contract duration of length N . Define the RV $\xi_-(\mathbf{C})$ and $\xi_+(\mathbf{C})$ to be the number of times that the random process $\{r_n\}$ crosses the associated contract sequence from above and below respectively. The $\xi_-(\mathbf{C}) + \xi_+(\mathbf{C})$ can be interpreted as the number of *energy arbitrage events* associated with the contract portfolio $\mathbf{C}$. Let $c = \frac{\pi + \pi^+}{\pi^- + \pi^+}$, $e_0 = 0$ and there is no constraint on

charged/discharged power. Then the marginal expected optimal profit with respect to $\bar{e}$ at the origin is given by $\left. \frac{dJ^*}{d\bar{e}} \right|_{\bar{e}=0} = \pi^- \eta^2 \mathbb{E}[\xi_-(C^*)] + \pi^+ \eta^2 \mathbb{E}[\xi_+(C^*)]$ and optimal contract C^* is given by the c -quantile of the time averaged distribution Ψ explained earlier,

$$C^* = Q(c) = \inf \{x \in [-1,1]: c \leq \Psi(x)\} \quad (5 - 26)$$

The expected profit, shortfall and spillage corresponding to the contract C^* are given by

$$J(C^*) = \pi^- h \int_{-1}^c Q(r) dr - \pi^+ h \int_c^1 Q(r) dr \quad (5 - 27)$$

$$S_-(C^*) = h \int_{-1}^{\Psi(C^*)} [C^* - Q(r)] dr \quad (5 - 28)$$

$$S_+(C^*) = h \int_{\Psi(C^*)}^1 [Q(r) - C^*] dr \quad (5 - 29)$$

Our previous result has an intuition that the marginal value of storage capacity is proportional to the expected number of energy arbitrage events. Consider an FA with small storage capacity $\epsilon > 0$. Each time there is an imbalance in system the FA has the opportunity to extract/absorb ϵ energy from its available storage and lower the financial penalty by $\pi^- \eta^2 \epsilon$ or $\pi^+ \eta^2 \epsilon$. Authors in [32] calculate the profits of 500 PEVs participating in the markets of primary, secondary and tertiary control in Sweden and Germany. They conclude that the secondary frequency control market in Germany is the most profitable due to its favorable capacity and energy prices, with a monthly profit of € 80 per vehicle, while none of the Swedish regulating power markets are profitable. Furthermore, they outline the ideal characteristics of a regulating market for vehicle provision: energy and capacity payments, asymmetric power bids, short contract times and small minimum bid sizes. Aforementioned case study confirms our analytical approach and obtained results.

Figure 46. Normal distribution fit to regulation signal, $N(0.0099, 0.0351)$

Figure 47. Probability plot of actual data

Figures 46 and 47 show the normal distribution fit to regulation signal and its probability plot respectively. The optimal expected profit, energy shortfall and energy surplus graphically represented as areas A1, A2 and A3 respectively bounded by the time averaged CDF $\Psi(r)$ as illustrated in Figure 48 for $\Psi(C^*) = 0.6$. The decision criteria outlined above can be derived from the different scenarios. No inter-temporal constraints are considered, so each hour can be analyzed independently.

Figure 48. Graphical interpretation of optimal profit, shortfall and spillage for $\Psi(C^*) = 0.6$

5.4 Stochastic Modeling of Market Uncertainties

Uncertainties of day-ahead market price, charging power realization and reserve price are characterized as stochastic processes which are sampled independently and combined using scenario tree [84]:

- 1) Generate a set of price scenarios for the day-ahead market with associated probabilities
- 2) Generate a set of reserve price scenarios for each realization of the day-ahead market prices
- 3) Simulate set of charging power scenarios for each reserve price realization.

Graphically, a scenario tree comprises a set of nodes and branches. The nodes represent the points where stochastic decisions are made. Each node has a single predecessor and can have several successors. The first node is called the root node which is the beginning of the planning horizon. In the root node the first-stage decisions are made.

The nodes connected to the root node are the second-stage nodes and represent the points where the second-stage decisions are made. The nodes in the last stage are referred to as leaves. Each single path between the root node and a leaf is named scenario. A scenario is a single realization of a stochastic process. In a scenario tree, the branches represent different realizations of the random variables. Each branch has associated with a probability of

occurrence. In this way, the probability of a scenario is the product of all branches probabilities associated with that scenario shown as $prob(\omega)$.

Figure 49. Schematic of scenario tree

PJM day-ahead and reserve prices on August 2011 were taken as different scenarios which may occur on the next day. The day-ahead and reserve price scenarios are shown in Fig. 2(a) and 2(b) respectively. Figure 50 demonstrates the price variation over the course of the month at each hour of the day.

Figure 50. (a) Day-ahead; (b) reserve price variation over the course of the August 2011

Usually the system operator tries to balance between the amounts of up and down regulation so that the overall energy dispatched from the generator (battery) sums to zero. It should be noted that historical data was used for scenario generation.

