Grid-able Plug-in Electric Vehicles in Smart Grids: Incorporation into Demand Response

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Electric transportation has attracted a great deal of interest within the transport sector because of its notable potential to become a low-carbon substitute for conventional combustion engine vehicles. However, widespread use of this form of transportation, such as plug-in electric vehicles (PEVs), will constitute a significant draw on power grids, especially when associated with uncontrolled charging schemes. In fact, electric utilities are unable to control individual PEVs in order to manage their charging and avoid negative consequences for distribution lines. However, a control strategy could be directed at a single vehicle or group of vehicles. One effective approach could be to build on a supervisory control system, similar to a SCADA system that manages the aggregation of PEVs, a role that could be filled by aggregators that exchange data and information among individual PEVs and energy service providers. An additional consideration is that advances in intelligent technologies and expert systems have introduced a range of flexible control strategies, which make smart grid implementation more attractive and viable for the power industry. These developments have been accompanied by the initiation of a new paradigm for controllable PEV loads based on a number of advantages associated with a smart grid context. One of the established goals related to smart grids is to build on their ability to take advantage of all available energy resources through efficient, decentralized management. To this end, utilities worldwide are using IT, communication, and sensors to provide enhanced incorporation of operational tools and thus create a more robust and interactive environment able to handle generation-demand dynamics and uncertainties. One of these tools is demand response (DR), a feature that adjusts customers' electricity usage through the offer of incentive payments.

Motivated by this background, the goal of the work presented in this thesis was to introduce new operational algorithms that facilitate the charging of PEVs and the employment of their batteries for short-term grid support of active power. To allow both public parking lots and small residential garages to benefit from smart charging for end-user DR, a framework has been developed in which the aggregator handles decision-making through real-time interactions with PEV owners. Two interaction levels are implemented. First, for charging coordination with only one-round interaction, a fuzzy expert system prioritizes PEVs to determine the order in which they will be charged. Next, for smart charging, which includes battery discharging, a multi-stage decision-making approach with two-round interaction is proposed. Real-time interaction provides owners with an appropriate scheme for contributing to DR, while avoiding the inconvenience of pre-signed long-term contracts. A new stochastic model predicts future PEV arrivals and their energy demand through a combination of an artificial neural network (ANN) and a Markov chain.

A new method is proposed for promoting collaboration of PEVs and photovoltaic (PV) panels. This technique is based on a determination of the ways in which smart charging can support simultaneous efficient energy delivery and phase-unbalance mitigation in a three-phase LV system. Simulation results derived from 38-bus and 123-bus distribution test systems have verified the efficacy of the proposed methods. Through case-study comparisons, the inefficiency of conventional charging regimes has been confirmed and the effectiveness of real-time interactions with vehicle owners through DR has been demonstrated.

The most obvious finding to emerge from this study is that the use of a scoring-based (SCR) solution facilitates the ability of an aggregator to address urgent PEV energy demands, especially in large parking lots characterized by high levels of hourly vehicle transactions. The results of this study also indicate that significantly greater energy efficiency could be achieved through the discharging of PEV batteries when PEV grid penetration is high.

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Dedication

To

Kiyan,

Hendooneh & Agha-khosro,

the sweetest things in my life

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List of Acronyms

AER	All Electric Range
ANN	Artificial Neural Networks
CC	Constant Current
CSP	Charging Schedule Planner
CV	Constant Voltage
DER	Distributed Energy Resources
DG	Distributed Generation
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operator
EE	Energy Efficiency
EMS	Energy Management System
ENS	Energy Not Supplied
EPRI	Electric Power Research Institute
ESP	Energy Service Provider
FCFS	First Come First Serve
FERC	Federal Energy Regulatory Commission
FERC	Federal Energy Regulatory Commission
FLC	Fuzzy Load Controller
FVC	Fuzzy Voltage Controller
HEV	Hybrid Electric Vehicles
ICE	Internal Combustion Engine
ISO	Independent System Operator
LOL	Loss of Life
MDP	Markov Decision Process
MC	Markov Chain
O&M	Operating and Maintenance
OM	Outage Management
PEV	Plug-in Electric Vehicles

PV	Photo-voltaic panels (PV)
SCADA	Supervisory Control And Data Acquisition
SCR	Scored Charging
SOC	State-of-Charge
TOU	Time of Use
UC	Unit Commitment
UNCR	Uncoordinated Charging
V2G	Vehicle to Grid
VSC	Voltage Source Converter

Chapter 1
Introduction

The power grid is expected to change dramatically over the coming decades, in part because the number of customers, their requirements, and their expectations has grown dramatically. On the other hand, planners and operators need to operate the grid under progressively more complex conditions due to utilization of renewable generation, energy storage systems, to name a few. Accordingly, utilities all over the world are making efforts to incorporate operational tools into the power grid by means of information technology, communication, sensors, and digital knowledge so as to create a more robust and interactive intelligent environment better capable of handling all the uncertainties related to generation and demand.

On the other hand, the automotive industry has devoted extensive efforts to explore alternative energy resources for transportation, largely due to concerns about increased emissions and increasing oil prices. Electrification of vehicle fleets presents a promising solution, since the power sector has in place a reliable and highly efficient infrastructure that can provide energy for such vehicles. Furthermore, electric vehicles are inherently more efficient at turning energy into miles driven[1], and they have a salient feature in common: their batteries. According to [1, 2], the average daily distance for North Americans to drive is 45 km (Figure (1-1)), and the average daily time during which cars are parked is 90% (almost 22hrs) [3]. Thus, the energy storage capacity in electric cars with significant well-aggregated penetration presents great opportunities for better integration of "intermittent" energy resources[2] with the power grid [4][3]. However, charging plug-in electric vehicles (PEVs) imposes an additional load on the power grid. More importantly, the penetration of PEVs is going to become relatively high compared to the electric generation capacity; 20% of eligible new Ontario Public Sector vehicle purchases will be electric by 2020 [4]. The trend towards additional electrical load growth in Ontario has been pointed out in [5]. Table (1-1) shows the significant additional demand expected due to PEV penetration, which can be compared to the in-service generation capacity illustrated in Figure (1-2) [6].

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[1] - Electric cars are much more efficient than internal combustion engine (ICE) drive trains (about 75% vs. 25%) [7].

[2] - Such as solar and wind energy.

[3] - This capability is of particular interest when combined with micro-grids; as a potentially self-sufficient segment of the grid that is connected to the power grid at large but has the ability to provide and manage its own energy.

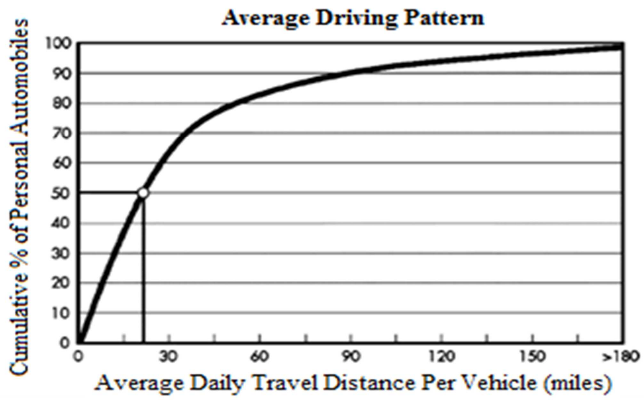


Figure 1-1 American Daily Vehicle Travel [2]

Table 1-1Additional Loads due Incremental Growth of EV Penetration [5]

	Canada	Ontario
Number of vehicles	27,577,524	9,990,267
10% penetration (GVA)	8.27	3
50% penetration (GVA)	41.37	14.99
100% penetration (GVA)	82.73	29.97

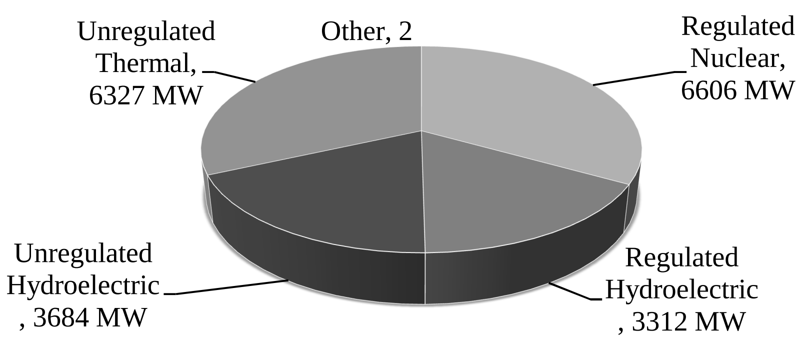


Figure 1-2 In-service generation Capacity in Ontario (Dec. 2010), [6]

Although, opinions are divided about the impact of PEVs on distribution grids, there is a general agreement with respect to the considerable effects that mass PEV operation under an uncontrolled charging scheme will have on electric grid assets (mainly on local distribution infrastructure and possibly on the transmission sector). Studies and reports classify the consequences of uncontrolled charging as follows:

- Phase imbalance,
- Harmonics and other power quality issues,
- Line congestion,
- Transformer degradation and failure due to thermal overloading, and
- Circuit breaker and fuse blowout.

Electric grid operators and planners are therefore concerned with deploying PEVs effectively and mitigate their impacts. Planning alternatives include meeting demand growth through upgrades to grid infrastructures or installation of Distributed Generation (DG) [8, 9]. However, planning alternatives reflect long-term horizons, and feasible solutions require consideration of several prospective factors, such as load growth, updated PEV models, and newer technologies.

Operational solutions are thus being proposed as a means of minimizing the additional costs related to planning solutions. Demand Side Management (DSM) is a fundamental operation component that seeks to involve end-use customers in shaping energy demands, which, in turn, results in peak clipping, valley filling, load shifting, strategic conservation/load growth, and flexible load shape. Electric utilities often understand DSM to include two components: (1) Energy Efficiency (EE), which is designed to reduce electricity consumption during all hours of the year, and (2) Demand Response (DR), which modifies customers' electricity usage from their normal consumption pattern, in response to incentive payments designed to encourage lower electricity use at times of high prices or when system reliability is at risk [2].

Some DR studies propose scheduling of PEV charging during off-peak hours [3]. However, with a high penetration of PEVs, even if all charging occurs at off-peak hours, upward pressure on distribution components will still exist. As well, a convenient time for the owner to charge the vehicle and the preference of the utility might conflict [10]. Consequently, grid operators are trying flexible and smart charging scenarios that simultaneously accommodate the technical limits of the grid and also satisfy vehicle owners. The success of such strategies is dependent on a bidirectional medium, a role that can be filled by aggregators, which collect information from PEVs, send it to the energy service providers, and vice versa.

Integration of storage systems would also lead to great opportunities for DR programs, even though their applications for end-use customers are still restricted due to the installation costs of such storage devices. Deployment of grid-able PEVs, however, holds the promise of using their batteries for DR without imposing the additional infrastructure and costs associated with domestic storage systems [11]. Along with proper charging and communication infrastructure, PEVs may play a dual role in smart grids; they may eventually either turn into Interruptible Loads (IL) when plugged in for charging or act as grid-able storage responding to pricing commands, a concept generally referred to as vehicle-to-grid (V2G). These features make PEVs appropriate for providing short-term ancillary services for the grid. As with other DR programs, the idea behind V2G is simply to allow owners to profit and to gain more revenue. That is, if the vehicle owner changes the battery from charging to discharging back to the grid at a rated power, the energy payment direction should be reversed [12].

Most research and studies reveal potential profits that electric utilities or policy makers would make from V2G. Questions, however, have been raised about vehicle owners' interest in V2G. Recent surveys by Hidrue et al., [13, 14], indicate that, due to the stochastic nature of the arrival and departure of vehicles, the conventional approach–PEV drivers signing pre-specified contracts, in return for annual cash back– is unlikely to appeal to drivers under current market conditions.

The research presented in this thesis investigates the collaboration of PEVs in customer-side demand management by means of smart charging. It explores the ways an aggregator can enable decision-making by interacting with vehicle owners and thus dynamically manage PEV charging in real-time. Two different approaches are realized based real-time interaction with owners. In the first, PEV owners send data to the aggregator and the aggregator optimizes charging action with respect to other PEVs and power-grid operation practice. The second approach provides a higher interaction level, whereby the aggregator processes the data received from owners and offers charge and discharge options regarding real-time energy tariffs. Accordingly, owners choose among the options and based on the owners' responses, the aggregator optimizes the decision making. The next sections move on to describe in greater detail the thesis objectives and outline.

1.1 Research Motivations

Investing vast sums to upgrade the distribution grid for the charging of PEVs (for a limited number of hours per day) would be economically non-viable. Although charge-management scenarios have been introduced as a component of operational plans for facilitating the adoption of PEVs, not all-encompassing regulation is yet available for managing PEV aggregators with respect to producing optimal decisions. The motivation for the widespread adoption of PEVs and the development of regulations is predicated on a broad understanding of the possible benefits and advantages of PEVs, such as the following:

- **Economy and Environment:** Not only is it costly to upgrade the existing power grid to accommodate PEVs, but doing so would also require the installation of additional power plants, which would result in a larger carbon footprint and increased emissions, and would be counter to the primary goal of fleet electrification.

- **Demand Response and Load Management:** Mass PEV operation would significantly amplify energy demand. Shifting PEV charging to off-peak hours or applying smart charging regimes based on demand control and the safe operation of the system would become primary concerns for electric utilities in the near future. Any consequent effects should ideally benefit both customers and utilities through reduced energy costs and lower grid-operating expenses, respectively.

- **Grid Support with Small-scale and Decentralized Power Sharing:** Based on an enhanced "smart" concept, future smart grids will facilitate power sharing through the employment of all available energy resources and their efficient decentralized management. An additional consideration beyond charge management is the possible use of PEVs for supplying the electric grid in the form of short-term ancillary services. Theoretically, their power-electronics-based converters are able to switch quickly to the grid and provide such services as voltage/frequency regulation, peak shaving, and outage management contribution. It is worth mentioning that peak shaving would not only include shifts in the charging time, but also incorporate additional PEV battery power to serve some loads (such as supporting the charging of other PEVs in vehicle-to-vehicle (V2V) mode). Of course, the realization of this vision is dependent on a guarantee that society would move toward the widespread adoption of PEVs.

1.2 Research Objectives

The research presented in this thesis addressed five main objectives:

- Accommodate the charging associated with high PEV penetration while meeting the operating constraints inherent in the available electric infrastructure.
- Realize demand-side management (DSM) through flexible charging and V2G/V2B/V2V PEV moods to provide specific benefits for vehicle owners and to collaborate with electric utilities in the reshaping of the load so as to expand the capacity of the electric infrastructure to serve additional loads to some extent (i.e., from the utility's economic perspective).
- Work toward greater owner satisfaction by exploring real-time interactions and by offering a strategy that would encourage PEV adoption by drivers (i.e., from a vehicle owner's economic and fairness perspective).
- Implement a prediction module that would better facilitate charging coordination.

- Analyze charging coordination in a three-phase LV distribution system and so determine how smart charging could support unbalance mitigation while PEV owners participate in DSM.

In view of smart grid's components, as illustrated in Figure (1-3), this thesis contributes mainly in employments of PEVs, customer options, and energy efficiency under the smart grid umbrella. However, market and extensive incentive mechanisms roles in smart grids are beyond the scope of this study. Figure (1-4) presents the research objectives along with the corresponding chapters that cover them. The objectives are described in detail in the following subsections.

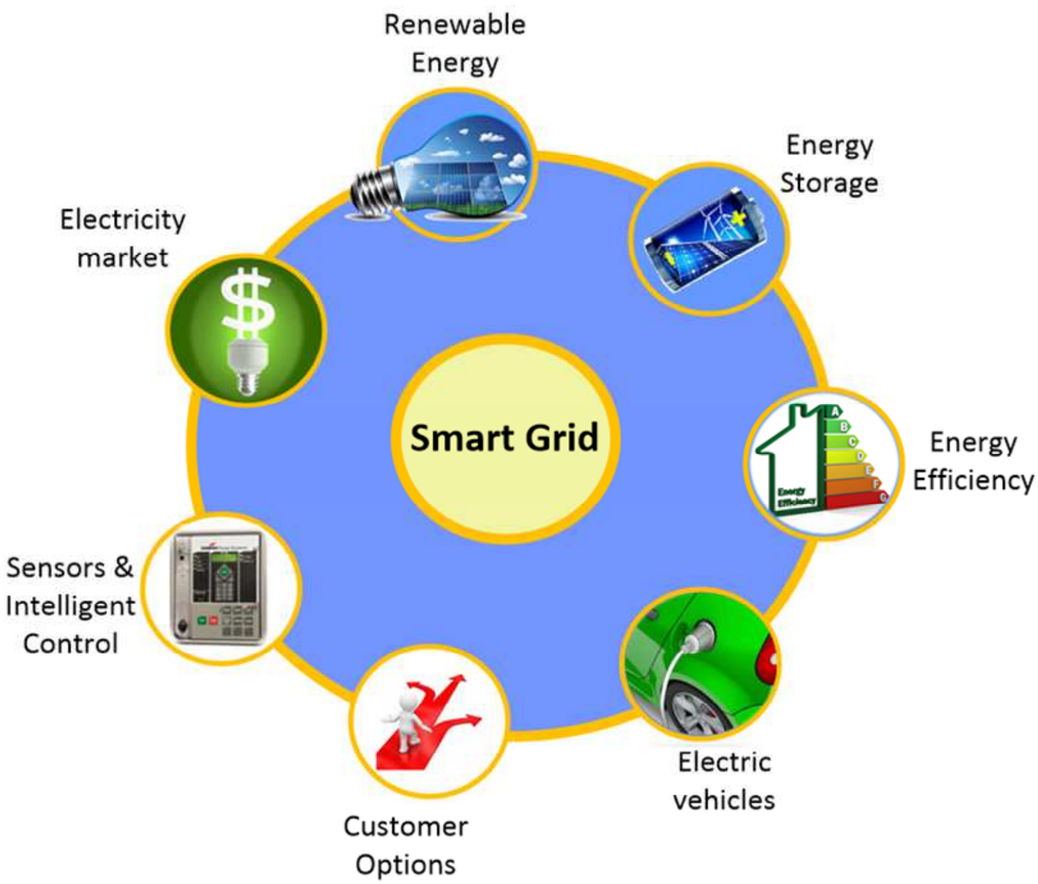


Figure 1-3Smart Grid Components

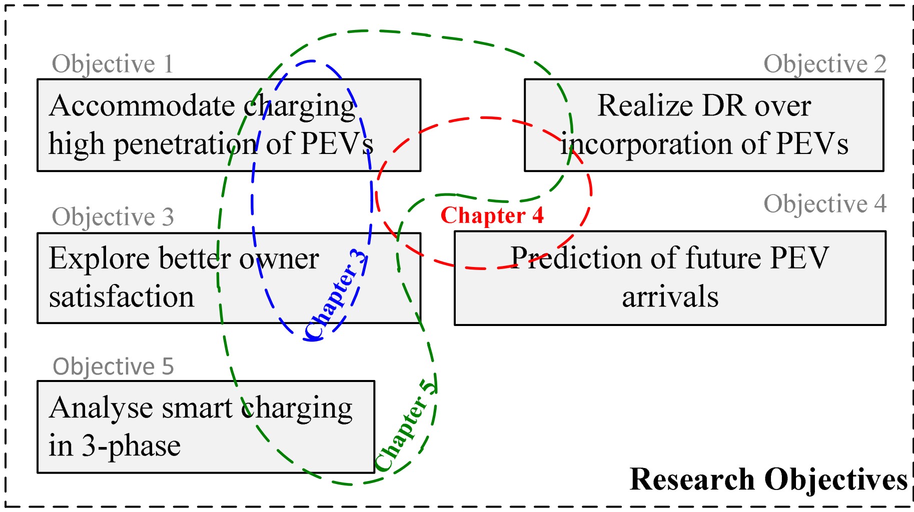


Figure 1-4 Research Objectives

1.2.1 Accommodate Charging High Penetration of PEVs

This study begins by introducing a novel method of coordinating the charging of PEVs in smart parking lots. An intelligent and on-line control method is proposed based on a fuzzy expert system that assigns scores to PEVs in a charging queue. This methodology offers a trade-off between the concerns of the utility and the needs of the vehicle owners to achieve greater satisfaction for both. The developed solution assigns each PEV a charging priority, the determination of which includes consideration of the grid, the vehicle, the battery, and the charger. To allocate priorities to PEVs located in a parking lot, an aggregator employs a number of decision factors. The charging service will thus be allocated to higher-priority PEVs but without violation of the operational practice constraints of the grid. Two case studies evaluate the algorithm for the proposed method.