Figure 51. Optimal charging power bounds based on a price-based charging algorithm

The energy surplus in EV batteries can be effectively used due to the correlation between load and electricity price in power system operation. Optimizing the charging times of vehicle batteries based on price variation is essential for utilizing less expensive electricity. This also reduces the peak of the overall load. Moreover, daily price fluctuations provide a clear potential for arbitrage profits. Charging pattern is calculated by the proposed price based algorithm. The algorithm is based on plug accessibility and forecasted day-ahead price. It is assumed that 80% of users give up the charging control of their EVs to the fleet operator and others follow uncontrolled domestic charging.

After creating the individual schedules, they will be aggregated at a regional level. Final result is shown in Figure 51 as boxplot which is used to find equiprobable scenarios for charging power realization. Different Charging power realizations serves as different optimal POPs. In real-time, aggregator controls the charging of each single EV and selects a particular POP so as to minimize variations of fleet power consumption around that selected POP.

Probability of price scenarios is statistically described by the produced probability mass function (PMF). PMF is obtained from the non-parametric fit to the cumulative probability of historical data. PMF of day-ahead price scenario for the first hour is shown in Figures 52 and 53 as an example. Same procedure was used to find occurrence probability for other stochastic processes. Price scenarios and charging demands are divided into 10 and 5 bins respectively.

Figure 52. Non-parametric fit to cumulative probability of day-ahead price scenarios for the first hour

Figure 53. Probability mass function of day-ahead price for the first hour of a day

In this way, the probability of a single scenario ω is defined as

$$prob(\omega) = prob(\omega_D)prob(\omega_R)prob(\omega_c) \quad (5 - 30)$$

Where ω_D , ω_R and ω_c are the day-ahead price, reserve price and charging power scenarios associated with that single scenario respectively.

In summary, the general procedure to solve the optimal aggregator bidding strategy problem is as follows: 1) model the uncertain processes; 2) generate possible scenarios and construct the scenario tree; 3) choose an appropriate risk measure which will be discussed in next section; 4) model decision problem as a stochastic problem and 5) solve the optimization problem. FA bidding strategy problem can be solved by using a two-stage stochastic programming approach.

5.4.1 Risk Management

The uncertainty in the available battery capacity for charging or discharging is obviously of importance for FA bidding into the electricity market. The strategy for bidding in the day-ahead and real-time market will influence revenues, imbalance costs and affect the overall profit for the FA and consequently vehicle owners. Rockafellar and Uryasev [81]-[83] developed new method for quantification of risk in stochastic optimization. If we assume that the FA is risk neutral, the optimal bidding strategy can be derived by maximizing the expected profit as shown in (5-31). Another formulation which considers the FA risk preferences is to maximize the expected utility as shown in (5-32). We assume that a standard exponential utility function can be defined for FA over the range of possible profit outcomes. The risk is shown by parameter w where positive/negative β refers to risk prone/averse decision making. In final formulation, in order to consider risk preferences of FA and balance between mean profit and risk we measure the risk in terms of the conditional value at risk, i.e., the expected profit below a certain threshold defined by th . An objective function taking into account both expected profit and $CVaR_h$ is shown in (5-34). The parameter β determines the weight assigned to $CVaR_h$.

$$\pi_h^* = \text{Max}_{q_h} \sum_{m=1}^M \text{prob}_m \cdot \pi_h^m(q_h) \quad (5-31)$$

$$U_h^* = \text{Max}_{q_h} \sum_{m=1}^M \text{prob}_m \cdot U_h^m(\pi_h^m(q_h)) \quad (5-32)$$

where

$$U_h^m = \frac{1}{1 - e^\beta} \left[1 - \exp\left(\frac{w(\pi_h^m - \pi^{min})}{\pi^{max} - \pi^{min}}\right) \right] \quad (5-33)$$

$$\mathbf{C}_h^* = \text{Max}_{q_h} \left\{ \sum_{m=1}^M \text{prob}_m \cdot \pi_h^m(q_h) + \beta \cdot \text{CVAR}_h(q_h, th) \right\} \quad (5-34)$$

5.5 Problem Formulation

The aim for an FA is to maximize profit through providing reserve during high price periods and charging EVs during low price period and to minimize trading risks under various system uncertainties through managing the reserve capacity and delivered regulation. The total profit $\mathfrak{R}$ consists of reserve capacity payment (RCP), delivered reserve payment (DRP), the charging cost of electric energy (CHC), total imbalance cost (IMC). A weighted factor of the conditional value at risk ($\beta.CVaR$) is introduced in the objective function to minimize trading risk. The objective function is to maximize the total benefit $\mathfrak{R}$ as follows:

$$\text{Max } E[\mathfrak{R}] = RCP + DRP - CHC - IMC + \beta.CVaR \quad (5-35)$$

$$RCP = \sum_{\omega} \sum_t h [\text{prob}(\omega)(\pi_{t\omega}^c P_t^{up} + \pi_{t\omega}^c P_t^{dn})] \quad (5-36)$$