1.2.2 Realize Demand-side Management/Demand Response by Incorporation of PEVs

The second objective addresses an approach that realizes demand response (DR) by developing an energy management system (EMS) for incorporating aggregated PEV in parking lots. This approach includes real-time interaction between the aggregator and PEV owners, whereby the aggregator proposes a number of offers and the owner responds based on his/her preference. The offers include opportunities for both charging and discharging batteries, with a corresponding discount for the latter. Here, the aggregator incorporates a number of different modules to facilitate real-time decision-making. Case-studies compare the proposed solution with conventional charging regimes, to ascertain the effectiveness of the real-time interactive model.

1.2.3 Explore Better Owner Satisfaction

New studies debate that the conventional approach–PEV drivers signing pre-specified contracts in return for annual cash back– is unlikely to appeal to drivers. The third objective of this study thus focuses on giving PEV owners flexible options at the moment of plugging-in the vehicle, i.e., in the on-line interactive method. This approach supports the owner in DR-cooperation by providing convenience, whether or not he/she wants to discharge the battery for cash back, or he/she wants to postpone charging until the lower energy tariff interval arrives. Therefore, there will be no pre-signed contract violation penalty for these PEV owners.

1.2.4 Prediction of Future PEV Arrivals and their Status to Support Smart Charging

In addition to any already-present PEVs, the pattern of future arrivals also affects the aggregator's decision making. The fourth objective of this research is to implement a prediction module for the aggregator, one that carries out two prediction tasks: the number of future vehicle arrivals and their corresponding energy-demand status.

1.2.5 Analyses Smart Charging Impacts in 3-Phase LV distribution system

Significant growth of asymmetric single-phase chargers in the domestic area and, more importantly, the uncertainties associated with PEV charging time and duration, would present substantial phase-unbalance and consequently reduce power-supply reliability and quality.

The last main objective of this thesis is to apply the smart charging into the three-phase system through adopting a more generalized form of the proposed interactive-structure, not only to provide owners with an appropriate scheme for contributing to DR, but also to ensure that the three-phase existing infrastructure distribution grid operates within acceptable unbalance limits.

1.3 Thesis Outline

The thesis is structured into six chapters and is organized as follows:

Chapter 2 provides a brief review of the relevant background and the literature related to this study. It begins by laying out the theories for PEV modeling and then goes on to review impacts and applications of PEVs in smart grids.

Chapter 3 presents an online intelligent charging coordination of PEVs in distribution systems. It develops a strategy that enables aggregators in public parking lots to dynamically manage PEV energy demands.

Chapter 4 tackles the demand response (DR) by developing an energy management system (EMS) for incorporating aggregated PEVs in parking lots. This approach includes real-time interaction between the aggregator and PEV owners and explores the effect of various charge/discharge offers on total demands.

Chapter 5 addresses how smart charging can be used to support more efficient energy delivery and phase unbalance control, while improve DR contributions by the PEV owners. It extends the idea presented in chapter 4 to evaluate the impacts of PEVs in three-phase LV distribution systems. Moreover, the potential of PEVs and V2G application in mitigating phase-unbalance is studied.

Chapter 6 summarizes the thesis findings and outcomes, contributions, and suggests potential future works.

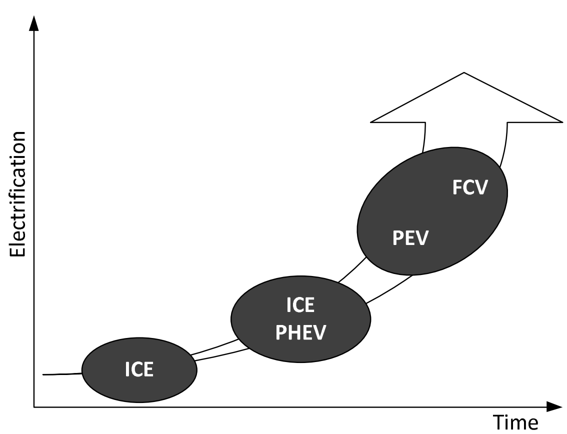
Chapter 2

Literature Related to PEVs: Background and Previous Research

Interactions between plug-in electric vehicles (PEVs) and an electric grid, especially the distribution sector, can be viewed from two different standpoints: the impact of the PEVs on the grid and their potential applications with respect to grid support. This chapter first provides background about PEV modelling and then addresses the impact of high PEV penetration on the distribution grid. The research and solutions related to charge coordination that have previously been reported in the literature are then examined. The application of PEVs as smart grid loads that are controllable by means of smart charging/discharging schemes is then reviewed. The chapter ends with the identification and a discussion of the gaps in and drawbacks of prior studies.

2.1 Infrastructure: Aggregation Role in Public Acceptability

Although emissions and oil prices are the primary drivers impelling policy makers to deploy electric cars, if customers are unwilling to pay for these vehicles, the transition to electric transportation will be impeded because very few drivers would rely on grid-based electricity as an energy resource. Public acceptance is therefore an essential component of policy making. With the goal of achieving customer acceptance, a number of alternatives are currently offered by the automobile and power industry; hybrid vehicles that provide the advantage of operating in a non-electric mode were the first of these solutions. However, a new generation of advanced vehicles, including fully electric PEVs, is emerging every day and will be available over the next few years (Fig (2-1)) [4].



ICE: Internal combustion engine BEV: Battery electric vehicle FCV: Fuel cell vehicle

Figure 2-1 Electrification trend of advanced vehicle technologies [4]

The fully electric cars of the near future will require an infrastructure of electric stations and parking lots distributed throughout cities, as well as batteries capable of rapid recharging. The infrastructure must be reliable and able to ensure the charge required to reach the next destination. According to *SAE J1772*[1], the North American standard for electric chargers, two connections are necessary [15]:

- A power connection for electrical energy flow, and
- Bidirectional communication between vehicles and the distribution sector as well as control

Electrification of vehicle fleets presents a promising solution, since the power sector has in place a reliable and highly efficient infrastructure that can provide energy for such vehicles. However, charging plug-in electric vehicles (PEVs) imposes an additional load on the power grid. Although, opinions are divided about the impact of PEVs on distribution grids, there is general agreement with respect to significant effects of mass operation of PEVs with uncontrolled charging regime[2] on electric grid assets. In fact, electric utilities cannot communicate with each individual PEV to manage their charging and avoid any congestion in the distribution line. A controlling strategy could be directed to a single vehicle, or to a group of vehicles. An effective approach would benefit from a supervisory control system, similar to SCADA systems that manage aggregation of PEVs. Therefore, the concept of an aggregator has been developed to represent a commercial medium/agent between a grid operator and multiple vehicles through a reliable bidirectional communication link (see Figure (2-2)) [16].

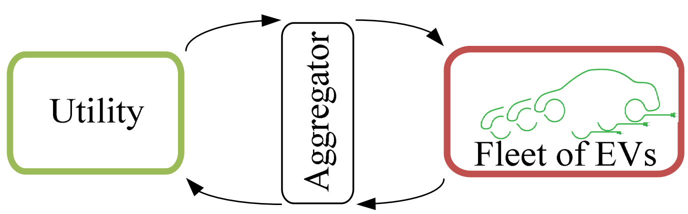


Figure 2-2 Aggregator's Role as a Medium

The aggregator collects the available energy of PEV batteries to deal with grid operators, or Energy Service Providers (ESPs), and to manage the charging schedules of the batteries. Aggregation of the

[1] - SAE J1772 is a North American standard for electrical connectors for electric vehicles maintained by the Society of Automotive Engineers, which covers the general physical, electrical, communication protocol, and performance requirements for the electric vehicle conductive charge system and coupler. In Europe, IEC 61851 applies to equipment for charging electric road vehicles.

[2] - When a vehicle starts getting charge right after it is plugged in to the grid.

PEVs would also be utilized to support smart grids by offering ancillary. Stated simply, the aggregation role involves how the battery state-of-charge (SOC) is managed.

2.2 PEV Modeling: Battery and Charger

The literature proposes integrated models for PEVs in system-level studies. These models mainly include the battery and the charger. To model a battery's real-time charging power and demand profile, the battery's SOC, voltage, current, and grid side interface are required.

As the most important component of a PEV, a battery characterizes the vehicle under several points of view, such as energy and power capacity, all electric range (AER), lifetime, etc. The lithium-ion (Li-ion) battery-type has become the most popular type of rechargeable battery[1] due to its good energy density, memory-less effect, and slow loss of charge (when it is not in use). Recent studies have modeled vehicle batteries using SOC as the only state variable [17, 18]. Here, the battery is modeled using a controlled voltage source (V_{oc}) in a series with an equivalent battery pack resistance (R_i), as shown in Fig (2-3). The terminal voltage of the battery is V_t, and the SOC, the only state variable, is defined as (2-1):

$$SOC = \frac{Q}{Q_{nom}} \tag{2-1}$$

where,

Q = the actual capacity/energy (Ah) stored in the battery,

Q_{nom} = the nominal capacity (Ah) of the battery.

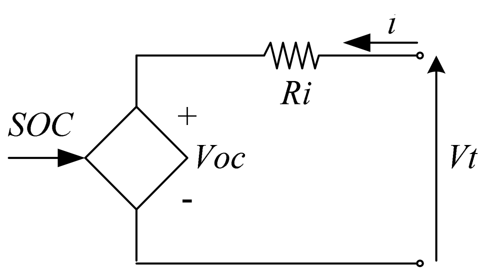


Figure 2-3 A typical battery model [17]

Neglecting the battery efficiency, the SOC variation during charging/discharging is expressed as (2-2):

[1] - According to [18], 70% of PEV batteries in 2015 are be Li-ion.

$$\frac{d\,SOC}{dt} = \frac{i}{Q_{nom}} \tag{2-2}$$

where,

i = the charging/discharging current

In [18], battery voltage is shown as a function of the actual capacity, (Q), and consequently is a function of the SOC level. The terminal voltage of the battery pack, (V_{pack}), is thus in (2-3). Voltage drop is positive during charging and negative during discharging. Hence, an integrated PEV model could be represented simply as a battery and charger, as in Figure (2-4). On the grid side, the PEV charger is supplied with grid voltage (V_c) and absorbs the current i_c during charging. On the battery side, V_{pack} and i identify the terminal voltage and the current absorbed by the battery.

$$V_{pack} = V_{oc} + \mathrm{R}_{eq}\,.i \tag{2-3}$$

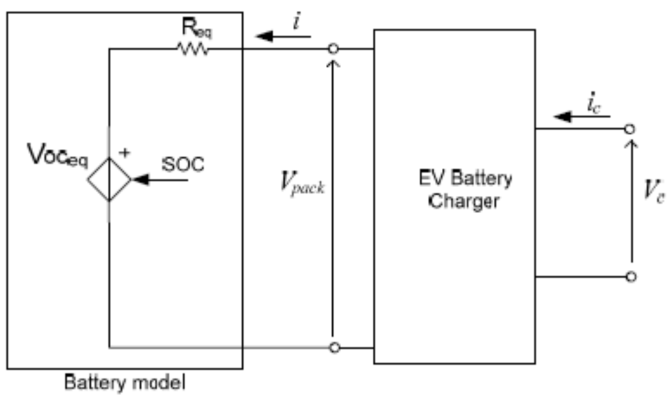


Figure 2-4 A integrated PEV model [18]

2.2.1 Charging Characteristics

The standard charging of a Li-ion battery is composed of two distinct operational regions (Figure (2-5)): the constant current (CC) until the voltage upper limit is reached, and constant voltage (CV) until a SOC level of 100% is reached [18]. Since the output voltage of the battery is a function of its SOC, the battery power is also being a function of it, as (2-4). Consequently, the energy exchange for each individual vehicle will vary based on the battery SOC.

$$P_{Bat}(SOC) = v(SOC).\,i \tag{2-4}$$

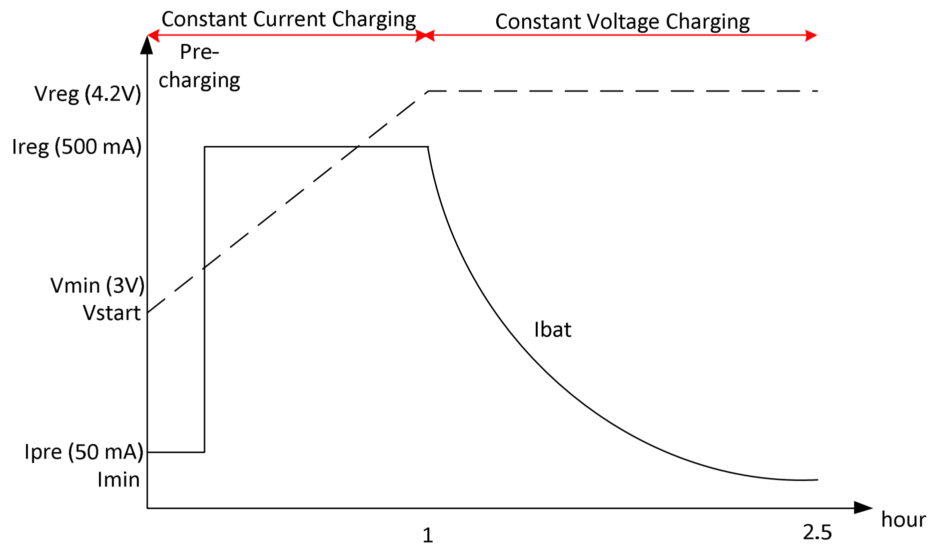


Figure 2-5 Voltage and current characteristics of the Li-Ion battery during charging [19]

2.2.2 Discharging Characteristics

Similar to charging characteristics, discharge voltage is a function of the SOC, which drops according to the SOC's reduction. Figure (2-6) illustrates the voltage discharge curve versus the SOC of a Li-ion battery [20]. The non-linear voltage depends on the actual battery charge, meaning that when the battery is almost completely discharged and no current is flowing, the voltage will decrease significantly. The battery has a flat declining voltage curve in the usable discharge range. Studies show that an SOC window of 20-90% is a suitable energy window to use for PEV batteries [18].

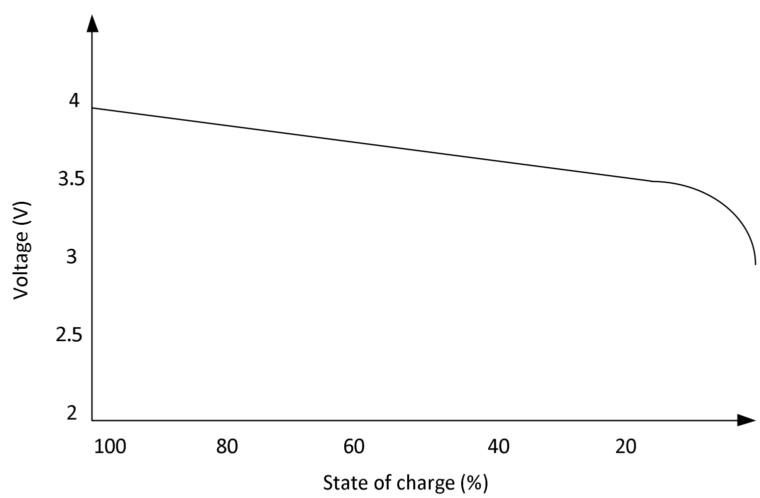


Figure 2-6 Voltage and current characteristics of the Li-Ion battery during discharging [20]

2.2.3 Li-Ion Battery Cycle Life

The SOC vs. cycle-life curves show the percentage of the original charge capacity as a function of cycle use (i.e. charge, then discharge). Fig (2-7) shows the SOC vs. cycle-life for Li-Ion battery technology. As can be seen from this figure, the discharge capacity decreases approximately linearly with the cycle number. If the SOC criterion is set at 80%, this particular battery can last roughly 7,000 cycles [21].

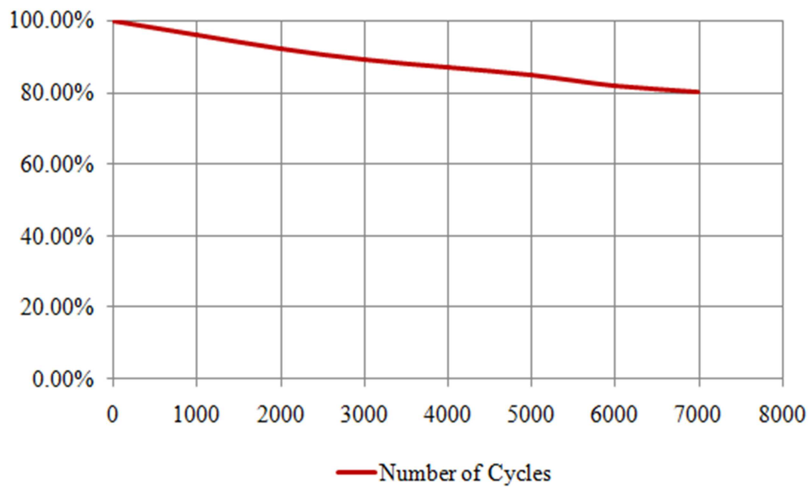


Figure 2-7 Battery SOC as a function of cycle-used [21].

2.2.3.1 Battery Efficiency

At higher SOC, the battery has larger open circuit voltage and smaller resistance. These two parameters are sometimes regarded as constants, since they do not change much over the full battery operating range, e.g. 30/20–90%. Fig (2-8) illustrates the efficiency of the typical battery during discharging and charging. The battery has a high discharging efficiency with high SOC and a high charging efficiency with low SOC. It seems that the net cycle efficiency is maximized at the middle range of the SOC [22]. Therefore, the battery operation control unit of a PEV should control the battery SOC in its middle range so as to enhance the operating efficiency and depress the temperature caused by energy loss (high temperature would damage the battery).

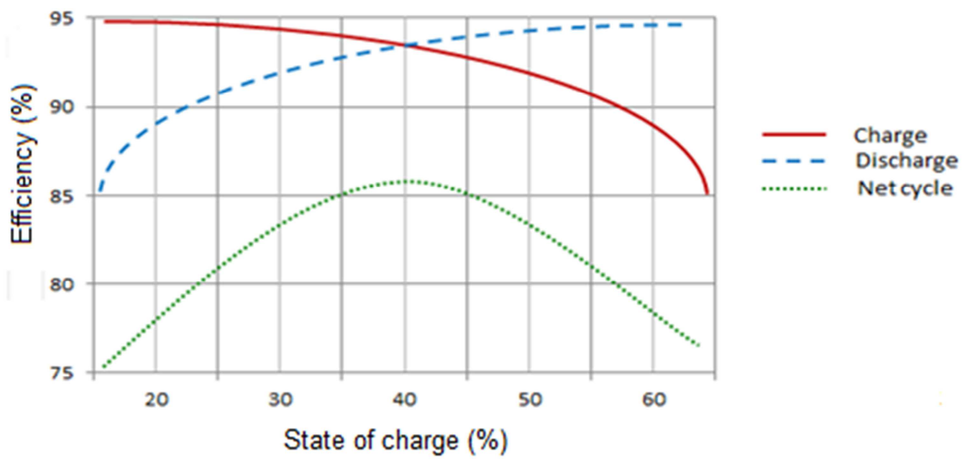


Figure 2-8 Typical battery charge and discharge efficiency [22]

2.2.4 Charger Characteristics in Smart Parking lots

The introduction of smart garage with charger facility represents an interface between the transportation network and electric power system, where, the charging/discharging infrastructure and control system needs to be widely available [2]. The parking facility should be capable of bi-directional power flow to either charge or discharge car batteries, and should be able to hold either process for more flexible controlling purposes.

The bi-directional charger should charge the PEV's battery while producing minimal harmonic currents, and also should be able to provide energy back to the grid (V2G) or to the building (V2B) or to other PEVs (V2V). The charger should function smoothly in both directions and draw a clean sinusoidal current in phase to avoid harmonic currents and poor power factor. Similarly in battery discharge mode, the charger should return current in a similar sinusoidal. Different electronic circuits with the same topology shown in Fig (2-9) can fulfill this requirement[1] [23].

[1] - In the battery charging mode, the AC current passes through a filter to remove unwanted frequency components. Then, the AC current is rectified into DC current as it passes through the bidirectional AC-DC converter. Since this AC-DC converter output voltage might not match the voltage of the DC energy storage, a bi-directional DC-DC converter ensures the proper charging voltage is supplied to the battery. In discharge mode, the process is reversed. The leaves the battery and is changed back to the proper DC voltage with the bi-directional DC-DC converter. This DC current is then inverted into AC by the bi-directional AC-DC converter. Then, it passes through the filter, which smooths out the AC current so it is suitable for injection back into the grid [23].

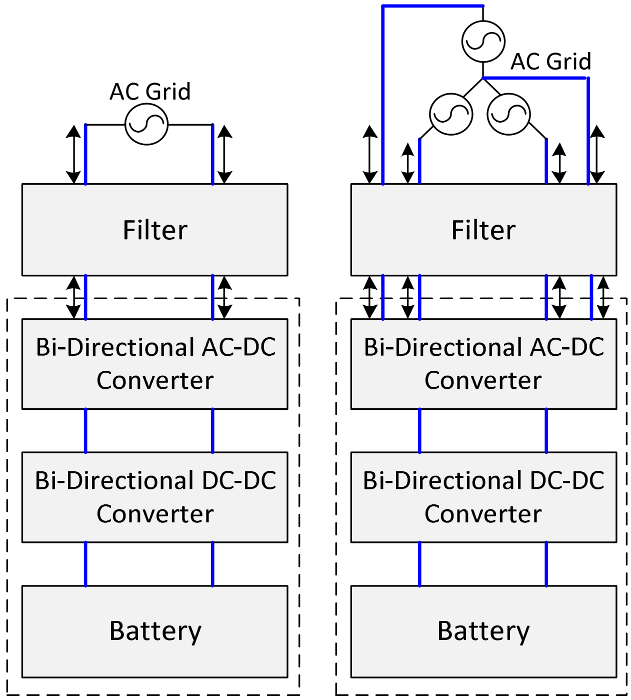


Figure 2-9 General bi-directional charger topology for single/three phase [23]

Charger facility level affects the energy exchange. EPRI introduced three levels of charger standard applicable for North America (Table (2-1)) [1]. For smart garage with charging and discharging abilities, Level-1 and Level-2 will be ideal choices, since a Level-3 charging station will dramatically increase the power flow capacity requirement. Level-1 charging only provides a small amount of power (maximum of up to 1.44 kW), and results in prolonged charging time. The Level-2 (also known as fast charger) method uses a 208 to 240-VAC, single-phase, up to 80-amp branch circuit. Since the typical charging time for a 10 kWh battery pack will be 1-2 hrs, it is the primary charger facility for the PEV in both private and public facilities [2]. Table (2-2) also shows where charging stations can be located by charger type [25].

Table 2-1 Charging Levels Standard for North America [24]

Charging Level	**Specification**
1	120 VAC, 15A* (12A), Single-phase, 1.44 kW/h
2	240 VAC, 40A** (32A), Single-phase, 7.7kW/h
3	480 VAC, Three-phase, 60-150 kW/h

* Could be 20 A
** Could reach to 80 A (100 amp rated circuit)

Table 2-2 Charging stations based on charger type [25]

	Charging Station Type		
	Level-1	Level-2	Level-3
Residential			
Single family houses	✓	✓	
Multi-family units	✓	✓	
Commercial/Employment Centers			
Privet (offices complex, business campus)	✓	✓	
Commercial/Retail (fleet and delivery service)	✓	✓	
Public access (airport, hotel, grocery store, hospital, mall)	✓	✓	✓
Government, university, and municipal facility	✓	✓	
Transit hubs		✓	✓
Fueling stations		✓	✓
Public			
Parking lots	✓	✓	✓
Street		✓	✓
Interstate and highways			✓

2.2.4.1 Communication and control

Smart grid is all about how data are efficiently connected. The primary purpose of employing communication infrastructure is optimizing grid energy transfer to PEVs. There are two basic approaches currently being adopted for communication between PEVs and the aggregator. One is the wireless communication approach and the other is over-line signaling approach.

In the first approach, control links mainly include wireless access, positioning, and on-board metering. Secure wireless communication between the aggregator and the PEVs, and between the aggregator and the control center is required include PEV verification, and PEV and owner privacy protection. The on-board charger needs to be equipped with Telematics[1] communication unit is used for the transmission of data, GPS geographic location information, and receiving information from the aggregator and the control center. The standard called Wireless Access for the Vehicular

[1] - Telematics, which is the integrated use of telecommunications and informatics

Environment (WAVE)[1], is the standard that addresses and enhances intelligent transportation system. An example of control panel, suggested in [26], is shown in Figure (2-10).

The SAE standard series[2] established various protocols for communication-over-power line including Level-2 outlet and on-board charger as well as DC chargers and PEVs. The data signals as follows:

- Identifications: vehicle ID and customer ID;
- Energy requests: energy request, power rate request, energy available, power available, etc.;
- Timing information: time charging to start/end;
- Pricing: request scheduled prices, publish price, define rate time period, etc.;
- Load control: load control, cancel load control, report event status request/response, request scheduled events;
- Vehicle info/status: time at connection, battery SOC start, battery SOC end, battery SOC actual, vehicle type, usable battery energy, customer mode preference.

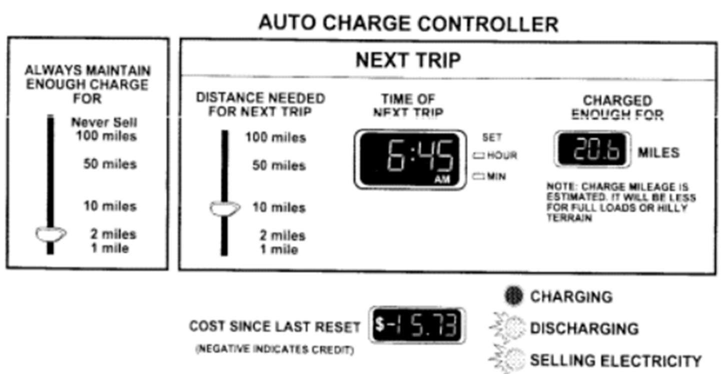


Figure 2-10 Suggested design of vehicle smart dashboard control [26]

2.2.5 Cost of Charging versus Gas: A Case in Ontario

According to Ontario Ministry of transportation, [27], a PEV typical battery will cost less than $300 per year on average, or about $0.78 per day to charge at night (Value for Nissan Leaf, adapted from Natural Resources Canada 2013 Fuel Consumption Guide, using Ontario off-peak electricity prices as of May 2013, based on an average annual driving distance of 20,000 km).

While, a typical plug-in hybrid EV will cost about $700 per year, or $1.92 per day for fuel including gasoline and electricity costs (Value for Chevrolet Volt, adapted from Natural Resources

[1] - From IEEE 1609 family.

[2] - SAE J1850, SAE J2293, SAE J2836.

Canada 2013 Fuel Consumption Guide, using Ontario off-peak electricity prices as of May 2013 and a gas price of $1.30/litre, based on an average annual driving distance of 20,000 km). Comparable gasoline cars can cost between $1,000 and $2,500 per year to fuel - up to eight times more money spent each day (Estimate based on values from Natural Resources Canada 2013 Fuel Consumption Guide and a gas price of $1.30/litre).

2.3 Impacts of PEVs on the Distribution Grid

Market trend estimation is important to precisely assess and predict the potential impacts of PEVs on the energy sector. By 2018, there will be at least 500 000 highway-capable PEVs on Canadian roads [28]. According to International Energy Agency (IEA), the number of charging stations has increased fivefold between 2010 and 2012, where slow charger infrastructures have been growing dramatically greater than the fast charging stations as shown in Fig (2-11) [29]. Significant growth of asymmetric single-phase chargers in the domestic area and, more importantly, the uncertainties associated with PEV charging time and duration, would present substantial phase-unbalance and consequently would reduce power-supply reliability and quality as well as the transformer utilization rate. In addition, phase-unbalance may lead to excessive current in the neutral line, and voltages at the customer side may fall outside acceptable levels [30, 31].

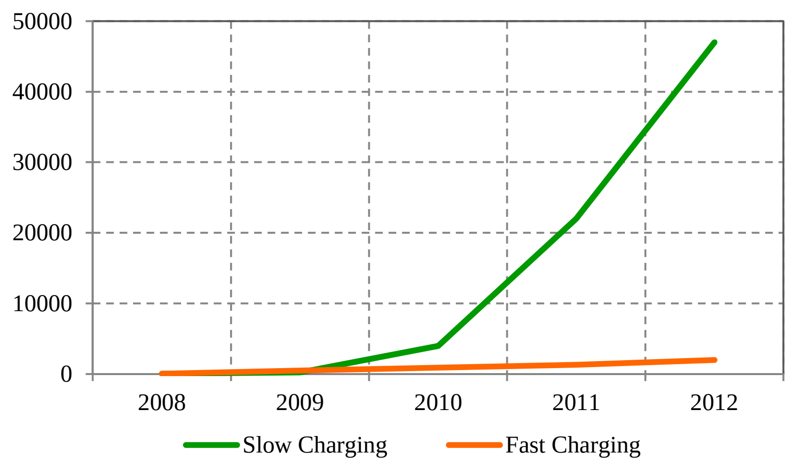


Figure 2-11 AC fast charger growth versus slow charger growth between 2008-2013, [29]

Preparing for the rapid growth of PEV penetration and proper installation of charging stations needs distribution networks to be expanded and developed through careful research, planning and investment. Overall, potential impacts of the PEVs on the power grid, especially on the distribution sector would include as follows [25]:

- phase imbalance;
- harmonics at the battery charger and other power quality issues[1];
- line overloading and congestion;
- reactive power demand;
- transformer degradation and failure due to thermal overloading;
- circuit breaker and fuse blowout.

Recharging the PEV battery is typically carried out in residential garages equipped with standard outlets and taken several hours. The uneven distribution of single-phase chargers can results in severe voltage magnitude deviations and voltage unbalance [32, 33]. A qualitative analysis done in [34] illustrates that charging high penetration of the PEVs increases fault currents significantly. Different fault analyses have been simulated for a distribution system. Fig (2-12) shows two scenarios of fault current due to single phase to ground and phase to phase faults in the feeder.

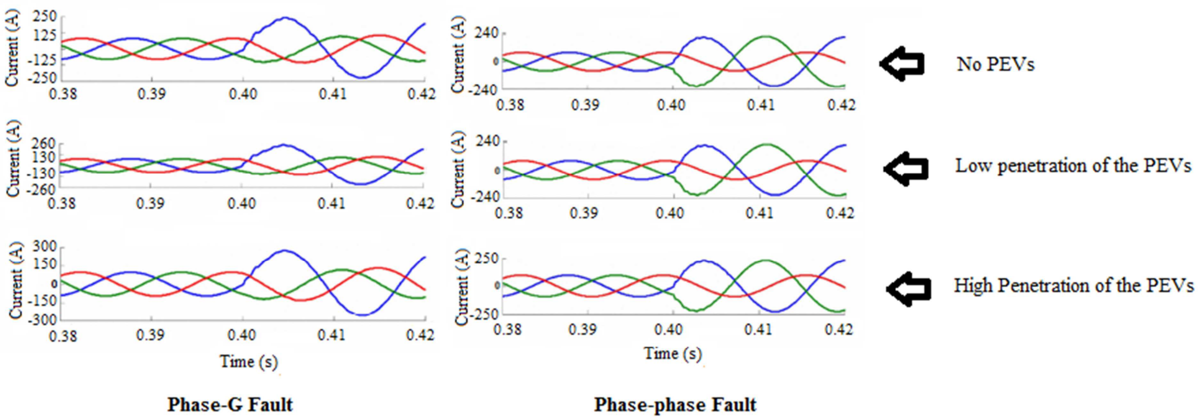


Figure 2-12 Feeder current with different penetration of the PEVs

A study in the UK reports that with fewer chargers (e.g. lower percentage of PEVs being charged), the load diversity is lower, resulting in a larger variation in the current imbalance. Conversely, when the number of chargers switched on is high, the diversity was high, resulting in a lower average current imbalance [35]. It is shown in another work by F. Shahnia *et al.*, [36], that PEVs have minor effect on the voltage unbalance at the beginning of a LV feeder. While, the voltage unbalance is increased at the end of the feeder to more than the standard limit.

[1] - Such as sub-harmonics signal generation [24]

There are two approaches currently being adopted in unbalance studies of PEVs. One is the effect of converter-based PEV chargers on the distribution grid such as the research conducted [24] and the other is the aggregated effects of the PEVs on the system's phase unbalance [37]. In [24] voltage unbalance is analyzed through incorporating the voltage source converted (VSC)-based PEV model into a three phase distribution power flow algorithm. The PEV model in load flow analysis comprises a voltage source converted (VSC) and a battery pack. The proposed schematic diagram and equivalent circuit of the VSC-based PEV for reactive power control in power flow studies are presented in Fig (2-13), where the model allows active power exchange and regulation of bus voltage magnitude.

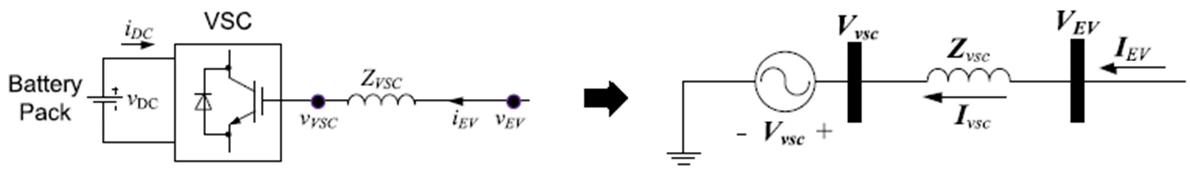
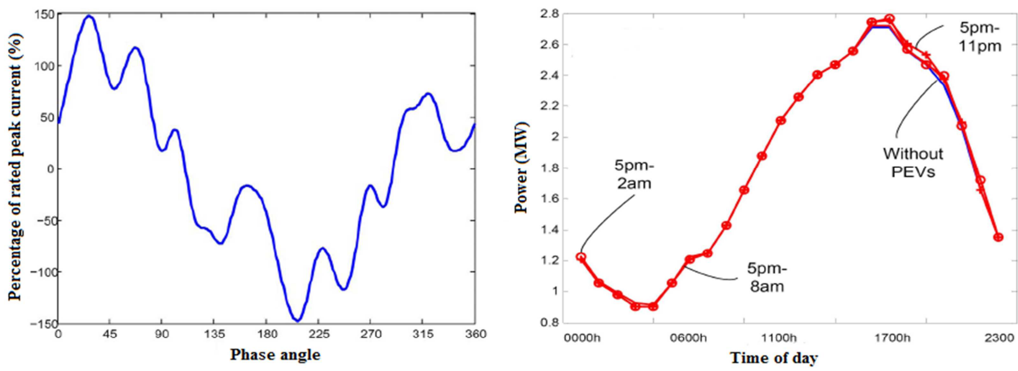


Figure 2-13 VSC-based PEV schematic and the equivalent diagram [24]

To determine effects of PEV charging on the distribution transformer life-time, M.-J. Rutherford *et al.* compare transformer's aging acceleration factor (FAA) and the Loss-of-Life (LOL) for different scenarios of Lithium-Ion battery charging load [38]. The author found that an intelligent residential charging station, in which charging would be delayed or coordinated so that one or limited number of them could be charged at once, can minimize the charging impact on the distribution transformer aging. Similarly, in [39] impacts of the PEV charging on transformer hot spot temperature and loss of life are simulated. The results confirm the findings of [38], in which charge control would help utilizing the capacity of transformers more efficiently.

Perhaps harmonics are the most serious disadvantage of converter-based devices in smart grids. PEV battery chargers are high power nonlinear devices that can generate a significant amount of current harmonics by drawing low voltage AC power and converting it to DC. This process involves rectifying the AC signal and running the rectified signal through a DC/DC converter. Both of these processes produce harmonic distortion in the distribution system, which cause problems on the power system, including excessive neutral current and transformer hot spots. A number of studies address how fundamental and total harmonic distortion caused by battery chargers lead to suboptimal generation dispatch to serve the large PEV charging loads [40-42]. The analysis, presented in [42], is based on harmonic power flow for non-linear loads. At harmonic frequencies, the power system is modeled as a combination of passive elements and harmonic current sources, each injecting harmonic currents at different frequencies into the system. Fig (2-14) and Fig (2-15) illustrate a sample of charger waveform, system load profile and total THD of voltage in a distribution system with a low penetration of the PEVs.



Current waveform for nonlinear PEV charger load

System load profile for different charging time zones

Figure 2-14 Current waveform for the PEV charger and the system load profile [42]

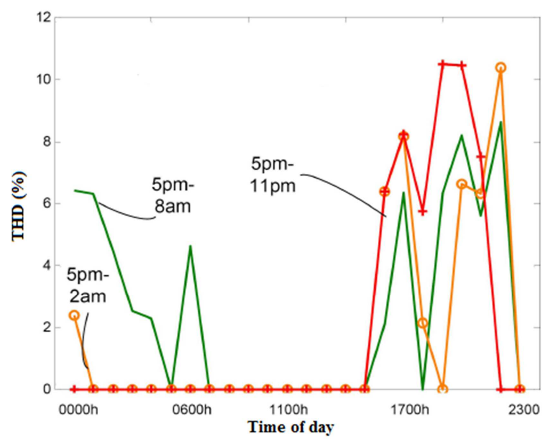


Figure 2-15 System total THD of voltage due to low penetration of the PEVs [42]

2.4 PEV Charging Coordination

Recent years have seen a rapid growth of large body of literature on the deployment of PEVs in smart grid. Energy flow direction is a major area of interest within the literature devoted to PEV charge scheduling, which is classified into two main categories: 1) charge-only and 2) V2G/V2B[1] scheduling. On the other hand, to tackle the probable pressure due to additional energy demand of PEVs, electric grid operators and planners have explored various solutions to properly adopt PEVs

[1] - Vehicle-to-Building

and mitigate their impacts. Planning alternatives mainly include meeting the demand growth through upgrades to grid infrastructures or installation of Distributed Generations (DG) [8, 43]. However, planning alternatives reflect long-term horizons, and feasible solutions require consideration of several prospective factors, such as load growth and updated PEV models and newer technologies. Operational and demand response solutions are thus being proposed as a means of minimizing the additional costs related to planning and renewal solutions.

Among the studies that address PEV charging coordination, some propose scheduling of PEV charging during off-peak hours [3]. However, with a high penetration of PEVs, even if all charging occurs at off-peak hours, upward pressure on distribution components will still exist. As well, a convenient time for the owner to charge the vehicle and the preference of the utility might conflict [4]. Consequently, grid operators are trying flexible charging scenarios that simultaneously accommodate the technical limits of the grid and also satisfy vehicle owners. The literature reports the investigation of price-shift charging coordination as a more-easily managed strategy [44-46], or the use of variable charging power set points [32], both approaches involve different objective functions [9, 10, 12, 18, 22], [47- 56]: either through the adjustment of grid operational objectives, including loss minimization and maximizing load factor, peak shaving, reliability and demand response [3]-[55], or through the maximization of vehicle owner revenue [47] and [51-53]. The focus tends to be either on individual or aggregated PEV management [55,57, 58].

To determine the effect of PEV charging on power losses, Clement-Nyns *et al.* use the quadratic programming technique (QP) to minimize losses of individual vehicle batteries charging at residential outlets [57]. Regarding the hourly distribution of the vehicle's trip, three charging periods are chosen based on their availability at home. Two different approaches are compared regarding the load profile at any charging duration. The first approach is based on a deterministic (i.e. historical data) load profile. However, due to the inadequacy of the measured data, the second approach applies an error in the forecasted daily load profile (i.e. the stochastic approach)[1]. They also compare the dynamic programming (DP) approach with the QP to find the faster optimization method[2]. It has been proven by Sortomme *et al.* that load factor (LF) and load variance correlates with system losses. They demonstrate how loss minimization can be realized with less computational time through minimizing LF as the objective function and consequently it can better support coordination of PEVs in real-time [58].