$$DRP = \sum_{\omega} \sum_t h [\text{prob}(\omega) \pi_{t\omega}^R R_t^{up}] \quad (5-37)$$

$$CHC = \sum_{\omega} \sum_t h [\text{prob}(\omega) \pi_{t\omega}^{DA} R_t^{DA}] \quad (5-38)$$

$$IMC = \sum_{\omega} \sum_t [\text{prob}(\omega)(\lambda_{t\omega}^+ \pi_{t\omega}^{DA} \Delta_{t\omega}^+ - \lambda_{t\omega}^- \pi_{t\omega}^{DA} \Delta_{t\omega}^-)] \quad (5-39)$$

$$\beta.CVaR = \beta \left(\xi - \frac{1}{1-\alpha} \sum_{\omega} \text{prob}(\omega) \delta_{\omega} \right) \quad (5-40)$$

Subject to the following constraints:

$$\text{Positive imbalance constraint,} \quad 0 \leq \Delta_{t\omega}^+ \leq P_{t\omega}^{DA} h \quad \forall t \forall \omega \quad (5-41)$$

$$\text{Negative imbalance constraint,} \quad 0 \leq \Delta_{t\omega}^- \leq P^{max} h \quad \forall t \forall \omega \quad (5-42)$$

$$\text{Upward reserve constraint,} \quad P_{t\omega}^{up} \leq A_t \left(P_{t\omega}^{DA} + \frac{\Delta_{t\omega}}{h} \right) \quad \forall t \forall \omega \quad (5-43)$$

$$\text{Downward reserve constraint,} \quad P_{t\omega}^{DA} + P_{t\omega}^{dn} + \frac{\Delta_{t\omega}}{h} \leq A_t P^{max} \quad \forall t \forall \omega \quad (5-44)$$

$$\text{Power exchange constraint,} \quad \sum_t (P_{t\omega}^{DA} + P_{t\omega}^{dn} - P_{t\omega}^{up}) h + \Delta_{t\omega} \geq \sum_t Q_{t\omega} \quad \forall \omega \quad (5-45)$$

$$\begin{aligned} \text{CVaR constraints,} \quad & -\sum_t [\text{prob}(\omega) h (\rho \pi_{t\omega}^{DA} P_t^{up} + \rho \pi_{t\omega}^{DA} P_t^{dn} + \pi_{t\omega}^R R_t - \\ & \pi_{t\omega}^{DA} P_t^{DA}) - (\lambda_{t\omega}^+ \pi_{t\omega}^{DA} \Delta_{t\omega}^+) + (\lambda_{t\omega}^- \pi_{t\omega}^{DA} \Delta_{t\omega}^-)] + \xi - \delta_{\omega} \leq 0 \quad \forall \omega \end{aligned} \quad (5-46)$$

$$\delta_{\omega} \geq 0 \quad \forall \omega \quad (5-47)$$

Constraint (5-41) ensures that positive energy deviation is equal or below the electrical energy bid in the day ahead market. This happens when FA bids in day-ahead market for hour t , but in real time does not consume anything. The constraint of (5-42) defines upper limit of negative energy deviation when FA does not bid in day-ahead market for hour t , but in real time consumes energy at maximum level. Constraint (5-43) enforces the upward reserve bid to be less than the sum of day-ahead bid and total power deviation. Sum of total power deviation, day-ahead and downward reserve bid should be less than the maximum available power for charging all EVs plugged-in as expressed in (5-44). Constraint (5-45) ensures that the overall power exchange during the day is always greater than the charging requirement. Constraints (5-46), (5-47) are required for the linear formulation of the CVaR. A more detailed mathematical description of the CVaR is included in Appendix C.

Total expected profit $E[\mathfrak{R}]$ is the sum of each scenario profit multiplied by its probability. The profit in objective function consists of several components. The reserve capacity payment can be calculated using (5-36). $prob(\omega)$ represents the scenario probability. The reserve price offered by the aggregator is a fraction of day-ahead price $\pi_{t\omega}^c = \rho\pi_{t\omega}^{DA}$, which is assumed to be low enough for having the bid accepted. P_t^{up} and P_t^{dn} are upward and downward reserve bids. The delivered reserve payment (DRP) is calculated by (5-37). Note that FA provides reserve by following the negative of reserve signal since it is on demand side. For the reserve signal dispatched from ISO, up and down reserve are defined as in (5-48) and (5-49). Delivered reserve power R_t is decomposed into the sum of up and down reserve as shown in (5-50).

$$R_t^+ = r_t^+ P_t^{up} \quad \forall t \quad (5-48)$$

$$R_t^- = r_t^- P_t^{dn} \quad \forall t \quad (5-49)$$

$$R_t = R_t^+ - R_t^- \quad \forall t \quad (5-50)$$

The purchase costs of electric energy for EVs in day-ahead market is calculated by (6). Total Imbalance costs (IMC) is calculated using (5-38) consists of two parts. Total deviation of energy incurred by FA is decomposed into the sum of the positive and negative deviations in (5-51) so that no binary variables are required as in [11].