[1] - The fixed input parameters are converted into random input variables with normal distribution.

[2] - Due to larger matrices, DP is slower than QP [57].

A methodology is proposed in [48] for scheduling PEVs energy transactions in the same way of the unit commitment (UC) practice for generation units. The objective is to reduce carbon emissions and to maximize profit while fulfilling different practical constraints, such as the forecast load, parking lot limitations, SOC, charging/discharging efficiency. However, Khayyam *et al.* latter declared, in [22], that adopting the UC method with PEVs adds additional complications and that the optimization cannot respond to operational requirements in a timely manner. The proposed objectives in [48] are also viewed only from the grid perspective without consideration of the needs of the vehicle owners.

To determine the driver charging pattern, authors in [59] implement fuzzy logic system which simulates the charging pattern based on the current battery SOC level and parking duration. Therefore, an estimation of vehicular charging load profile and its impact on the total grid loading is addressed. This study argues that the battery's SOC and the estimated parking duration are the two main factors that govern a driver's decision whether or not to charge. Other factors such as driver income, electricity availability (especially during on-peak demand hours), charging rates (i.e., slow/fast), and other economic factors have been neglected in [59]. It also mentions that additional factors such as climatic conditions may affect a driver's decision to charge. These additional factors are not investigated by the authors due to their region-specific nature. However, the effect of climate on the SOC is addressed in [8]. The proposed fuzzy inference system in [59] uses the SOC and the expected duration of parking as the inputs in the model. Using a centroid-based de-fuzzification, the output indicates whether the driver will start charging the vehicle or not. This decision-maker, however, is only responsible to simulate a driver's decision to start the charging process. Once a decision to charge is made, charging will continue until the battery pack is fully charged or the parking period ends, whichever occurs first.

To better formulate dynamics of vehicles' arrivals and its effects two solutions are proposed in [52], namely, Global Scheduling and Local Scheduling optimization. The global optimal scheduling searches for the optimal charging power for all PEVs during a day by solving a single global scheduling optimization in order to obtain the minimal total cost. However, the global scheduling solution appears to be unreasonable due to lack of information regarding future loads, new vehicle arrival time and SOC. Therefore, local scheduling optimization is performed in an independent and distributed manner to tackle large numbers of PEVs with dynamic arrivals. Two assumptions were considered in [52]: losses are negligible, and no congestion happens in lines. Although, these assumptions allow the algorithm to neglect the spatial electricity price on the study, it might over-simplify the analysis and results due to neglecting overloading issues as operational limits.

In contrast, a coordinated charging solution for public stations is addressed in [59] using a stochastic model for the PEV's arrival at the parking lot. It applies the Poisson model for the vehicle's arrivals[1] and assumes that charging is constant. Two coordinated charge scheduling methods are compared; (1) Shortest Charging-time First Serve and (2) Longest Charging-time First Serve. Both methods attempt to minimize the number of PEVs that miss the deadline for getting charged (meaning, to be served before departure). This study, however, neglects the effect of the SOC of the batteries, which has a significant effect on the charging schedules.

A few authors have addressed the PEV owners' preference in charging procedure. A real-time PEV load management method is proposed in [51] by minimizing the total energy cost for charging PEVs and the corresponding grid loss and voltage deviation. It assigns preference time zones, which have different energy tariffs, to the customers for charging their vehicle. In each step of the algorithm a sensitivity index was used to identify the more appropriate PEV to be recharged with the objective of causing less of an increase in power losses. In a different work, a method similar to the *Internet traffic service* differentiation is proposed in [53] as a means of controlling charging of PEVs, based on which, owners who are eager to pay more can charge more quickly than other owners. Also in [60], we see how historical driving data are used to assign the lowest adjusted electricity price among the charging hours of an individual PEV. The aggregator clusters a set of transport behavior from previous days and matches them with the most similar PEV that plugs in.

Moreover, a number of authors have considered PEV charging coordination by means of renewable DGs. Franco *et al.* address PEV charging coordination in an unbalance three-phase distribution system with the presence of active and reactive power injection by DG units [37]. Their results indicate how unbalanced PEV-loading deteriorates the voltage profile and increase the operational costs. A priority scheme allows PEV owners to choose between charging the batteries as quickly as possible and charging them with a minimum energy tariff. An energy economic analysis is conducted in [61] to charge PEVs using photo-voltaic panels (PV) at a workplace parking garage. Three cases (night time at-home charging, daytime charging without a PV and daytime charging with a PV panel) are compared. The results show that there is an optimal size of the PV panels that balance the installation cost and the cost of electricity purchased from the power grid to give the smallest

[1] - The Poisson model was used for bus passenger and supermarket customer arrivals before [49].

payback period. It is discussed in [61] that employing PV panels to charge PEVs not only does help to reduce the load from the power grid and affects the cost of charging, but to help displace CO2 emissions from the power grid (specifically when the carbon tax is realized). Similarly, authors in [46] present a real-time energy management scheme for grid-connected commercial charging stations with the presence of PV-based renewable resources. The algorithm aims at reducing the overall daily cost of charging the PEVs and contributing to shaving the peak of the load curve. Uncertainties associated with PV power generation and PEVs' SOC status and departure time are taken into consideration through proposing a fuzzy controller to manage the random energy available in the batteries.

In contrast, grid-connected and islanded fast-charging stations are analyzed in [62]. The main goal is proper control of the fast charging infrastructure, in combination with wind-based renewable generation, to compensate active and reactive power in different conditions, so as to improve the operation the system. Two supervisory control strategies are developed to manage the flow of active and reactive power. Fast-charging stations is controlled to optimize the operation of the network, while in grid-connected condition, the frequency is maintained by a large external grid, and so the main issue is how to control the fast-charging procedure to regulate reactive power for voltage support. The control strategy includes applying the required reactive power in order to maintain zero voltage variations. The supervisory control at a high level first verifies the availability of power on each charging station and then decides the reactive contribution per station, whereas in the islanding condition, the concern is to maintain the balance between active and reactive power. A synchronous generator is switched on to control the frequency and voltage of the islanded network.

In addition to public stations, some research focus on individual homes, equipped with solar panels, with one or few PEVs in the garage. A household electricity management system is proposed in [63, 64] with collaboration of PV panels and PEV batteries as a part of Yokohama Smart City project. Using an agent-based transportation simulator, the authors in [63] find that to have carbon-neutral vehicles PEVs need to be charged by renewable energy sources such as PVs. However, this finding seems like a significantly region-specific solution.

2.5 Applications of Grid-able PEVs in Smart Grids

The idea of vehicle-to-grid[1] (V2G), also named as Grid-able vehicle, established in 1997 by Willett Kempton, explores the potential economics of PEVs connected to the power grid. The basic goals of

[1] - Providing power to the grid by electric vehicles within their parking duration.

V2G studies are basically to explore the environmental and economic benefits of the PEVs and enhance the product market. Recently, a number of V2G studies were introduced as pilot projects. The *Electric Power Research Institute* (EPRI) estimates that, by 2050, V2G would reduce the dependency on global, central-station generation capacity by up to 20% [65].

All studies investigated V2G applications focus on controlling the reverse power flow between the charging station/plug-in and the connected node to the grid regarding a specific objective and number of constraints. However, the key issue in V2G depends on the proper scheduling of grid-able vehicle power transactions in parking lots/charging station. Since PEVs have a limited capacity in the kW range and grid demand power is carried out on MW ranges, aggregation plays a vital role in collecting the available energy of PEV batteries for grid support. Studies confirm that, practically, V2G cannot provide base load power at a competitive price, and it should only be sold to high-value, short-duration power markets that offer ancillary services/spinning reserves to the grid [12].

More importantly, economic analysis indicates that the profits from participating in frequency regulation, as a component of the ancillary service, are higher than those from reserve services [12, 66]. Consequently, as observed between 2008-2012, V2G research and pilot projects have mostly been dominated by utility-side profits of grid-able PEVs, such as grid regulation and balancing renewable generation, [12, 49, 67, 68, 69], as well as minimizing losses through voltage profile improvement [50, 51, 70].

2.5.1 Frequency Regulation

Frequency regulation (or simply regulation) is an ancillary service responsible for maintaining the frequency of the grid at its nominal value[1], i.e. controlling frequency fluctuations in the grid mainly due supply-demand imbalances[2].Two different regulation services can be found based on the matching between power generation and total load (Figure (2-16)) [12]:

- Regulation-down service: matching generation and load when the former is larger than the latter, i.e., there is an excess of power in the grid that causes an increase in the value of the frequency.
- Regulation-up service: matching generation and load when load is larger than generation. Regulation services can be provided by dispatching generation to match the load.

[1] - It is 60 Hz in North America, and 50 Hz in Europe and Asia.

[2] - Frequency regulation is conventionally done in power plants by Automatic Generation Control (AGC).

Fast-responding generators are usually required for frequency regulation in wind power systems, photovoltaic generators, or natural gas and coal units. However, they tend to be expensive and/or have large carbon emissions. Controllable loads such as batteries and flywheels can also provide regulation-up and -down services. Among the ancillary services provided by PEVs, regulation has one of the highest market values. Moreover, it is profitable for both PEVs and market operators, since they can quickly switch through their power electronic interface [12, 71].

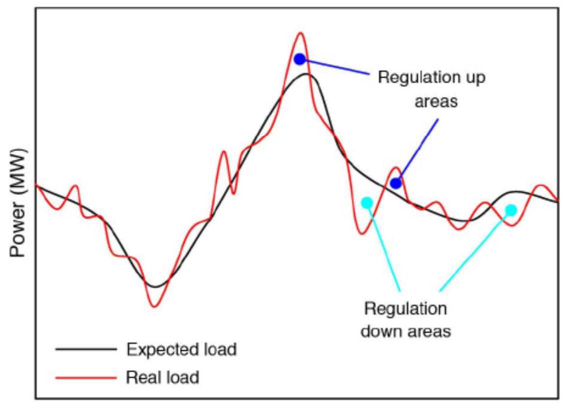


Figure 2-16 Examples of the frequency regulation [12]

Frequency regulation by PEVs provides regulation-down/up during battery charging/discharging, respectively. If frequency regulation is needed by the power grid, the ISO requests V2G regulation to the aggregators and determines market price[1] based on bids submitted by aggregators. The revenue scheme adopted by [67] considers that although a PEV receives energy while providing regulation-down, it provides a service that must be paid for by allowing some energy to be exchanged[2]. Therefore, the total revenue of PEVs will be the result of both capacity price and electricity price. The goal here is to allocate power among the PEVs forming part of an aggregator for frequency regulation service while at the same time achieving the SOC of the PEVs regarding the minimum variance from the average. The objective function optimizes the aggregators' profits.

[1] - Different structures of the ancillary service market price are available. A simple one is where the price has two components: 1) a capacity price (which is paid for having power available for a specific service for up- or down-regulation) and, 2) an electricity price (which is paid for the power actually being delivered in real time for up- or down-regulation) [71]. Capacity price is paid to have reserved available power, whereas electricity price is paid only when power is actually used. However, a study of market price structure is beyond the scope of this proposal.

[2] - The cost for regulation down is 0, given that regulation-down is the same as charging the vehicle; thus, it is "free charging" when the PEV provides regulation-down.

On the other hand, vehicles under the control of an aggregator have two strongly related aspects: (1) the consumer side aspect, and (2) the supplier side aspect. It may seem reasonable that a vehicle being charged could be interrupted by a regulation command. Thus, even the charging duration of a battery could be accounted for by regulation[1]. The motivating idea regarding V2G is profit and revenue. That is, if the vehicle changes from charging its battery to providing service for the grid, the energy payment direction should be reversed [47][2]. How system-wide optimality would be achieved by single vehicle optimality is discussed in [47], such that the optimal charging control to maximize revenue of each vehicle would lead to the maximum revenue of the aggregator.

Additionally, parking departure time is an important factor in optimal charging/discharging control for PEVs. A driver would sign a contract to keep the vehicle connected to the grid for a certain duration in return for incentives (such as, for instance, a life-time battery warranty) [67]. There may, however, be occasions when drivers drive away before the pre-notified departure time and thus the aggregator may not succeed in reaching the pre-calculated optimal result to provide the contracted regulation power. Optimal control depends on optimal charging/discharging sequences, including charging/discharging duration and rate. Since the grid operator initiates a contract based on the daily and hourly basis of required power, a minimum of hourly control unit would be applicable. In [67], a charging sequence control problem for PEVS is addressed in order to maximize the aggregator’s revenue in a given charging period. By applying the dynamic programming technique, the optimal charging sequence would maximize profit while satisfying the state of charge at the end of the charging period.

In [47], it is assumed that target SOC is always given as a point value and solves the control problem with respect to charging sequence and charging rate only. Moreover, for charging control to maximize revenue, the charging rate should be either 0 or 1. Therefore, the proposed method in [47] considered only when to turn the charging operation on or off to achieve an optimal control result. To do so, it employed dynamic programming to extract the optimal charging pattern for individual vehicles.

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[1]- However, as the scale becomes significant by being simultaneously operated by an aggregator, it would cause a serious oscillation to the generation amount. Therefore, a regulation request should not interrupt vehicles that are under-charging operation for their own sake [47].

[2]- Regular one is a supplier-side operation and V2G mode is a consumer-side operation, and hence the payment direction is opposite.

It is discussed by authors in [22] that the pricing method employed in [47] is based on day-ahead pricing and that neither a frequency regulation signal nor real-time power is required for regulation. However, [72] proposed an algorithm using real-time pricing1. Shi *et al.* apply the Markov Decision Process (MDP) to design a V2G control algorithm under price uncertainty, in which both frequency regulation and bulk power selling were considered [72]. They propose a real-time pricing model, in which the aggregator receives the pricing information a few minutes, e.g. 10 min, prior to the beginning of each hour. Consequently, the V2G control algorithm runs for each individual vehicle, which will stay parked for the next hour, to ascertain whether the aggregator should charge its battery for the next trip, discharge for selling power, or use its available power capacity to provide frequency regulation service. After gathering the controlling signals of all of the PEVs, the V2G aggregator sends the contract information (i.e., total power to buy, total of power to sell, and total capacity for frequency regulation) to the electric utility prior to the start of the next hour. This process is carried out hourly. An energy management system from the utility company will dispatch appropriate regulation signals to the V2G aggregator based on the contracted capacity.

Similar to [47], the objective of the V2G control algorithm in [72] is to maximize profit for PEV owners. Profit here represents selling power and providing frequency regulation service minus the costs of purchasing power from the grid. This objective needs to be maximized, as prices for subsequent hours of a vehicle's parking duration are unknown and this uncertainty should be modeled.

2.5.2 Voltage Regulation

In the same vein, much of the available literature address how PEVs charging management results in dynamic voltage supports, while avoiding costly grid upgrades [22, 50, 70, 73]. Grid losses are minimized through voltage profile improvement in [50] and [70]. An energy flow is proposed which acted as a control mechanism between PEVs and the grid using fuzzy logic controllers for voltage compensation and peak shaving. Two fuzzy-based controllers are designed: (1) the charging station controller[2] (at the charging station), and (2) V2G controller[3] (at the distribution node level)[4.] The

[1]- Real-time pricing and day-ahead pricing are two different pricing models in the electricity market.

[2]- This controller decides on the individual participation of the EVs for charging or discharging.

[3]- The main purpose of the V2G controller (2nd controller) is to control the power flow between the concerned node and the charging station.

[4] - The inputs include voltage and SOC, and the output is energy flow.

objective of a V2G controller is to control the power flow between a particular node and the charging station to meet peak power demand and reduce voltage sag. Voltage rise caused by injection of PEV energy into the i^{th} node is approximated by (2-5):

$$\Delta V_{EV} = \left(P_{EV}\, r_i + Q_{EV}\, x_i \right) / V_i \tag{2-5}$$

Grid support is provided by injecting active power with a constant power factor of 0.9. However, reactive support is not considered in this work. The power injection by a PEV battery reduces power losses and improves bus voltage of the network. One drawback of the model is its static and scenario-based solution that does not take into consideration the passage of time. A fuzzy-based solution is proposed in [22], for controlling PEV charging, where two controllers continually regulates and stabilizes the load and the voltage. The authors show how large-scale aggregation of PEVs (such as 10 parking lots) would provide a significant power share for the grid and affect voltage and load stabilization. The proposed smart grid model uses two intelligent controllers for optimizing grid stability of load and voltage, including: (i) fuzzy load controllers, and (ii) fuzzy voltage controllers. The controller measures the average of voltages, total grid loading and total active generated power, and continually regulates the generation to match the demand loads.

- The fuzzy load controller (FLC) measures the voltages, total load grid and total active power generated. The controller, then, continually regulates the generation to match the demand loads.
- The fuzzy voltage controller (FVC) adjusts the capacitors and reactors in the power grid. It measures the voltages, generation and consumption of power reactive from all buses. The controller continually regulates the voltage and stabilizes the grid. This controller regulates a number of capacitors.

The proposed controllers were implemented in three scenarios, where a set of data for 10 parking lots are employed:

- without parking loads and no intelligent control;
- with parking loads and no intelligent control;
- as intelligent controller of V2G.

However, [22] did not mention how to develop a fuzzy role basis for both controllers, which is an essential part in fuzzy expert systems. More importantly, there was no model evaluation to verify if the results were the best possible results. In an analysis of charging coordination, Foster *et al.* show how effective PEV grid integration could minimize costs, avoiding costly grid upgrades, and disruptive impacts on the transmission and distribution networks, coordinate with renewable generation, and incorporate individual users and their usage profiles [73]. Considering real-time price signals, on the time scale of seconds, PEVs provides dynamic voltage support for the distribution network, which may allow increased penetrations of distributed photovoltaic (PV) solar arrays.

2.5.3 Phase balancing

Power grid operation is facing increasingly complex conditions arising from renewable generation and domestic energy storage systems at the end-user side. Photovoltaic (PV) panels/solar units, a good illustration of easy-to-setup intermittent energy source technology promoted for individual household usage, are experiencing rapid growth and falling costs worldwide. However, their large-scale penetration will introduce challenges to the power-grid daily operation, particularly in its distribution sector [74, 75]. In a more general sense, now that the gradual transition to smart grid is underway, the already-existing 3-phase electric grid is likely to experience challenges due to the random and stochastic nature of solar energy and PEV demands [46, 76].

Research is currently being done to determine whether current and voltage unbalance can be diminished through the distributed action of energy sources or active loads, including PEVs. As discussed by S. Weckx *et al.*, dynamic switching actions across the three phases to balance residential loads are costly [77]. Another approach is replacing single-phase inverters of PV units with 3-phase ones, so as to inject more power into the phase with the highest power consumption [77]. However, this solution exposes owners to additional costs of upgrading the infrastructure. Moreover, the majority of residential areas are equipped with a single-phase power supply and only large households have three-phase connections.

Additionally, the authors of [44] employ multi-agent control of solar units and PEVs to reduce the imbalance factor. They do so by minimizing the cost of increasing imbalance due to renewable resources and PEV demand. To better understand the negative effects of phase unbalance, some research addresses the relevant issues through economic analysis. A linear approximation of voltage drop and network constraints is used in [30] for real-time smart charging coordination of PEVs in a three-phase system. The study by J. A. Fernandez *et al*. shows that one application of vehicle-to-grid (V2G) and smart charging could be unbalance minimization by means of an economic profit formulation [76].

2.5.4 Power quality enhancement

Although PEVs might cause some power quality issues due to their converters and frequent switching, various studies contend that PEVs can improve power quality through contributing with a renewable energy source. For instance, PEVs offer the opportunity of storing wind and solar energy at times of extra generation and use the power whenever necessary to improve power quality and stability of renewable energy sources.

In [78], PEVs were employed as an active filter with solar energy sources. They present a control design that allows for the correction of power factor dynamics as well as for the dynamic compensation of harmonics currents. As photovoltaic power varies with climatic conditions, there is no explicit reference power for tuning. PV voltage needs to be adjusted according to solar radiation to extract the maximum photovoltaic current. This adjustment is made possible by regulating the generator voltage and inductor current and by varying the transistor cyclic ratio. Compensating currents are then required for power oscillation. The controller measures the amount of current to be injected by the active filter to compensate for the harmonics in the load.

The effectiveness of power quality V2G services are addressed in [79] for keeping systems stable through short-term local active and reactive power injections by PEVs connected to the grid through a single-phase chargers. The reactive power injection compensates for voltage drops caused by motor start-up or inductive loads, while active power is injected shortly during PV transients in cloudy weather or during low voltage ride-through of the PV sources. In a similar work, voltage sag is mitigated by means of large dispersion of PEVs such as an airport parking aria or a mall parking lot [80]. An index, called the compensation vehicle factor (CVF) is defined as the ratio between the energy requested by the vehicle batteries during V2G compensation and the total storage capacity installed onboard. This index is used to analysis energy and power and to evaluate the feasibility of the V2G compensates for voltage sag. However, none of these studies address the uncertainty associated with the availability of PEVs and their impacts on power quality enhancement.

2.5.5 Revenue Optimization

In contrast to utility-side profits of grid-able PEVs, some recent PEV research shifts attention to customer-side profits, which seek to maximize profits of either the parking lot owner/aggregator or the PEV owner by providing grid operators with a limited number of capacity bids [81-84]. One approach to maximizing aggregator revenue is system-wide optimality achieved by single-vehicle optimality, such that the optimal charging control to maximize the revenue of each vehicle would lead to maximum revenue for the aggregator [12], [82, 83]. Conversely, others assume that the aggregator maximizes its profits, as a market participant, within a number of constraints set by PEV owners and utilities [81, 84]. As a more up-coming and realistic application of V2G, various studies propose V2B applications to involve PEVs in benefits obtained from DR programs.

An energy cost sharing model and proposes a distributed algorithm is designed in [85] using game theory to encourage PEV owners to participate in the charging and discharging batteries. Authors in [86] optimize appropriate charge and discharge times throughout the day. Price curves from California ISO database are used to obtain realistic price fluctuations. Every vehicle is assumed to have the same desired departure SOC of 60% (it can never be discharged below this level). The output of the optimization is presented as three statuses, namely: vehicle selling power, vehicle buying power, and vehicle not buying nor selling. Two scenarios are compared: (1) sell at maximum price/purchase at minimum price for single transaction per day, (2) multiple purchases and sells. Due to issues surrounding the scheduling independency of each vehicle, separated optimization is applied to schedule vehicles individually. However, the proposed optimization solution does not reflect the aggregation impacts of PEVs on the distribution system (especially in the case of multiple charging; i.e. aggregated loads).

In another work dynamics of vehicles' arrival are employed for scheduling charging-discharging schedules, where two solutions are proposed: Global Scheduling and Local Scheduling optimization [52]. The global-optimum scheduling searches for the optimum charging power for all PEVs over the course of a day through solving a single-cost minimization. However, the global scheduling solution seems unreasonable due to a lack of information of future loads and new vehicle arrival times as well as their SOC. Therefore, the local scheduling optimization is performed in an independent and distributed manner to tackle a large number of PEVs with dynamic arrivals. Two assumptions are considered: (1) losses are small and negligible and (2) no congestion happened in lines. Although these assumptions allow the algorithm to neglect the spatial electricity price in the study, they nonetheless simplify the analysis and results by neglecting overloading issues as operational limits.

Unlike [52], another study addresses energy losses in the cost optimization of PEV energy transactions [51]. It proposes a real-time PEV load management method by considering the minimization of the total cost of purchasing/producing the energy for charging PEVs plus the corresponding grid energy losses. It assigns preference time zones, with different energy tariffs, to the customers for charging their vehicle. The energy price is employed in a similar work, establishing a decision-making strategy for PEV batteries with regard to the state of charge, time of day, electricity prices and vehicle charging requirements [87]. The decision-making find an optimum strategy on how to dispatch the battery power through three rule sets: (1) three states of

Charging/Discharging/Undetermined are assigned to the PEV based on the SOC, (2) an enable/disable control signal from the aggregator is introduced to specify whether a vehicle is available for V2G service, (3) the final rule used for selecting the level of discharge/charge current in time period reflects the prevailing price (i.e., Day time/Night time price). The 3rd rule is designed to take into account the price arbitrage opportunity, charging the PEV at the high current rate when prices are low and discharging vice versa.

In [88], an aggregated charging management is developed for a Danish power grid in which three different entities – the aggregator, the retailer, and the distribution system operator (DSO) – influence the charging schedules. This management approach mainly concerns the planning of the aggregator's interaction with other power system entities. The grid congestion is also considered to handle voltage constraints. It benefits from a good estimation of the future trip behaviour of PEVs using the historical data. The data predicted includes time of departure, time of arrival, energy need, and location of each trip for each vehicle. The goal of optimization is to derive a charging schedule for each vehicle that ensures sufficient energy for the predicted trips. The aggregator can buy the electricity on the wholesale markets only if it aggregates a sufficient number of vehicles to meet the minimum bid volumes. Then it can optimize its bids according to the predicted demand and the available flexibility in time of charging. If the aggregator does not aggregate sufficient vehicles to enter these markets, it must be able to outsource the charging flexibility to an existing market player, such as a retailer.

2.5.6 V2G in Demand-side management, Demand Response and Outage management

For an electric utility, demand-side management (DSM) is defined as "the planning, implementation, and monitoring of distribution network utility activities designed to influence customer use of electricity in ways that will produce desired changes in the load shape," which includes peak clipping, valley filling, load shifting, strategic conservation, strategic load growth, and flexible load shape". However, as mentioned in chapter one, for the utility end-users, DSM includes two components: energy efficiency (EE)[1] and demand response (DR)[2]. The Federal Energy Regulatory Commission (FERC) defines demand response (DR) as changes in electric usage by customers from their normal consumption patterns in response to changes in the price of electricity

[1] - EE is designed to reduce electricity consumption during all hours of the year.

[2] - DR is designed to change on-site demand for energy in intervals and associated timing of electric demand by transmitting changes in prices, load control signals or other incentives to end-users to reflect existing production and delivery costs.

over time or to incentive payments designed to induce lower electricity use at times of high prices or when system reliability is at risk. The utility and customer cooperatively participating in DSM will provide benefits to the customer, utility, and society as a whole, as summarized in Table (2-2). The DSM idea is simply to shift the charging time to a lower energy price rate than the discharging time [2, 85]. Studies show that by utilizing DR using a multi-agents system, a high penetration of PEVs can reduce the consumer cost of electricity [89]. Many current pilot projects and studies pay particular attention to the role of PEVs in DR programs; various publications, such as [2, 11, 13, 19, 85, 90], have proposed promising solutions.

Table 2-3 Benefits of the DMS for the utility and customer [2]

Customer benefits	**Social benefits**	**Utility benefits**
Satisfy electricity demand	Reduce environmental degradation	Lower cost of service
Reduce/stabilize costs	Conserve resources	Improved operating efficiency
Improve value of service	Protect global environment	Flexibility of operation
Maintain/improve life style	Maximize customer welfare	Reduce capital needs

The idea of managing individual PEVs at the residential level would be similar to other DR programs in which a customer would respond to variable electricity prices. For instance, the impacts of Time of Use (TOU) electricity tariff are analyzed in [55] to illustrate the customer's behavior on charging their PEV. The customer shifts charging to the less expensive electricity rates and receives incentives for contributing in peak demand level control.

In [2], PEVs are tackled as dynamically configurable dispersed energy storage in a V2B mood[1] , where the focus is DR during high demand and outage management (OM) when the main supply is accidentally lost. The batteries would contribute to the grid restoration process during OM application to increase reliability when a fault occurs. The proposed model is a cost-optimization problem, where the cost of active power generation of vehicles is minimized. However, the results provided by the authors indicate that the proposed solution exposed system to significant unbalanced situation which would cause considerable damage to the grid.

[1] - Authors in [2] believe that V2B is a more near-term V2G application.

An energy-cost sharing model is introduced in [85] between a building and a group of PEVs in the garage to optimize the energy consumption profile of the building. The optimization method includes a distributed algorithm in which each PEV owner determines independently its best charging and discharging profile to minimize its total energy payment to the building. The proposed distributed algorithm can reduce both the total energy cost of the building and the peak demand. From the building controller viewpoint, the load profile should be as constant as possible, taking into account the extra energy demand of the vehicle's battery charging. Any energy demand less than the average demand will cause poor utilization of the existing infrastructure system and any energy demand exceeding the average demand will increase the energy cost as well as endanger the reliability of the building's operation. Therefore, the optimization problem searches for energy charging and discharging schedule to minimize the square Euclidean distance (SED) between the instantaneous load profile and the average demand.

Similar work is proposed in [89] for optimizing the demand response (DR) by updating the grid generation resources and controlling the customer load. The multi-agent system is designed to switch customer load and control the charging of PEVs depending on their SOC to reduce cost and avoid overload during peak hours.

2.5.7 Role of PEVs in Micro-Grid Context

Micro-grids, a new trend of power grid capable of standalone operation from the main grid, facilitate the integration of distributed generations, distributed energy resources (DERs), energy storage, and controllable loads by their physical proximity for ease of control, power sharing and management. In combination with distributed renewable energy, PEVs can be considered as a new form of distributed storage and, specifically, can support buildings in the form of a micro-grid system. With a number of considerations, PEVs' different mode of operation is applicable to standalone micro-grids as to main grids. Much of the current literature reveals that it is more common, yet economical, to employ aggregated PEV-batteries for flattening electricity demand of a small-scale micro-grid such as a building during peak hours [32, 91]. Minimizing the operational cost of the micro-grid is another initiative/motivation of PEV engagements/contribution in standalone micro-grids [92].

To determine the economic benefits of PEVs, Beer *et al.* calculate energy costs using a detailed representation of supply tariff structures and fuel prices along with operating and maintenance (O&M) expenditures [91]. Two modes of operation, i.e. the grid-connected and the islanded mode, are compared to examine the impacts of the aggregated PEVs on the reliability of a building. The condition of the utility power grid decides which operation mode to choose. Normally, the grid-connected mode would ensure sufficient energy to satisfy customer demands, but the islanded mode should be used when an unexpected disturbance occurs in the utility-side or when the power rate is higher than a customer's willingness to pay.

The role of commercial buildings in future micro-grids is discussed in [32]. A heuristic operation strategy is proposed to improve the self-consumption of PV panels and reduce the dependence on the power grid. The charging rate of PEVs is dynamically adjusted in the real-time mechanism considering the battery SOC and variation of PV output. In another work, a number of comfort levels are defined for the owners and the goal of optimization is maximizing these levels [93]. To tackle the inherent intermittency and variability of renewable energy resources a stochastic formulation is developed by authors in [92] to minimize the expected operational cost and power losses of micro-grids.

2.6 Discussion

In light of the research points addressed by prior studies, it can be concluded that coordinated charging of PEVs is one of the main concerns in deploying mass operation of PEVs in near- future smart grids. Furthermore, two other important themes emerge from the studies discussed so far: (1) the substantial impacts to be expected with asymmetric high penetration of PEV loading in LV distribution grids and (2) the need to incorporate grid-able PEVs into smart grids. Throughout this chapter, the potential impacts of the PEVs on the distribution sector (including phase imbalance, power quality issues, line overloading, transformer degradation, circuit breaker and fuse blowout) and the proposed remedy have been reviewed. Moreover, various objectives, solutions and scenarios surrounding applications of PEVs and their aggregated batteries, as power back-up for grid support such as voltage and frequency regulation, peak shaving, outage management, and three-phase balancing, have been studied. Despite the ingenious methods proposed in the literature regarding coordinated charging of PEVs, they fall short of considering a number of additional issues required for proper aggregation and control of PEVs:

- Most of the works involved in charging coordination are based on consideration of either safe grid operation or financial benefit for the vehicle owner, mainly with respect to energy prices. However, another key issue is owner satisfaction, which is related to successful charging. Not only should the charging strategy ensure normal grid operation, but the battery charge demanded by each PEV owner should also be guaranteed so that vehicles leave their parking lots with the specific amount of charge ordered.

- A comprehensive evaluation of the decision-making performance on each individual vehicle is lacking. Only in [93] is vehicle-owner satisfaction addressed, through a probabilistic model of daily power consumption and vehicle charging initiating time based on drivers' travelling habits. However, only the qualitative satisfaction of the aggregated group of PEVs with respect to charging duration is measured in [93] (i.e., the longer the charging duration, the greater the satisfaction for that group). More importantly, probabilistic models would be more practical for planning studies rather than real-time operations, where the status of variables is instantaneously exposed to change.

Returning briefly to the applications of PEVs in smart grids, we saw the shifting trends to customer-side profits through employment of PEVs in DR programs. More importantly, it was discussed that with pre-signed contracts, PEV owners' profits are controversial. Looking at the PEV applications, especially in the DR area, the following concerns are valid:

- The issue of owner satisfaction would become even more pivotal with V2G mode implementation. A conflict arises between the primary role of PEVs when parked (which is providing required energy for the battery) and the key idea of V2G applications (which is bi-directional power transactions) for grid support. A dynamic[1], yet precise, model is required to represent the behavior of vehicles as an elastic load (i.e., an energy consumer-provider component).
- However, due to the frequent turnover of vehicles in a parking lot, scheduling issues arise that make it difficult to determine the appropriate time for a given vehicle to buy or sell energy.
- The conventional approach of PEV drivers signing pre-specified contracts in return for annual cash back is unlikely to encourage the owners to contribute to DR using their vehicles.
- Most studies to date propose solutions for implementing DR through proper real-time scheduling of PEV charging, but, as discussed by Shaaban *et al.*, in [94], they fail to include the effect of upcoming PEV demand on real-time charge coordination. In [94], a model based on queuing theory is employed to predict the number of PEVs that will arrive at parking lots in the near-future, although only the worse scenario of full charge demand has been implemented by these authors.

[1] - Here the term "dynamic" indicates 24-hour behavior of the grid and the PEVs.

Further to charging coordination, many other challenges that will arise with mass usage of PEVs have been outlined in Section (2-3). PEVs and asymmetrical LV chargers would cause un-reasonable phase unbalance. However, PEVs could, on the other hand, provide voltage support for the distribution network, which may allow increased penetration of distributed photovoltaic (PV) solar arrays. From the system-level perspective, further consideration is needed when it comes to incorporating PEVs in three-phase systems. The following are highlighted gaps:

- The studies presented thus far provide important insights into PEV impacts on the grid. However, particularly for system-level studies, the simulations are mostly based on single-phase models generalized to three-phase systems.
- All smart charging and DR programs would be more realistic when three-phase operation constraints are included in the decision-making models.

Motivated by the above shortcomings, the existing grid-able PEV-related initiatives will be improved by the research conducted in this thesis. The next three chapters describe the work undertaken to address these deficiencies and to develop a methodology for better serving customers and utility operators.

Chapter 3
Online, Intelligent Demand Management of Plug-in Electric Vehicles in Future Smart Parking Lots

3.1 Introduction

This chapter introduces the proposed online intelligent charging coordination of plug-in electric vehicles (PEVs) in distribution systems. It explains the development of a strategy that enables aggregators in public parking lots to manage PEV energy demands dynamically. The strategy is based on the prioritization of PEVs in order to determine the order in which they will be charged. Priorities are assigned by an expert system based on PEV attributes. The proposed solution addresses the drawbacks mentioned in Chapter 2 by taking into account the following:

- The uncertainty associated with human interactions (i.e., PEV owners) involved in the decision-making process,
- Variations in the load and type of customer sector, and
- Consideration of owner satisfaction in the performance evaluation.

The next two sections present the problem statement and the proposed algorithm. The last four sections of the chapter describe and discuss the modelling aspects, problem formulations, and case studies.

3.2 Problem Statement: Demand Management in Public Lots with PEVs

Investing vast sums on upgrading the distribution grid for the charging of PEVs may be economically unfeasible. Charge management scenarios have therefore been introduced as a component of operational plans for facilitating the adoption of PEVs in smart grids. No standard or inclusive regulation is yet available for managing aggregators with respect to producing an optimum decision [60].

3.2.1 Benchmark 1: Uncoordinated Charging

No aggregator involves in management charging of PEVs using uncoordinated charging scheme (UNCR). In the UNCR, each PEV starts charging upon plugging in regardless of the distribution system technical constraints and operational practice. As discussed in chapter 2, the uncoordinated and random charging of PEVs could significantly stress the distribution system causing voltage fluctuations, degraded system efficiency, and increasing the likelihood of tripping protection devices due to network overloads.

3.2.2 Benchmark 2: First Come, First Served

A straightforward charging strategy for an aggregator involves the tracking of real-time transformer loading and the holding of charging if it is overloaded [95]. To implement this strategy, [56] suggests a so-called "first come, first served" scenario (FCFS) as a benchmark solution for avoiding grid overloading. Although this strategy satisfies grid limitations with safe operation, it is unfair and inconvenient for those vehicles that may arrive later but need urgent service because they will be parked for a shorter time than earlier arrivals that plan to leave much later. Fig (3-1), symbolically, compares how FCFS would be unfair for a PEV arrives latter with shorter parking duration, which needs the same amount of charge as for another PEV with longer parking length.

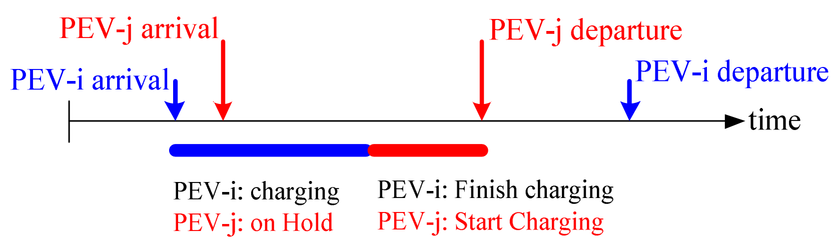


Figure 3-1 Charging sequence using FCFS would be unfair for a PEV arrives later and will leave earlier (PEV-j)

3.3 Proposed Intelligent Decision-Making Algorithm

This section presents an online charging solution that offers a trade-off between the concerns of the utility and the needs of the vehicle owners, and consequently results in more satisfaction. The method proposed here is based on assigning each PEV a charging priority, named as scored-priority (SCR), the determination of which includes consideration of the grid, the vehicle, the battery, and the charger. Although the idea of owner fairness has been used before, it was only based on the departure time of PEV; Geng B. *et al* attempt to address the owners' fairness based on departure schedules, where a charging coordination is employed to achieve a well-shaped transformer load profile [96]. First, the overall charging power demand for the aggregator is determined. Then, the power demand is allocated among all PEVs based on their departure time, in which the higher priority is assigned to the vehicle scheduled to depart earlier. Although the solution in [96] goes one step further to please the vehicle owners, it only considers a vehicle's departure time, whereas additional factors such as the SOC amount, battery capacity, etc., also have significant impacts on the charging priority of vehicles.

To allocate priorities to PEVs located in a parking lot, the aggregator employs a number of decision factors. The charging service will thus be allocated to higher-priority PEVs but without violation of the operational practice constraints of the grid. Framework of the proposed SCR charging coordination is demonstrated in Figure (3-2). It is compared with the FCFS bench mark to reveal a wider range of decision possibilities and a better performance. In the FCFS scenario (scenario 1), the aggregator tracks new PEV arrivals and assigns priorities based on their arrival times. During each time step, vehicles that arrive earlier and that do not violate the operational constraints of the grid begin charging; however, the second scenario, the proposed SCR charging scheme, unfolds in the same way as the FCFS, except for the manner in which the priorities are assigned. In the SCR scheme, final decision is made within two levels of actions. In the first level, PEVs with a higher priority and not necessarily an earlier arrival are scored. The scores are evaluated using a fuzzy expert system. Score decision factors include battery KWhr requirements, charger max power rating and parking duration of the vehicle, all of which are determined based on the data provided for the aggregator through a smart dashboard/meter [60] and [96]. Then, in the second level, charging is delivered to the maximum number of highest-scored vehicles, with respect to the final SOC required and the technical constraints of the grid operation.