$$\Delta_{t\omega} = \Delta_{t\omega}^+ - \Delta_{t\omega}^- = h(P_{t\omega}^{DA} - P_{t\omega}) \quad \forall t \forall \omega \quad (5-51)$$

If imbalance is positive (positive deviation between bid and consumption), imbalance prices are as (5-52).

$$\begin{cases} \pi_t^+ = \min(\pi_t^{DA}, \pi_t^R) \\ \pi_t^- = \pi_t^{DA} \end{cases} \quad P_{t\omega}^{DA} > P_{t\omega} \quad (5-52)$$

If the imbalance is negative (negative deviation between bid and consumption), imbalance prices are as (5-53).

$$\begin{cases} \pi_t^- = \max(\pi_t^{DA}, \pi_t^R) \\ \pi_t^+ = \pi_t^{DA} \end{cases} \quad P_{t\omega}^{DA} < P_{t\omega} \quad (5-53)$$

Considering (5-52) and (5-53), FA incurs opportunity cost and it is penalized if it does not contribute to restore the system imbalance, from the discussion above positive and negative imbalance penalty ratios are defined as (5-54) and (5-55) respectively.

$$\lambda_t^+ = \frac{\pi_t^+}{\pi_t^{DA}} \leq 1 \quad \forall t \quad (5-54)$$

$$\lambda_t^- = \frac{\pi_t^-}{\pi_t^{DA}} \geq 1 \quad \forall t \quad (5-55)$$

The risk is measured by the conditional value at risk (CVaR) at the confidence level α defined in (8). This metric can be expressed linearly within an optimization problem and exhibits good mathematical properties [81]. For maximizing a discrete profit distribution, $\alpha - CVaR$ can be defined as approximately as expected profit of $(1 - \alpha)100\%$ scenarios with lowest profit. FA is risk neutral if weighting factor is $\beta = 0$. While $\beta \neq 0$ represents a risk averse FA. This weighting factor enforces the tradeoff between expected profit and risk. The higher the value of β , the more risk averse the FA is.

To take into account the operation of EV fleet as one aggregated storage unit we have

$$e_{t\omega} = e_{(t-1)\omega} + \eta(d_t P_{t\omega} + \Delta_{t\omega}) \quad \forall t \forall \omega \quad (5-56)$$

$$\underline{e} \leq e_{t\omega} \leq \bar{e} \quad \forall t \forall \omega \quad (5-57)$$

$$P_{t\omega} \leq A_t \frac{\bar{e} - e_{t\omega}}{d_t} \quad \forall t \forall \omega \quad (5-58)$$

Equation (5-56) considers dynamic operation of storage and ensures the energy balance of the aggregated battery. It keeps track of energy supplied to the battery, including the real-time energy deviations. The $e_{t\omega}$ variable in constraint (5-57) is limited to the range between the minimum and maximum values. Constraint (5-58) ensures the fact that the plugged vehicles, cannot charge for the driving ones. They dictate that in any given hour the energy charged to the batteries cannot exceed the available capacity of the aggregated battery multiplied with the share of cars that are assumed parked and plugged.

Finally, non-anticipativity of the stochastic decision process is necessary to ensure that at time t , decision variables must not depend on future realization of the stochastic variables. Note that the two-stage model (5-35)–(5-53) is intended to find optimal bidding strategies for the day-ahead market. The first-stage decision variable is the offered power by FA in day-ahead market. Upward and downward reserves and total energy deviation are the second stage variable. The advantages of linear formulation stated above are simplicity and robustness which can be solved with commercial available solvers.

5.6 Simulation & Results

The proposed technique is tested by a FA with 10000 EVs. The parameters for an EV are shown in Table 13. Assume hour long reserve commitments. For simplification, all vehicles are assumed to be half charged. Scenarios with different probabilities model the distribution of the stochastic process for an hourly discretized time horizon of the next day. Input data obtained from PJM market [85] was used as explained. The proposed methodology is solved using GAMS [86]. SCENRED tool [87] was used for the reduction of scenarios modeling the random data processes. The scenario reduction algorithms provided by SCENRED determine a scenario subset (of prescribed cardinality or accuracy) and assign optimal probabilities to the preserved scenarios. The reduced problem is then solved by a deterministic optimization algorithm provided by GAMS. The solution of the optimization model contains the set of optimal bid for the day-ahead market and the set of up and down regulation capacity for daily operation. The model is performed for various risk levels. The results are presented and discussed in the following under a particular regulation signal and fleet realization. 95% confidence level was used.

Table 13. EV parameters

Parameter	Value
Connection capacity (charger rating)	7.2 kW
Average battery size	25 kWh
Average energy consumption	0.23 kWh/km
Charging efficiency	0.9
Minimum SOC	0.2
Maximum SOC	0.9

The expected total profits for five different reserve capacity prices are shown in Table 14 when $\beta = 1$.

Table 14. Expected total profit for different reserve capacity price

ρ	Expected Total Profit
10%	-3074.35 \$
20%	-229.78 \$
30%	1184.46\$
40%	5606.92 \$
50%	9554.08 \$

Capacity payments are the main drivers of the profitability of an FA as a reserve provider. In our case study, reserve capacity payment should be more than 20% of day-ahead price so that FA operation would be profitable. The following results are with $\rho = 0.3$ when FA receives 30% of day-ahead price for reserve capacity.

5.6.1 Effect of Risk Levels

Considering the stochastic nature of energy price and charging profile the FA total bids for different risk levels are shown in Figure 54. It is clear from Figure 54 that the total bid is decreased when β is increased. The reason is that FA becomes more risk averse and does not want to risk for high profit scenarios or experience any losses.

Figure 54. Total bid for different risk level with $\rho = 0.3$

The expected profit for different risk levels are shown in Figure 55. As weighting factor increases from zero to one, the expected profit decreases and then keeps constant of \$1184.46.

Figure 55. Expected profits for different risk levels with $\rho = 0.3$

Figure 56. Profit histograms with $\rho = 0.3$ for different risk levels (a) $\beta = 0$ (b) $\beta = 1$

When β is set to zero in spite of higher expected total profit, the profit scenarios have more variation and FA is subject to more risk. The expected total profit and standard deviation for the risk neutral case is 21.5% and 9.47% greater than the risk averse case respectively. However, its risk is not minimized and the FA is subject to more losses. The histograms of the profits for $\beta = 0$ and $\beta = 1$ are shown in Figure 56(a) and 56(b) respectively. When β is increased, the profit of scenarios are more concentrated and FA would not experience high and low profit scenarios as highlighted in Figure 56(a). However, the expected total profit will be decreased as mentioned earlier.

5.6.2 Optimal Schedule Strategy

The proposed charging pattern is related to the day-ahead market prices. Therefore, an increased consumption bid is observed when the prices are low and most of the vehicles are parked and connected in early morning as shown in Figure 57. It closely follows the pattern

of optimal charging shown in Figure 51. The available capacity for up reserve is limited and is always less than sum of total bid and total power deviation. This highlights the fact that symmetrical bid offering is not in favor of EV participation in reserve and regulation market.

Since $\lambda_t^- \geq \lambda_t^+$, the FA positive imbalance is higher than negative imbalance. Negative and positive imbalance energy is 2.61 MWh and 8.86 MWh respectively. In case of equal positive and negative penalty ratio, the FA positive and negative imbalances are almost the same. Fig. 8 also shows that the imbalance penalties would force the FA to accurately bid in day-ahead market. Reserve capacities during the periods of high energy prices are greater. The reason is that penalties are proportional to energy prices and high energy price means high imbalance cost.

If there is no penalty, FA will not bid in day-ahead market. In this case, FA allocates the capacity for up and down regulation with respect to price variation in real time. Therefore, it is essential to penalize the FA for its energy imbalances. Otherwise it would not be serious about its day-ahead operation planning. Because EVs should have enough energy in their batteries for the first trip, fleet capacity for regulation down power provision decreases drastically between 0500 and 0900. Thereafter, FA tries to increase the profit by proposing down regulation reserve. In real-time FA uses that capacity to benefit from high energy prices although it would be penalized for its imbalance in some scenarios.

Figure 57. FA schedule for the day-ahead and reserve market with $\rho = 0.3$ and $\beta = 1$

It is important to note that Fig. 8 does reveal the actual regulating power provided. Sometimes the fleet potential to provide reserve is very limited. Therefore, additional regulating reserves are needed. It should be noted that providing the power regulation will change EVs' charging pattern.

5.7 Concluding Remarks

A model for the optimal EV aggregator bidding strategy for day-ahead and balancing market is introduced. The objective is to maximize the expected FA profit. Different charging portfolio and energy price scenarios are used to build a scenario tree. Stochastic programming approach is used to obtain the optimal day-ahead operation planning and regulation capacity. *CVaR* method is used as risk-averse criterion. The model is applied to a real case study based on PJM market data.

The results show that a combined bidding from an aggregator would decrease the cost of participation in an energy market. FA profit is also decreased when its risk is minimized and it would not experience high profit scenarios or losses. The simulation shows that the bidding strategy of an FA is highly dependent on the capacity payment and imbalance penalty scheme. It is important for fleet aggregator to find the right balance between risk and return when bidding into regulation market. The analytical results show that the optimal bid is highly dependent on the expected day-ahead and real-time imbalance prices.

Chapter 6. Conclusion & Future Works

6.1 Conclusion

The electrification of transportation poses a challenge to the electricity grid while also offering unique opportunities to both energy and transportation sectors. Adoption, acceptance and full scale integration of PEVs is significantly related to optimal deployment of charging infrastructures into the electric power grid and reliable access to them. Fast public charging and distributed charging infrastructure is requested to support the fleet of PEVs.