Despite the fact that conforming to the technical limits of the distribution grid equipment means that, in both scenarios (FCFS and SCR), limited yet equal numbers of PEVs would be charged; this study shows how FCFS satisfies mostly the grid operators (i.e. electric utility only), while the proposed SCR solution is more convenient for the both the vehicle owners and the utility. The followings are the main contributions of the proposed method:

- Adopting an intelligent expert system that meets the fast response requirements for the grid operation and that represents the dynamics of PEVs arrival/departure;
- Superior performance of the aggregator with greater satisfaction for vehicle owners in terms of energy delivery, while other parties constraints are considered with no violation;
- Preparing more robust satisfaction for the critical PEVs, that needs longer charging time;
- Ease of modeling and implementation.

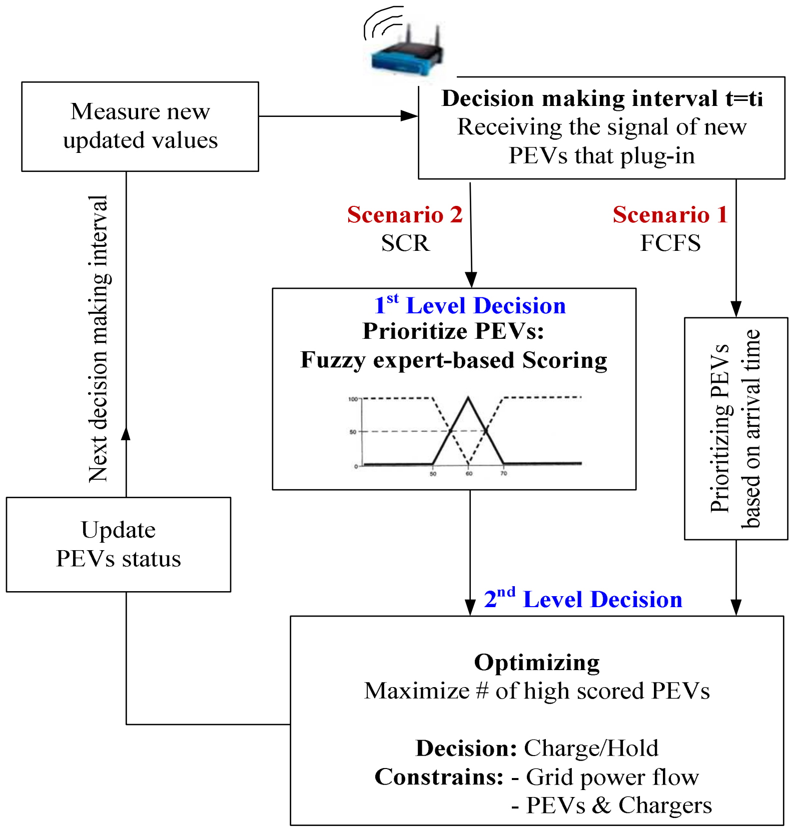


Figure 3-2 Proposed SCR framework for the PEVs charging management

3.4 Modeling Aspects

This section presents the modeling of parking lot chargers and PEV batteries. Moreover, the aggregator's decision making process includes the proposed fuzzy-based scoring model and the decision-optimization is described accordingly.

3.4.1 Smart Parking lot Model: PEV Chargers and Batteries

For system-level studies, an integrated PEV model is used, which includes the battery and the charger. As discussed in Chapter 2, the most important component of a PEV is the battery, which characterizes PEVs with respect to several elements, such as capacity, all electric range (AER), and lifetime.

Lithium-ion (Li-ion) batteries have become the most popular type of rechargeable battery for their good energy density, no memory effect, and slow loss of charge. Neglecting the efficiency and loss in constant temperature, SOC variation over the time is a function of nominal capacity of the battery; therefore, the output voltage (V_{oc}) is also a function of its SOC, as in (3-1).

$$V_{oc} = f(Q) \underset{SOC=g(Q)}{\rightarrow} V_{oc} = f(SOC) \tag{3-1}$$

At a specific charging sampling time (Ts), the battery SOC dynamics varies as shown in (3-2) [96]. The level of the charger facility also affects the energy exchange. Since a level 2 charger is recommended for public use [2], here, the assumption is that parking lots are equipped with level 2 chargers.

$$SOC(t+1) = SOC(t) + f_t\left(SOC(t), P_{ac}(t)\right).T_S \tag{3-2}$$

Upon plugging in the PEV, the owner delivers the required data to the aggregator through a smart dashboard, which is recognized by ID_j. These data cover the battery status including initial and required SOCs ($SOC_{in,j}$ and $SOC_{req,j}$, respectively), as well as the departure time. Moreover, for each charger and PEV, the ID carries data, such as charger rating and the battery capacity. From now on, the following assumptions are considered in all modeling of this thesis:

- Drivers use their PEVs as they would conventional internal combustion engine (ICE) vehicles;
- No reactive power is injected by PEVs;
- Battery efficiency remains constant as temperature varies;
- The aggregator is not a market participant, so only an agent responsible for convenient PEV charging;
- Vehicle owners own their batteries. Thus, no third party, such as battery manufactures, is involved.

3.4.2 Fuzzy Scoring Expert System

The first level of decision making tackles assigning scores to PEVs and prioritizing them for the charging demand queue using a fuzzy expert system. Due to having human interactions in the decision making process, in which the departure time and the final SOC are announced by PEV owners, a level of uncertainty exist in this study. More importantly, the input variables are totally in different directions and natures (i.e., departure time announced by owners, battery required charging energy and the charger power rating). As a result, an expert system would be more convenient to be investigated in this study[1].

The assigned scores are sent to the second level of the decision process (i.e. the optimization stage). As shown in Figure (3-3), the fuzzy scoring expert system consists of four principal components: fuzzification, a rule base, inference logic, and defuzzification. Inputs to the fuzzification block include three variables for each PEV: the battery energy required (KWhr), the charger max power rating, and the parking duration of the corresponding vehicle. The fuzzification interface converts numerical inputs into fuzzy variables, and the defuzzification interface changes the fuzzy variables back into numerical output, i.e. the scores. The scores are then utilized for the optimization stage, which is represented in Section 3-5.

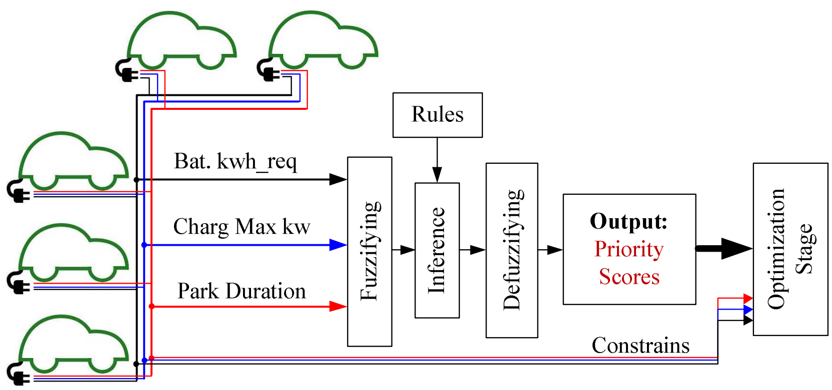


Figure 3-3 Fuzzy inference blocks

3.4.2.1 Variables Membership Function

The input variables are measured/calculated upon plugging a PEV and are updated in every decision making time window; accordingly, the output is continuously subject to change. Crisp scores are assumed a function of energy required, the charger rating and departure time; therefore, fuzzy

[1] - A common explanation of the smart grid is that it is the combination of the electric power and two-way communication infrastructures for bi-directional energy and data flow. However, it might give a wrong impression that only through the employment of the advanced metering infrastructure can implement a smart grid. Advanced sensing cannot afford the smartness for data analysis and decision making. Intelligent use of information can smarten the grid in many ways. In the first place, an expert-system can assist the operator with anticipatory information. Generally, the primary goal of controlling the grid is to maximize the overall comfort level of the controlled objects, which is distributed among different layers, with different functionalities in smart grids. As explained earlier in Section 3-3, in PEV-Grid interactions the concept of comfort level indicates safe operation of the power grid and assures vehicle owners with the delivered level of energy to their battery.

relations are represented, as in (3-3). For both inputs and the output, fuzzification is achieved by means of membership functions μ, determined primarily based on the choice of shape and the number of fuzzy signals. Table (3-1) lists the characteristics of the membership functions. By several trials and practices, trapezoidal shape is chosen for the battery energy required and the parking duration, respectively with three and five linguistic variables (Figs. (3-4) and (3-5)). While, triangular shape is selected for the charger rate and the scores, with Two and four linguistic variables, respectively (Figs. (3-6) and (3-7)).

Fuzzy variables for the KW-hr required are calculated considering the battery capacities of the PEVs available in the market, shown in Table (3-2), and the initial state of charge and final required state of charge, which is announced by the owner upon arriving at the parking (as in (3-4)). Therefore, a range of 0-85KWhr is used for the energy required fuzzy variable. Moreover, the parking duration is assumed as maximum of 10hrs (600min) for the second fuzzy variable regarding battery charging durations as well as public parking hours for commuting purposes. The last fuzzy variable is the charger rating, which is usually much less than battery accepting power. Here a range of 3-7.5 kW is used for the charger.

$$\begin{aligned} &f: reqEng\ , Char_{rate}, DeprtTime \rightarrow PEV\ Score \\ &\mu_{reqEng}, \mu_{Char_{rate}}, \mu_{Dep-t}(PEV_i) \rightarrow \mu_{Score}(PEV_i) \end{aligned} \tag{3-3}$$

$$\forall PEV: \quad reqEng = \left(SOC_{req} - SOC_{in}\right) \times Bat.Cap \tag{3-4}$$

Where

reqEng, $Char_{rate}$,and *DeprtTime* denotes required energy, charger rate, and departure time, respectively;

μ is the fuzzy membership function;

SOC_{req} and SOC_{in} are required and initial SOC, respectively.

Table 3-1 Characteristics of the Membership Functions

	Parameters	# of MF	MF type	Fuzzy Linguistic Variables
Input	Bat. KWhr req.	3	Trapezoidal	Low, Md, High
	Max Charger Power Rate	2	Triangular	Low, High
	Parking Duration	5	Trapezoidal	VSh, Sh, Md, L, VL
Output	Scores	4	Triangular	Low, Md, High, VHigh

Table 3-2 Battery capacity range available in market

PEV in market	Battery Size
Tesla Model S	85 kW·h / 60kWh
Nissan Leaf	24 kWh
BMW ActiveE	32 kWh
Chevy volt	16 kWh

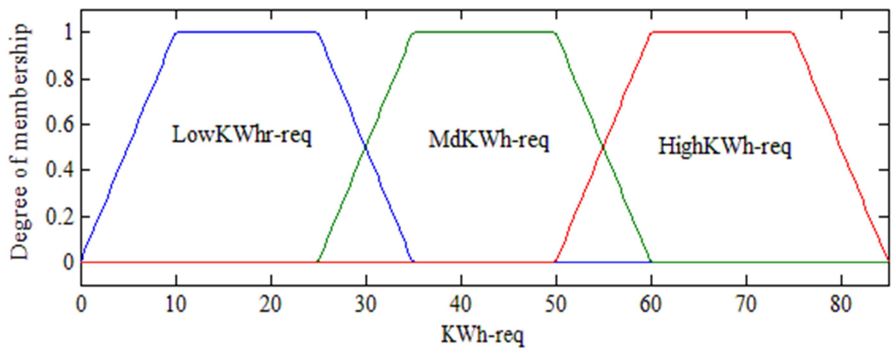


Figure 3-4 Membership functions for the battery KWh required (input 1)

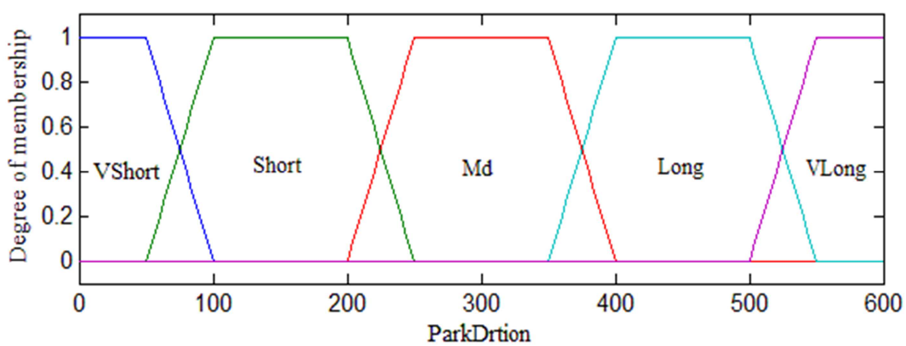


Figure 3-5 Membership functions for the departure time (Minute) (input 2)

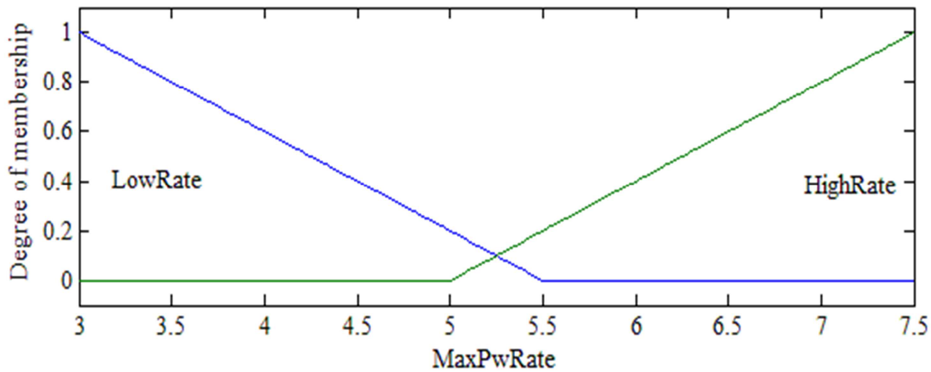


Figure 3-6 Membership functions for the Max charger power (kW) (input 3)

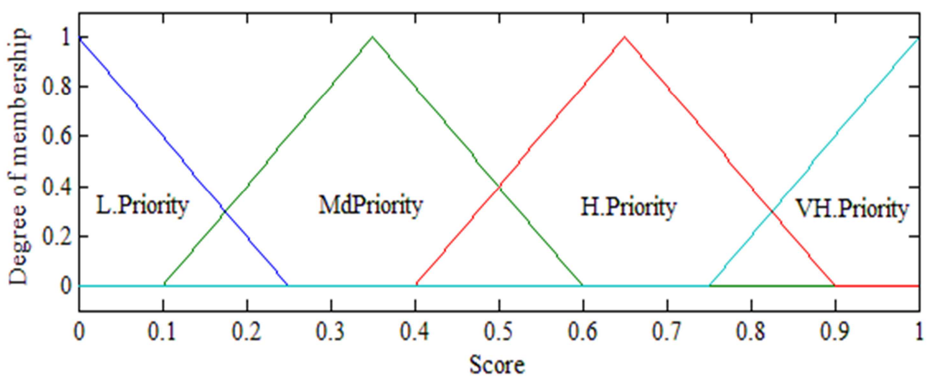


Figure 3-7 Membership functions for the scoring (output)

3.4.2.2 Tuning the Rule Base: Sensitivity Analysis

Proper rule base plays a significant role in the decision success of the expert system. Three input variables, with different natures, need careful attempts on developing suitable rules. Hence, a sensitivity analysis is run here to examine how the designed expert system response to variations of the input parameters, based on the logic behind the decision making. Each individual input parameter varies gradually for a sample set of 150 PEVs, while keeping the values of all other parameters unchanged, as in (3-5). Running the sensitivity analysis several times and tuning the rules, a set of 30 rules is achieved for the final desired rule base, as represented in Table (3-3). The output of each rule is deduced by the inference logic to arrive at a value for each output membership function. An intersection operation (i.e. fuzzy AND) is applied here, in which the correspondence of the membership function to each PEV is given by (3-6), [97].

Table 3-3 Proposed Rule Base

Battery KWhr Required	MaxChrRate (Low / High)	Park Duration (Departure time): **VShort**	**Short**	**Md**	**Long**	**VLong**
Low	Low	$H_{0.3}$	M_{1}	$M_{0.5}$	$L_{0.8}$	VL_{1}
	High	$H_{0.2}$	$M_{0.9}$	$M_{0.4}$	$L_{0.7}$	$VL_{0.9}$
Md	Low	$VH_{0.5}$	$H_{0.8}$	$H_{0.6}$	$M_{0.7}$	L_{1}
	High	$VH_{0.4}$	$H_{0.7}$	$H_{0.5}$	$M_{0.6}$	$L_{0.9}$
High	Low	VH_{1}	$H_{0.8}$	$VH_{0.6}$	H_{1}	$H_{0.8}$
	High	$VH_{0.9}$	$VH_{0.7}$	$VH_{0.5}$	$H_{0.9}$	$H_{0.7}$

*VH/H =Very High/High VL/L =Very Low/Low M=Medium

**Numbers indicate the weights assign to that specific rule

$$S_{input\,\mathrm{var}}^{Score} = \Delta Score / \Delta in\mathrm{var}_{reqEng,DeprtTime,Char_{rate}} \tag{3-5}$$

$$\begin{aligned}\mu_{Score}(PEV_i) &= \mu_{reqEng \,\cap\, Char_{rate} \cap\, Dep-t}(PEV_i) \\ &= \min[\mu_{reqEng}, \mu_{Char_{rate}}, \mu_{Dep-t}]_{PVEi} \qquad \forall i\end{aligned} \tag{3-6}$$

where

invar include the input variables of the fuzzy system (i.e., *reqEng*, *Depart Time*, $Char_{rate}$);

$\cap$ is the intersection operation used for setting fuzzy rules based on the input fuzzy signals;

μ_{score} is the membership function assigned to the score of the ith PEV;

μ_{reqEng} is the membership function assigned to the battery energy required;

$\mu_{Char\text{-}rate}$ is the membership function assigned to the charger power rating;

$\mu_{Dep\text{-}t}$ is the membership function assigned to the vehicle's departure time.

In the defuzzification stage, a non-fuzzy value must be extracted as the numerical output. Several methods are described in literature. Widely used in fuzzy logic designs, the centroid method is based on the center of gravity and is a relatively complete representation since the size and shape of the membership function affects the defuzzified value (expressed as in (3-7)), [97].

$$SC = \frac{\sum_{PEV_i \in S} PEV_i \, \mu(PEV_i)}{\sum_{c \in S} \mu(PEV_i)} \tag{3-7}$$

where

SC is the defuzzified control action, i.e. assigned scores;

$\mu(PEV_i)$ is the membership function of the inference;

S is the support set, i.e. all the PEVs inside the parking.

3.5 Problem Formulation

This section includes the second level of decision making, where PEVs' scores, and grid operational limitations are utilized for the optimization.

3.5.1 Objective Function

Since the aggregator assigns appropriate scores to the available PEVs using fuzzy inference, the objective function reflects serving maximum number of PEVs with highest scores. Therefore, the charging/holding decision for the PEVs is optimized as in (3-8), where the score assigned to each vehicle is the defuzzified function, as in (3-7).

$$\underset{X}{Max} \quad OF_{(t)} = \sum_{i \in N} \sum_{c_{(i)} \in CT_{(i)}} SC_{(c_{(i)},t)} \times X_{(c_{(i)},t)} \qquad \forall t \tag{3-8}$$

where

$OF_{(t)}$ is the objective function that must be optimized;

$SC_{(c(i),t)}$ is the PEV that is plugged in charger $c_{(i)}$ at time t with assigned score of SC;

$X_{(c(i),t)}$ is the binary variable representing the charging decision for each individual charger $c_{(i)}$ at time t;

N is the set of buses;

$CT_{(i)}$ is the set of chargers in the parking lot connected to bus i;

i and t are the indices of buses and time, respectively.