The energy consumed in the transportation sector is significant. With PEVs we make use of this consumption in the power system; from stabilizing the grid to supporting large-scale renewable energy. At this early stage, it is uncertain to tell whether PEVs will eventually take off commercially and replace ICE-based vehicles, or if they will be superseded by other competing technologies, such as hydrogen fuel cells. With the right technologies and infrastructures, the integration of PEVs with the power system provides an opportunity for small-scale distributed storage while they are plugged-in.

PEVs can contribute to significant increase the load demand at certain hours, although the charging demand is very limited most of the time. However, these high charging demands is found to decrease significantly when we consider the limited or short commuting mileage leading to significant levels of SOC on the PEV batteries when arriving for charging. With large numbers of PEVs and the communications and sensing associated with the smart grid, PEVs could provide ancillary services for the grid. In a price based charging scheme, if the PEVs are to aid the power system, then the price fluctuations have to be sufficiently high and if the PEVs should help implement higher shares of renewables, then these resources should have an impact on the power prices. The discharging of the PEV batteries to support the system demand, thus providing regulation capacity, has been reported in this research. The ability to support the demand depends on the SOC level of PEV upon arrival at parking after daily trip. It is observed that PEVs are able to provide notable amount of regulation capability because of the significant levels of SOC.

In this study, we assumed that a contract which includes price signals for every hour and imply broadcasting of the spot price exists. The price is published for each hour of the next day. The end-user in this scenario is motivated to move the electricity consumption from expensive hours to less expensive hours. Typical spot prices are in the in the order of 0.04 €/kWh. Prices around 0.20 €/kWh also occur. The end-users react to the general pattern in the prices.

A precondition for obtaining some level of demand response in the spot price scenario is a communication system that enables broadcasting of the hourly spot prices for the following day to the consumer. The end-users choose to give the task of optimizing the charging to the fleet aggregator. An advantage of this platform could be that the fleet operator may reduce the cost of the automation and control systems due to a large volume. However, this setup demands a two-way communication system where the retailer or fleet operator has knowledge of the state of the individual EV, such as driving patterns, charging preferences, state of charge of the battery, etc. The retailer can also include regulating power in the pricing in order to take advantage of the high variation in prices in the regulating power market compared to spot prices. For end-users with demand that can be controlled, regulating power can reduce the electricity cost, e.g. by dispatching demand to periods with low prices.

EV schedules optimization shift generation variability in time domain for more profits and decrease bidding imbalance error. Energy trading in the balancing market entails an opportunity cost for those market agents incurring deviations. The effectiveness of the EVs participation in the market is depending on the range of electricity price variations. While EVs may be used to increase base load consumption their role as energy buffer is limited as long as price variations are low. EVs are supposed to support the variability of the renewable generation. This may be feasible if the renewable generation has sufficient impact on the price.

6.2 Future works

One of the drawbacks of completely market controlled PEV charging is that the PEVs will charge and discharge only on market signals, not considering whether or not it is unfavorable for the power system. Congestions in the local grid have to be taken into account

with respect the behavior of the end-user. An increase in peak demand does not necessarily threaten the security of supply, but it could imply a more congested transmission grid and higher prices. Besides, discharging PEV batteries energy to the grid will change the system operating state since the new scheduling of generation will be different from the initial operating condition. This will have an effect on loss coefficients of the network which directly affect the economic dispatch.

Moreover, if battery wear costs were included in this study it might reduce charge fluctuations due to small costs changes, as a lower charge rate reduces battery wear. A lower charge rate to minimize battery wear would make a more even distribution of the night charging. The PEVs are assumed to be price takers as their interaction does not cause any change in prices, just as the charge/discharge patterns do not cause any changes in need for regulating power. This is probably a realistic assumption as long as the PEVs are following the predicted charge/discharge pattern with low penetration level.

PEVs could be the factor that unlocks the increased penetration of wind energy. It is difficult to evaluate to what extent the PEV infrastructures facilitates a higher share of wind power in the power system, because the regulating power from the PEVs will have to be available when the additional wind power requires it. From the viewpoint of the power grid; the objective functions are to minimize the abandoned wind energy along with the constraint set for aggregate PEVs' charging/discharging in order to maximize customers benefit considering system constraints. An empirical study and more realism to the analysis should be done by considering alternative market rules and profit formulation to see how market design affects the optimal bidding decisions. Evaluation of PEVs' impact on a model distribution network and modeling and incorporating renewable energy resources has to be done.

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Appendices

Appendix A: Charging infrastructure specifications

	Technical Features	Structural Features	Standards	Communication & Identification	Examples
Level 1	<ul style="list-style-type: none"> Power input 230V AC Tolerance 10 % •Frequency input 50 to 60 Hz • Power output 230V AC •Maximum current output 16 A per outlet • Current rating 10-12A • Temperature range -10 to +60 °C 	<ul style="list-style-type: none"> • Anti-vandalism body • Small size • Access and prepayment with proximity cards • Display for credit monitoring • Integrated energy measurement and electrical protections (optional) • Indoor use 	<ul style="list-style-type: none"> • EN 61851-1 : 2001 part 1, • IEC 61000, • IEC 60364-4-41, IEC 60884-1, • IEC61010, • UNE-EN55011, ISO 14443A 	<ul style="list-style-type: none"> • RS • Ethernet • ZigBee • PLC, GSM, GPRS • RFID • Barcode • Magnetic card 	<ul style="list-style-type: none"> Delphi Electromotive Circutor
Level 2	<ul style="list-style-type: none"> • Power input 230V AC • Tolerance 10 % • Frequency 50 to 60 Hz • Power output 230V AC • Maximum current output 32 A per outlet • Current rating 16-32A • Temp range: - 20 to +50 °C 	<ul style="list-style-type: none"> • Anti-vandalism body • Coated with anti-graffiti paint • Access and prepayment with cards or keys • Credit monitoring • Energy measurement and electrical protections • Protection against energy theft 	<ul style="list-style-type: none"> •EN 61851-1 : 2001 par1 • IEC 61000 • IEC 60364-4-41 • IEC 61008-1,IEC 60884-1 • IEC 60529 ,IEC 61010 • UNE-EN55011 - ISO 14443A 	<ul style="list-style-type: none"> • RS • Ethernet • ZigBee • PLC, GSM, GPRS • RFID • Barcode • Magnetic card 	<ul style="list-style-type: none"> POD point Electromotive Coulomb Power park Park & Charge
Fast charging Level 3	<ul style="list-style-type: none"> • Power input 230V AC / 400V AC. Tolerance 10 % • Frequency 50 to 60 Hz • Power output 230V AC / 400V AC • Maximum output current 32 / 63 A • Earth leakage protection Self-re closing system 	<ul style="list-style-type: none"> • Anti-vandalism body • Access and prepayment with proximity cards • Display for credit monitoring • Integrated energy measurement and electrical protections • Protection system against energy theft 	<ul style="list-style-type: none"> • EN 61851-1 : 2001 part 1, • IEC 61000, • IEC 60364-4-41, • IEC 61008 – 1, • IEC 60884-1, • IEC 60529, • IEC 61010 , • UNE-EN55011, ISO 14443A 	<ul style="list-style-type: none"> • RS • Ethernet • ZigBee • PLC, GSM, GPRS • RFID • Barcode • Magnetic card 	<ul style="list-style-type: none"> SEW Walther BRUSA Tegrel
Inductive Charging	<ul style="list-style-type: none"> • Power input 230V AC / 400V AC. • Tolerance 10 % • Frequency 50 to 60 Hz • Power output 230V AC / 400V AC • Maximum output current 32 / 63 A • Earth leakage protection Self-reclosing system 	<ul style="list-style-type: none"> • Anti-vandalism body • Access and prepayment with proximity cards • Display for credit monitoring • Push buttons for outlet selection • Integrated energy measurement and electrical protections 	<ul style="list-style-type: none"> • EN 61851-1 : 2001 part 1, • IEC 61000 , • IEC 60364-4-41, • IEC 61008 – 1, • IEC 60884-1, • IEC 60529, • IEC61010, • UNE-EN55011, ISO 14443A 	<ul style="list-style-type: none"> • RS • Ethernet • ZigBee • PLC, GSM, GPRS • RFID • Barcode • Magnetic card 	<ul style="list-style-type: none"> Conductix Wampfler ALPIQ SEW Small scale inductor systems Walther

Appendix B: Generating Availability and Reliability

Table 1. Generating Availability Report Based on NERC

Peer Group	AF
FOSSIL-All Fuel Types- All MW Sizes	86.97%
FOSSIL- Coal Primary- All MW Sizes	87.10%
FOSSIL- Oil Primary - All MW Sizes	82.61%
FOSSIL- Gas Primary - All MW Sizes	87.79%
NUCLEAR-All Fuel Types- All MW Sizes	90.14%
JET ENGINE- All MW Sizes	91.63%
GAS TURBINE- All MW Sizes	92.30%
COMBINED CYCLE- All MW Sizes	89.54%
HYDRO- All MW Sizes	86.26%
PUMPED STORAGE- All MW Sizes	87.36%
GEOHERMAL- All MW Sizes	96.73%
DIESEL- All MW Sizes	94.99%

Table 2. Generating Reliability Report Based on NERC

Peer Group	EDH	PH	DHR %	R %
FOSSIL-All Fuel Types- All MW Sizes	160.13	8647.77	1.85	98.15
FOSSIL- Coal Primary- All MW Sizes	217.17	8729.53	2.49	97.51
FOSSIL- Oil Primary - All MW Sizes	45.01	8652.28	0.52	99.48
FOSSIL- Gas Primary - All MW Sizes	45.55	8427.21	0.54	99.46
NUCLEAR-All Fuel Types- All MW Sizes	127.43	8730.48	1.46	98.54
JET ENGINE- All MW Sizes	18.56	8753	0.21	99.79
GAS TURBINE- All MW Sizes	2.29	8749.63	0.03	99.97
COMBINED CYCLE- All MW Sizes	109.6	8736.3	1.25	98.75
HYDRO- All MW Sizes	14.7	8759.51	0.17	99.83
PUMPED STORAGE- All MW Sizes	1.08	8764.98	0.01	99.99