$c_{(i)}$ is index of chargers at bus i;

3.5.2 Constraints

The objective function is subject to the following significant constraints:

3.5.2.1 Power flow constraints

$$P_{G(i,t)} - P_{L(i,t)} = \sum_{k \in N} V_{(i,t)} V_{(k,t)} Y_{(i,t)} \cos(\theta_{(i,t)} + \delta_{(k,t)} - \delta_{(i,t)}) \quad \forall i \in N, t \tag{3-9}$$

$$Q_{G(i,t)} - Q_{L(i,t)} = -\sum_{k\in N} V_{(i,t)} V_{(k,t)} Y_{(i,t)} \sin(\theta_{(i,t)} + \delta_{(k,t)} - \delta_{(i,t)}) \;\; \forall i \in N, t \tag{3-10}$$

3.5.2.2 Generated and consumed powers

The generated power at each bus is the injected power by any generation unit connected at this bus. The demand at each bus is the summation of both the normal load and the PEV demands which depend on the charging decision, battery characteristics, charger ratings, and the charger efficiency ((3-11)-(3-14)).

$$P_{G(i,t)} = P_{Gn(i,t)} \;\; , \;\; Q_{G(i,t)} = Q_{Gn(i,t)} \qquad \forall\, i \in NDG, t \tag{3-11}$$

$$P_{L(i,t)} = P_{NL(i,t)} + P_{EV(i,t)} \, , \;\; Q_{L(i,t)} = Q_{NL(i,t)} \quad \forall i \in N, t \tag{3-12}$$

$$P_{EV(i,t)} = \sum_{c_{(i)} \in CT_{(i)}} \frac{P_{CH(c_{(i)},i,t)} \times X_{(c_{(i)},t)}}{\eta_{CH(c_{(i)})}} \qquad \forall i \in N, t \tag{3-13}$$

$$P_{CH} = f_{BAT}\left(SOC, V_{CH}, I_{CH} \right)_{(c_{(i)},t)} \qquad \forall i \in N, c_{(i)} \in CT_{(i)}, t \tag{3-14}$$

where

k is the bus number;

$NDG \subset N$ is the set of buses where the generation units are;

P_G and P_L are the generated and load active power levels, respectively;

V and δ are the voltage magnitude and angle, respectively;

Y and θ are the admittance magnitude and angle, respectively;

Q_G and Q_L are the generated and load reactive power levels, respectively;

P_{NL} and Q_{NL} are the normal load active and reactive power levels, respectively;

P_{Gn} and Q_{Gn} are the active and reactive power generated from any generation source at bus i, respectively. Although here there is no generation source at any bus, the formulation is adopted properly to accommodate such case;

P_{CH} is the charging power in kW;

η_{CH} is the charger efficiency at bus i;

f_{BAT} is the function that relates the power delivered to a vehicle to its SOC.

3.5.2.3 Feeder current and bus voltage limit constraints

$$\left|I_{(i,k,t)}\right| \le I_{MAX(i,k)} \qquad \forall i,t \tag{3-15}$$

$$V_{\min} \le V_{(i,t)} \le V_{\max} \qquad \forall i,t \tag{3-16}$$

where

V_{min} and V_{max} are the voltage minimum and maximum limits, respectively;

$I_{(i,k,t)}$ is the current flowing from bus i to bus k in time t;

$I_{MAX(i,k)}$ is the feeder current limit between bus i and bus$k$.

3.5.2.4 Decision constraints

The decision variable X is a binary variable: 1 enables the charger, and 0 disables it (holds). This binary variable should be 0 when the SOC value of the connected vehicle reaches the final required value or when no vehicle is plugged into the charger, as in (3-17)-(3-19):

$$X_{(c_{(i)},t)} \in \{0,1\} \qquad \forall i \in N, c(i) \in CT(i), t \tag{3-17}$$

$$X_{(c_{(i)},t)} = \{0 \mid SOC_{(c_{(i)},t)} \ge SOC_{fnl(c_{(i)},t)}\} \qquad \forall i \in N, c(i) \in CT(i), t \tag{3-18}$$

$$X_{(c_{(i)},t)} = \{0 \mid Plug_{(c_{(i)},t)} = 0\} \qquad \forall i \in N, c(i) \in CT(i), t \tag{3-19}$$

where

SOC and SOC_{fnl} are the actual *SOC* and the required final SOC, respectively;

Plug is a binary variable indicating whether or not a vehicle is plugged in.

Figure (3-8) represents details of the proposed algorithm and summarized sections (3-4) and (3-5). In each sampling time (every 10 minutes here), data from the newly plugged-in PEVs are received by the aggregator, and the energy required for the battery is determined using equation (3-4). Then, different priorities are assigned to the PEVs in the fuzzy scoring sub-process. Accordingly, the numbers of scored PEVs are maximized to serve the most vehicles, taking care not to violate the power flow constraints of the grid.

After each decision action, the initial SOC is updated for PEVs that are charged but are still plugged in. Due to the departure of some vehicles, new spots will be available for PEVs that have a lower score in the previous decision action. The scoring and optimization is executed repeatedly over a short time interval in order to duplicate the dynamics of departures and subsequent arrivals in parking lots. Obviously, the scores are updated at the end of each interval due to changes in values of decision factors.

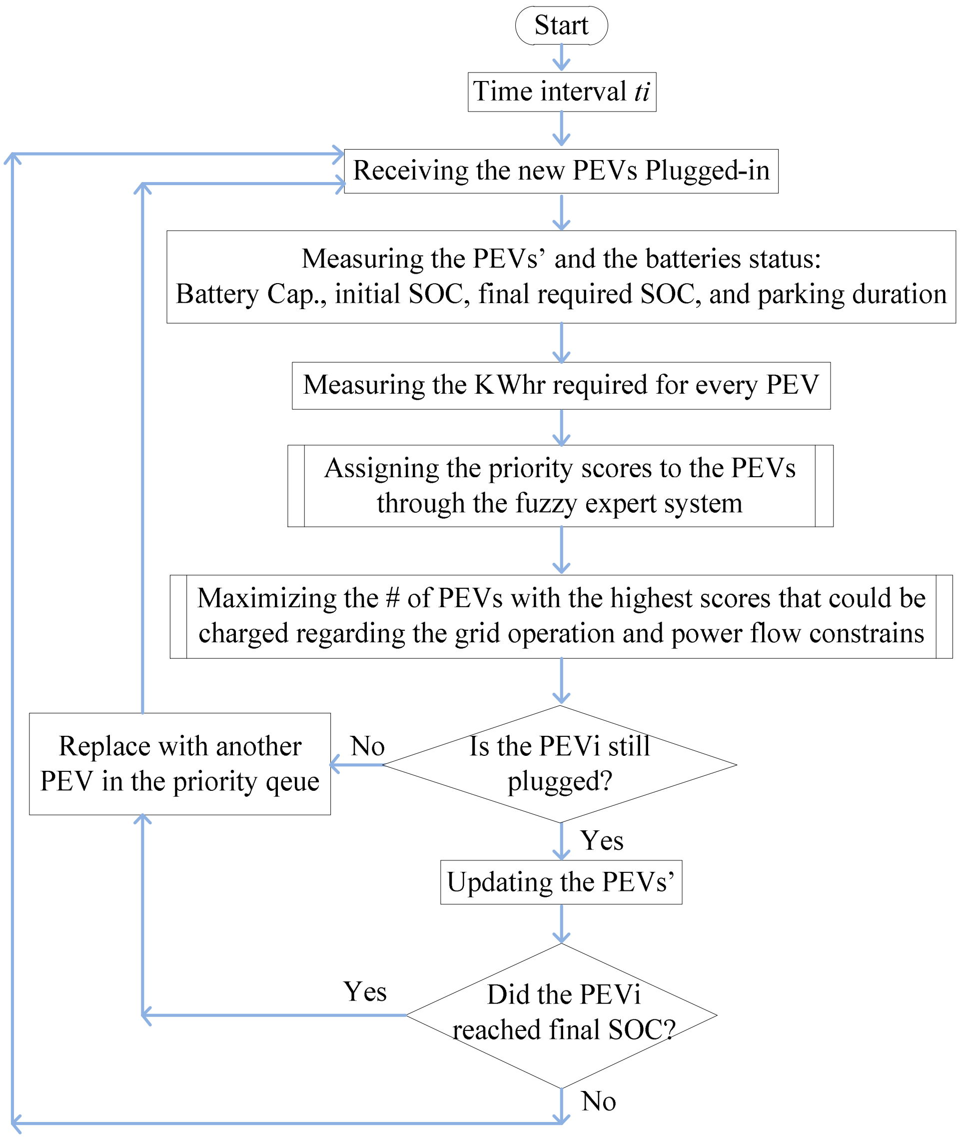


Figure 3-8 Proposed SCR charging coordination algorithm

3.6 Case Study

To evaluate the proposed algorithm, two case studies were examined. The first case is a simple example shows details of each of five individual vehicles, and the second case is a more practical illustration of a 38-bus system. The system under study is modeled in a MATLAB® software environment, where the values are measured and the fuzzy-based scoring is evaluated. The scores are then sent to the aggregator, which is modeled in GAMS software to optimize of the decision through the mixed integer nonlinear optimization. The results are sent back to MATLAB for the updating of the batteries' SOC and the remained required energy. This process is repeated every 10 minutes to replicate the dynamics of parking lot transactions.

3.6.1 Case Study Involving Five PEVs

In this case, it is assumed that, during a peak period, five PEVs arrive at a parking where only three PEVs can be charged simultaneously. Figure (3-9) shows the sequence of charging the PEVs in 15 intervals (a total of 150 min) based on the FCFS strategy. PEV2 with 75% initial SOC arrives first and plugs. PEVs3 and5 enter sequentially, and start charging upon arrival. PEV1 and PEV4 then arrive at the parking lot, where they must be held. It is assumed that the battery capacities and charger ratings are equal in these five PEVs.

As shown in Figure (3-9), PEV4 is not completely charged by the end of its parking duration. PEVs 2 and 3, however, are fully served. In contrast to FCFS, the proposed SCR strategy, in Figure (3-10), shows that upon the arrival of PEV1 within the first three intervals, PEV2 is held due to the higher priority assigned to PEV1. Similarly, when PEV4 plugs in, PEV3 is being held due to its greater SOC and longer parking duration. As shown in Figure (3-11), the total energy delivered to all PEVs in case of SCR scheme is larger than the FCFS charging scheme by almost 25%, yet the system constrains are still met. The SCR solution promises more efficient utilization of the system as well as superior charging coordination.

Figure 3-9 SOC (%) trend based on FCFS charging solution

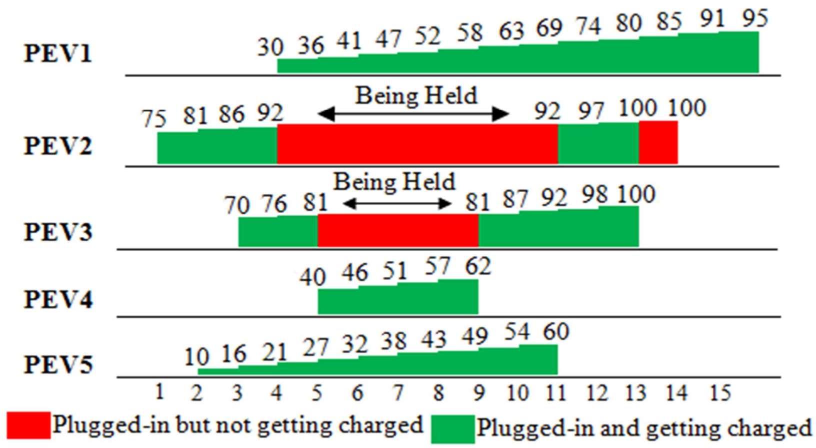


Figure 3-10 SOC (%) trend based on the proposed SCR charging solution

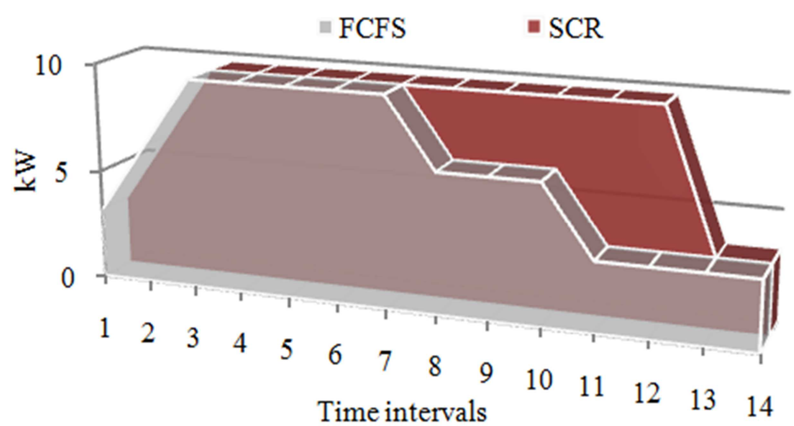


Figure 3-11 Consumed power by the five PEVs through both charging scheme

3.6.2 Case Study Involving a 38-Bus System

The second case study compares both FCFS and SCR charging solutions in more detail. It is implemented on a 38-bus distribution system (shown in Figure (3-12)) [98]. The feeder is energized through a 12.66kV transformer in the main substation, and the total system peak load is 4.37MVA. Four buses (buses 22, 25, 33, and 37) were chosen for parking implementation, which are assumed to be outcomes of a planning stage beyond the scope of this study. Each parking lot sends measured signals to the aggregator including the initial and the final required SOC, as well as the departure time for each PEV.

It is assumed that PL-1, PL-2, PL-3, and PL-4 are equipped with 150, 40, 30, and 40 chargers, respectively, which is proportional to the thermal limits of the feeders supplying the four parking lots.

The total penetration of the PEVs represents almost 21% of the system load. The chargers are assumed to be level 2. In addition to parking capacity, the daily vehicle transactions in the parking constitute another essential factor that affects decisions. Due to lack of real data for PEVs, the number of PEV transactions per week-day is generated virtually based on real data available in Toronto Parking Authority (TPA) and is illustrated in Fig (3-13). Moreover, it is assumed that the parking duration is not less than the required charging amount of the battery. This assumption is due to vehicle owner rational decision in choosing a minimum parking duration that is enough for his own PEV to be properly charged.

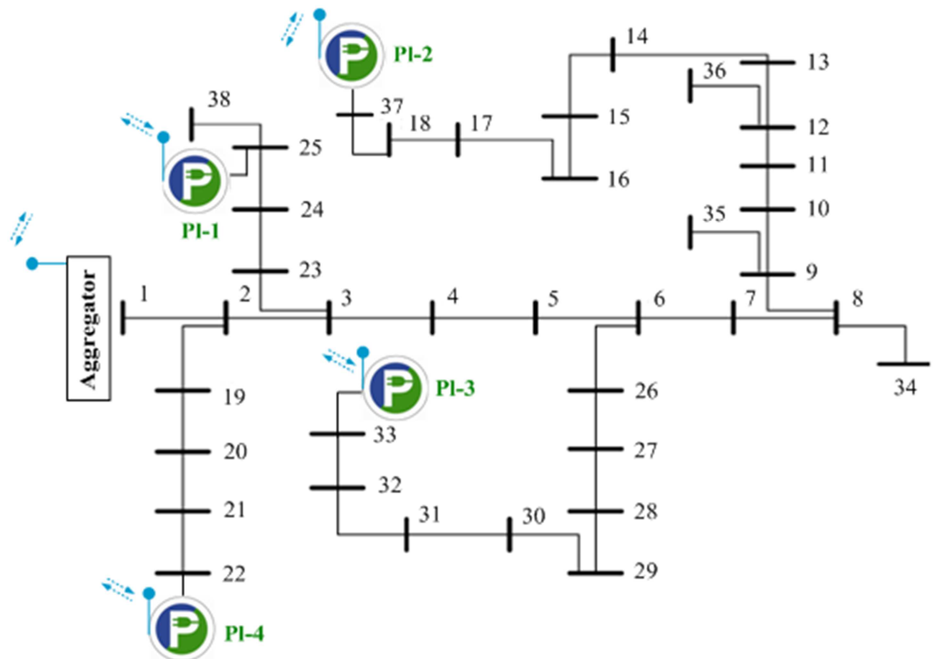


Figure 3-12 The 38-bus distribution test feeder

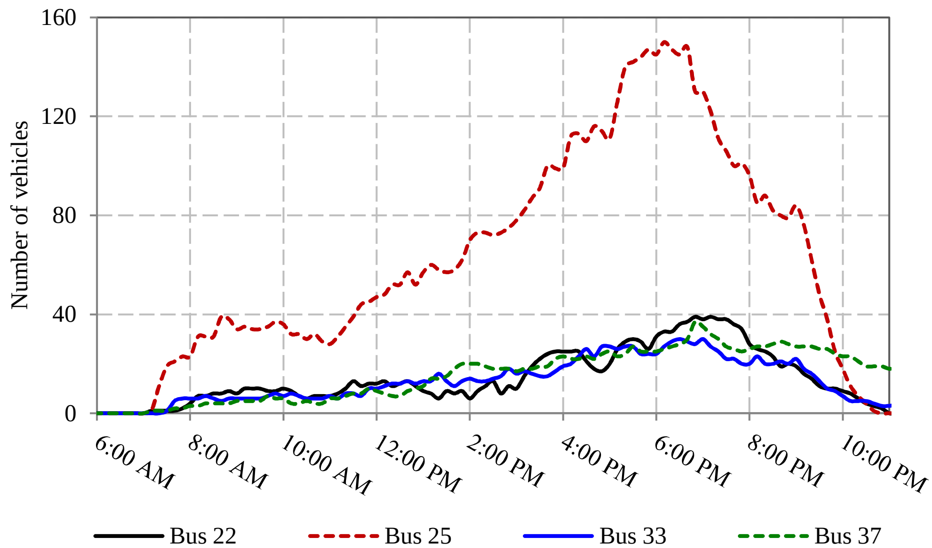


Figure 3-13 Daily PEV transactions at each parking lot

Three charging schemes are compared: uncoordinated (UNCR), FCFS, and the proposed SCR. In the UNCR, each vehicle connected to the system starts charging regardless of the power grid technical constraints. Fig (3-14) compares the system loading in base case (i.e., no PEV charging) with the three charging schemes. Also, the results of the load flow analysis are summarized in Table (3-4). As can be noted, although, there is no line limit violation in the base case; significant overloading of 298.6% occurs with no charge coordination. Moreover, the total energy loss (12.7MWhr) is almost four times higher than in the base case (3.33MWhr). Although, both FCFS and SCR schemes result in total losses more than double the base case (i.e., 8.5 KWh), their outcomes are still feasible since normal operation practice of the grid has not been violated. This significant rise in system losses is mainly due to the concentration of the charging stations only on four buses.

Details of the power delivered to the parking lots are illustrated in Figs (3-15)-(3-19). It is worth mentioning that, as clearly illustrated in Figure (3-14) and Table V, both the FCFS and SCR schemes result in an almost equal energy demand since they are both subject to the same optimization constraints from the distribution grid perspective. According to Figs (3-18) and (3-19), there is only a small difference between the FCFS and SCR schemes in the second parking lot, PL-2, from 10PM to 12AM. Obviously, this is due to variations in the PEVs' charging sequences in both schemes and not from the variation in the number of PEVs served.