GEOHERMAL- All MW Sizes	12.2	8764.93	0.14	99.86
DIESEL- All MW Sizes	53.23	8732.72	0.61	99.39

Appendix C: Conditional Value at Risk

Let $f(x, y)$ be a profit function that depends on a decision vector $x \in \mathbb{R}^n$ and a random vector $y \in \mathbb{R}^m$. The PDF of the random vector y is $p(y)$. Then, the probability of f not falling below a threshold ζ is

$$\Psi(x, \zeta) = \int_{f(x, y) \geq \zeta} p(y) dy \quad (\text{A.1})$$

As a function of ζ and for fixed x , $\Psi(x, \zeta)$ is the CDF of f associated with x . $\Psi(x, \zeta)$ is non-increasing with respect to ζ . For simplicity, $\Psi(x, \zeta)$ is assumed to be continuous with respect to ζ .

The value-at-risk of f for a confidence level $\alpha \in [0, 1]$ is

$$VAR_\alpha(x) = \max\{\zeta \in \mathbb{R} : \Psi(x, \zeta) \geq \alpha\} \quad (\text{A.2})$$

The CVaR at the α confidence interval is given by

$$CVaR_\alpha(x) = (1 - \alpha)^{-1} \int_{f(x, y) \geq VAR_\alpha(x)} f(x, y) p(y) dy \quad (\text{A.3})$$

In [81], $VAR_\alpha(x)$ and $CVaR_\alpha(x)$ are characterized in terms of a function

$$F_\alpha(x, \zeta) = \zeta + (1 - \alpha)^{-1} \int_{y \in \mathbb{R}^m} [f(x, y) - \zeta]^- p(y) dy \quad (\text{A.4})$$

where $[z]^- = \min(0, z)$. Accordingly, $VAR_\alpha(x)$ and $CVaR_\alpha(x)$ are

$$VAR_\alpha(x) = \underset{\zeta}{\operatorname{argmax}} F_\alpha(x, \zeta) \quad (\text{A.5})$$

$$CVaR_\alpha(x) = \max_{\zeta} F_\alpha(x, \zeta) = F_\alpha(x, VAR_\alpha(x)) \quad (\text{A.6})$$

Therefore, both $VAR_\alpha(x)$ and $CVaR_\alpha(x)$ can be obtained by maximizing $F_\alpha(x, \zeta)$ over x and ζ .

In stochastic programming, the random vector y is modeled by generating plausible scenarios that meet the statistical properties of y . Let $y_1, y_2, \dots, y_N$ be the set of scenarios generated for y , then (A.4) can be approximated by

$$\tilde{F}_\alpha(x, \zeta) = \zeta + (1 - \alpha)^{-1} \sum_{\omega} \operatorname{prob}(\omega) [f(x, y_\omega) - \zeta]^- \quad (\text{A.7})$$

where $prob(\omega)$ is the probability of occurrence of scenario y_ω .

Hence, maximizing $\tilde{F}_\alpha(x, \zeta)$ can be posed as follows

$$\underset{(x, \zeta, \delta_\omega)}{\text{Maximize}} \zeta - \frac{1}{1-\alpha} \sum_\omega prob(\omega) \delta_\omega \quad (\text{A.8})$$

Such that

$$-\delta_\omega \leq f(x, y_\omega) - \zeta, -\delta_\omega \leq 0, \forall \omega \quad (\text{A.9})$$

Publications

1. Nima H. Tehrani and Peng Wang, “*Stochastic-based Optimal Bidding Strategy for an EV Aggregator*”, submitted to Electric Power Systems Research Journal.
2. Nima H. Tehrani and Peng Wang, “*Probabilistic Estimation of Plug-in Electric Vehicle Charging Load Profile*”, submitted to Electric Power Systems Research Journal.
3. Nima H. Tehrani, G. B. Shrestha and Peng Wang, " *Vehicle-to-Grid Service Potential with Price Based PEV Charging/Discharging*", 2013 IEEE Power & Energy Society General Meeting, Vancouver, Canada, *July 21-25,2013*.
4. Nima H. Tehrani and Peng Wang, “*Exploitation of Vehicle-to-Grid in Regulation Market* ", 10th Conference of the PowerTech 2013, Grenoble, France, *June 16-20,2013*.
5. Nima H. Tehrani, G. B. Shrestha and Peng Wang, " *Optimized Power Trading of a PEV Charging Station with Energy Storage System* ", 10th International Power and Energy Conference (IPEC 2012), Ho Chi Minh City, Vietnam, *December 12-13,2012*.
6. Nima H. Tehrani, G. B. Shrestha and Peng Wang, "*Probabilistic Estimation of Systemwide Electric Vehicle Charging Demand*", 12th International Conference on Probabilistic Methods Applied to Power System (PMAPS 2012), Istanbul, Turkey, *June 10-14,2012*.