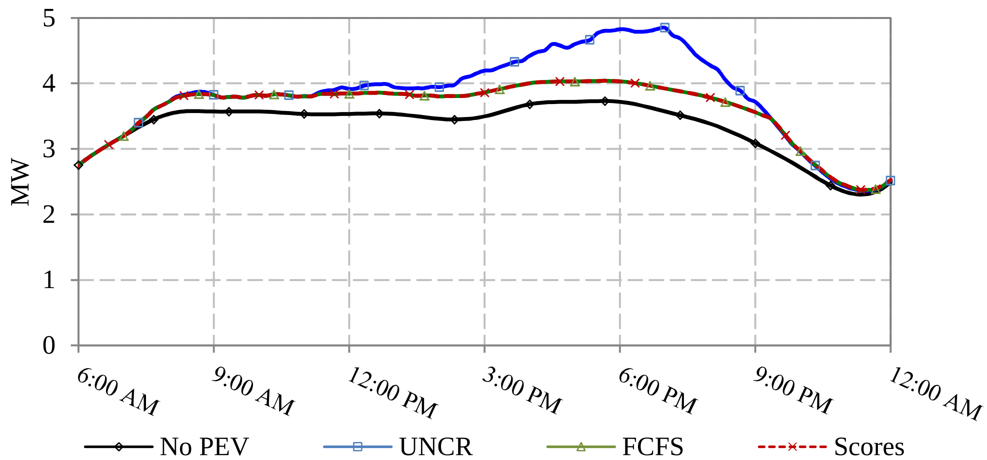


Figure 3-14 System loading in different PEV charging scheme

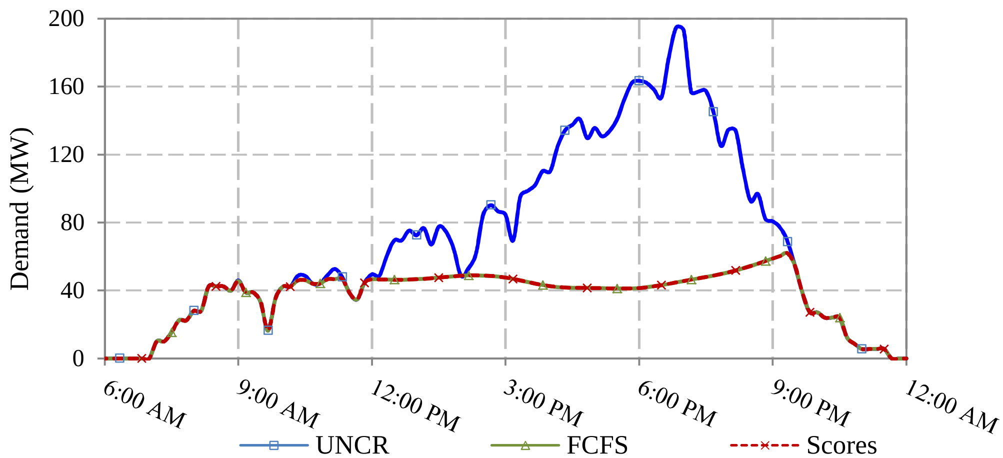


Figure 3-15 PEV charging demand at bus 22 (PL-4)

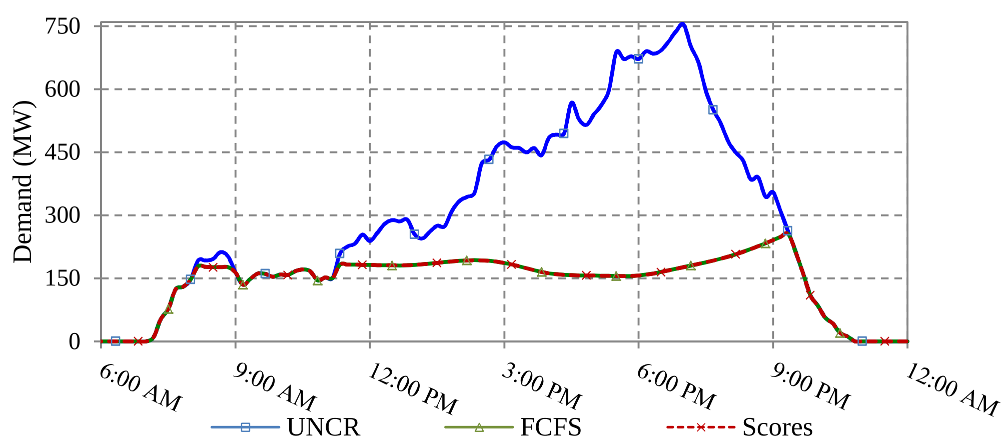


Figure 3-16 PEV charging demand at bus 25 (PL-1)

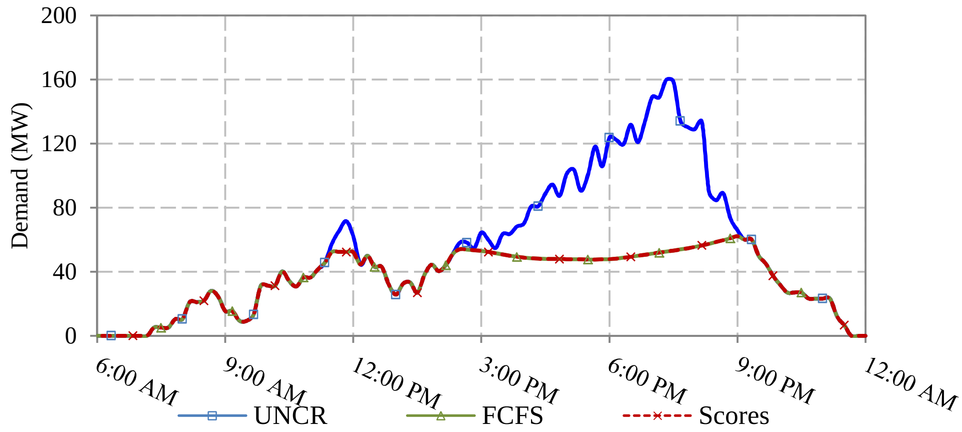


Figure 3-17 PEV charging demand at bus 33 (PL-3)

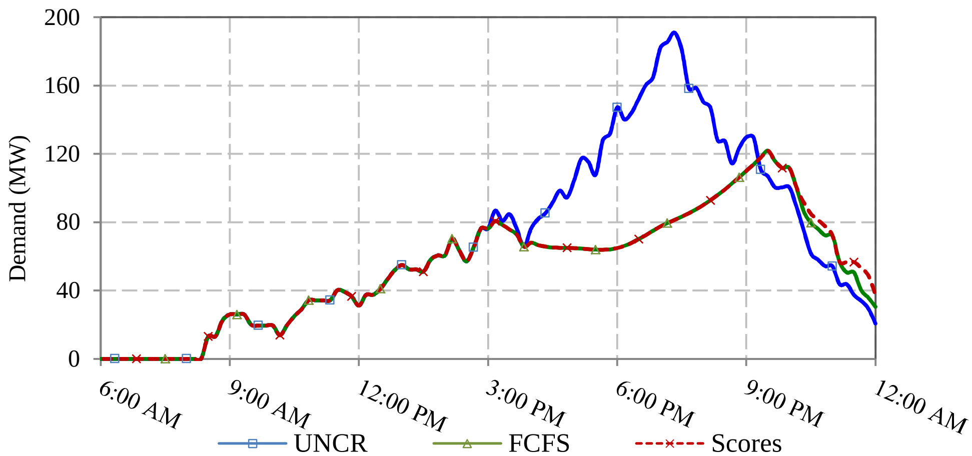


Figure 3-18 PEV charging demand at bus 37(PL-2)

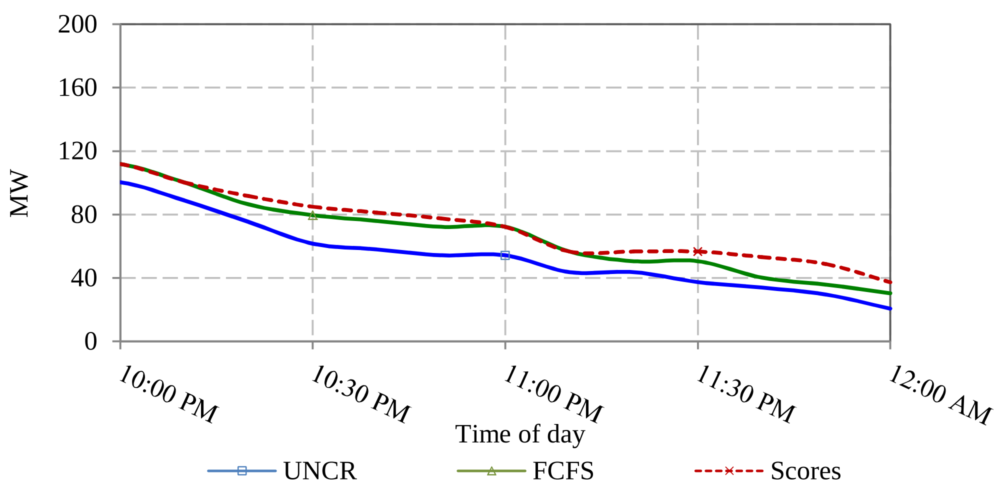


Figure 3-19 A snap shot of the demand at PL-2

Table 3-4 Results of the Load Flow Analysis

Load Flow Results	No PEV	UNCR	FCFS	SCR
Daily Energy Loss (MWhr)	3.33	12.7	8.51	8.52
Max. Line Overloading	-	298.6%	-	-
Feasibility	Feasible	Infeasible	Feasible	Feasible

3.7 Discussion: Performance Evaluation

In addition to energy flow management, the proposed SCR charging scheme is evaluated in terms of vehicle owner satisfaction and fairness, in which the deficiencies of both FCFS and SCR schemes are compared by calculating the root mean square deviation (RMSD) between the delivered energy and the required energy, as in (3-20). RMSD is a common measure, [99], frequently used for the differences between values predicted by a model and the values actually observed (i.e., here, the delivered energy and the required energy, respectively).

$$RMSD_{Enrg} = \left(\frac{1}{n} \sum_{i=1}^{n} \left(reqEng_{PEVi} - delEng_{PEVi} \right)^2 \right)^{1/2} \tag{3-20}$$

where

$RMSD_{Enrg}$ is the total root mean square deviation between the required energy and the delivered energy among n vehicles;

n is the number of PEVs;

$delEng_{PEVi}$ is the energy delivered to the i^{th} PEV.

To reveal how the decisions of the aggregator satisfy individual owners, another approach is also considered where, all PEVs served throughout the day are classified based on their parking duration. Those in the same class are also categorized based on their required charging time (i.e., the ratio of the required energy to the charger rating for every single PEV, as in (3-21)). The higher the required charging time, the more critical would be serving that PEV (as in (3-22)). Therefore, it is expected that the aggregator would serve them with less energy deficiency.

$$\forall PEV_i \quad t_{req.char} = \frac{reqEng_{PEVi}}{Char_{rate-PEVi}} \tag{3-21}$$

$$PEV_{criticl} = \max\!:\left(t_{req.char}\right)\Big|_{Specific\ Park\ Duration} \tag{3-22}$$

where

$PEV_{criticl}$ denotes the critical vehicle with the highest charging time.

Table (3-5) demonstrates the RMSD values for the aggregator and for the individual parking lots, while the RMSD for the critical/non-critical PEVs are shown in Table (3-6). Compared to FCFS, the RMSD values in the SCR scheme are lower not only for each individual parking lot, but also for the aggregator (i.e., the whole system). According to Table (3-5), there is a significant RMSD reduction in using SCR for the second parking lot (PL-2), followed by PL-3, PL-4, and PL-1.

Table (3-6) also indicates that for those critical PEVs, which require higher charging durations, the proposed SCR scheme outperforms in serving them. Both critical and non-critical PEVs are served much more robustly using the SCR scheme in the second parking lot (PL-2), as there is a meaningful reduction in the energy deficiency (5.94 versus 12.8 RMSDs in SCR and FCFS schemes, respectively). Looking at the RMSDs in PL-4, we can see that although both charging schemes serve non-critical PEVs with almost the same RMSD (4.01 and 4, respectively), the SCR scheme outperforms FCFS in serving critical PEVs (RMSD of 4.65 versus 6.52, respectively). The main reason for varying deficiency values across different parking lots is the variety of PEVs' transaction dynamics in different lots, as these dynamics are randomly generated. In addition to RMSD, standard deviation (S.D.) between the delivered energy and the required energy is also represented in the Tables (3-5) and (3-6), using (3-23). S.D. is typically used to represent the confidence or significance of the analysis.

$$S.D.=\left(\frac{1}{n}\sum_{i=1}^{n}\left(\Delta E_{PEVi}-\mu\right)^{2}\right)^{1/2} \tag{3-23}$$

where

ΔE is the difference between the delivered and the required energy of the i^{th} PEV, and μ is the mean of energy difference.

The S.D. values in Tables (3-6) illustrate a range of 3.1-4.9 kWh margin of error in the significance analysis of the proposed SCR solution. However, for the FCFS method, the margin of error varies between 3.73 and 7.78. Similarly, for critical and non-critical PEVs in Table (3-6), the margin of error remains lower in the SCR solution compared to the FCFS method, between 0.8-4.8 kWh and 1.62-8.3 kWh, respectively.

Overall, the results show that the proposed SCR gives lower deficiencies in the energy demand of the parking lots and is superior to FCFS. Undoubtedly, the UNCR scheme has no RMSD between the required and the delivered energy. However, it is not feasible, since it cannot secure proper operation of the power grid, especially during peak hours. The SCR-coordinated charging solution addressed here is formulated based on a simple algorithm that can run in a few seconds and update the decision action every 10 minutes. With a computer configuration of 6 GB RAM and a 2.8 GHz-4core processor, the run time is 4.9 seconds for each decision sampling. However, the actual running time in the field would be dependent more on analog delays, such as digital conversion delays, communication delays, etc. The 10-minute time window here can be significantly reduced based on the hardware and the communication medium implemented in the system.

Table 3-5 RMSD Results for the Aggregator and Parking Lots

	SCR		**FCFS**	
	RMSD	**S.D.**	**RMSD**	**S.D.**
Aggregator (total System)	3.4	3.5	5	3.9
PL-4 (Bus 22)	4.04	3.94	4.95	3.9
PL-3 (Bus 33)	4.62	3.9	6.18	4.11
PL-2 (Bus 37)	5.73	4.9	13.4	7.78
PL-1 (Bus 38)	2.75	3.1	3.1	3.73

Table 3-6 RMSD in energy delivered to the critical and non-critical PEVs

	Critical PEVs				**Non-Critical PEVs**			
	SCR		**FCFS**		**SCR**		**FCFS**	
	RMSD	**S.D.**	**RMSD**	**S.D.**	**RMSD**	**S.D.**	**RMSD**	**S.D.**
(PL-4) Bus 22	4.65	3.5	6.52	4.43	4.01	3.2	4	3.02
(PL-3) Bus 33	7.08	4.8	7.82	4.9	2.33	2.13	5.26	3.4
(PL-2) Bus 37	5.94	4.64	12.8	7.2	3.7	3.1	14.21	8.3
(PL-1) Bus 38	3.82	2.38	4.04	2.65	0.98	0.8	1.76	1.62

3.8 Summary

This Chapter developed an online intelligent decision-making strategy that enables aggregators in public parking lots to dynamically manage PEV charging. The strategy was based on prioritizing PEVs in order to determine the order in which they are charged. The priorities are based on designing a fuzzy expert system for the aggregator using PEV attributes including the SOC, battery capacity, charger max power rating, and departure time of the vehicle.

Case studies were simulated for a typical distribution system with different parking lots. The simulation results prove the effectiveness of the proposed methodology in dealing with the fast-changing dynamics of PEV charging coordination. More specifically, using proposed SCR, an aggregator can better address the energy demands of critical PEVs, which have short parking duration and high charging time. The proposed solution also benefits from a simple and fast implementation algorithm. However, there is a need for quantitative measure/regulation to reveal how much the aggregator fails to satisfy all the PEVs. Such measure needs to employ a monetary penalty scheme, which is under developed by the authors as a future extension and contribution of this study [100].

Chapter 4
New Energy Management System for Incorporating Smart Parking Lots into the Demand Response

4.1 Introduction

This chapter is focused on the methodology for implementing demand response (DR) through the development of an energy management system (EMS) for incorporating aggregated plug-in electric vehicles (PEVs) into parking lot. This approach includes real-time interaction between the aggregator and PEV owners, whereby the aggregator proposes a number of offers for charging/discharging and the owner responds based on his/her preference. The following considerations have been taken into account in the proposed method:

- The fact that long-term pre-signed contracts between PEV owners and the utility do not guarantee the willingness of the owners to contribute to V2G,
- The variable hourly energy cost, and
- The prediction of new arrivals.

The next two sections present the problem statement and the proposed algorithm. The last four sections of the chapter describe and discuss the modeling aspects, problem formulations, and case studies.

4.2 Problem Statement

Demand Response (DR) is a fundamental component that seeks to involve end-use customers in shaping energy demands, in turn, resulting in peak clipping, valley filling, load shifting, and flexible load shape. In other words, DR modifies customers' electricity usage based on their normal consumption pattern, offering incentive payments to encourage lower electricity use at times of high prices or when system reliability is at risk [101].

Even though storage system integration offers major advantages for DR programs, end-use customer applications are still restricted due to their installation costs. Deployment of grid-able PEVs, however, holds the promise of using their batteries for DR without imposing the additional infrastructure and costs associated with domestic-only storage systems [11]. When used with proper charging scheme and communication infrastructure, PEVs may play a dual role in smart grids, either turning into dispatch-able loads (DL) when plugged in for charging or acting as grid-able storage responding to pricing commands, a concept generally referred to as vehicle-to-grid (V2G). These features make PEVs appropriate source of short-term ancillary services for the grid. Like other DR programs, the idea behind V2G is simply to allow owners to make profit and to gain more revenue. That is, if vehicle owners change the battery from charging to discharging back to the grid at a rated power, the energy payment direction should be reversed [12]. Most research and studies reveal potential profits that electric utilities or policy makers would make from V2G. Questions, however, have been raised about the vehicle owners' interests in V2G. Recent survey-based studies by Hidrue et *al.* indicate that the conventional approach–PEV drivers signing pre-specified contracts, in return for annual cash back is unlikely to appeal to drivers under current market conditions [13, 14].

This paper provides an approach that realizes DR programs by developing EMS for incorporating aggregated PEVs in future smart parking lots. This approach includes real-time interaction between the aggregator and the PEV owner, whereby the aggregator proposes a number of offers and the owner responds based on his/her preference. The proposed method contributes to existing V2G-related efforts, mainly by providing owners with flexible options for immediately deciding whether they want to discharge their battery back into the grid. The paper's most significant contributions are as follows:

- A new multi-stage decision-making approach based on real-time interaction between PEV owners and aggregators. This interaction provides owners with an appropriate scheme for contributing to DR, while avoiding the inconvenience of long-term contracts.
- A new stochastic prediction model of near-future arrivals and their energy demand, employed in the decision making, using collaboration of an artificial neural network (ANN) and the Markov Chain.

4.3 Framework of the proposed EMS method

Figure (4-1) demonstrates the aggregator's decision making modules proposed in this chapter, including: 1) Owner Interface, 2) Grid interface, 3) PEV Prediction, 4) PEV Info and 5) Decision optimization module. Once a PEV arrives at the parking lot, the owner plugs it in and communicates with the aggregator to exchange the required data to the owner interface module. These data include the vehicle ID, the battery status, and the vehicle departure time, which are explained in detail in Section IV. In addition to the already-present PEVs, the pattern of future arrivals also affects the aggregator's decision making. PEV prediction module is an intelligent component inside the aggregator, responsible for estimating the loading effect of this pattern. Moreover, the grid operator requirements, SCADA data, and energy pricing information are fed to the grid interface module.

Using all the data available, the aggregator, accordingly, offers the owners charging options. Based on the owners' responses, the aggregator optimizes the decision making and sends charging/discharging signals to individual chargers. Obviously, the decision is continuously subject to change as all input data are updated in every decision making window. This study is based on the following assumptions:

- Drivers use their PEVs as they would conventional internal combustion engine (ICE) vehicles.
- No reactive power is injected by PEVs.
- Battery efficiency remains constant as temperature varies.
- The aggregator is not a market participant, so only an agent responsible for convenient PEV charging.
- Vehicle owners own their batteries. Thus, no third party, such as battery manufactures, is involved.

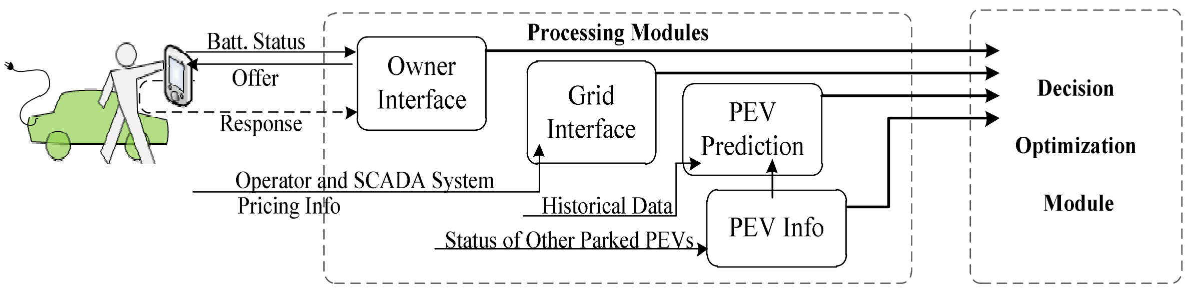


Figure 4-1 Aggregator's modules for the proposed method

4.4 Aggregator's Controlling Modules

4.4.1 Processing Modules

This section provides details of the first four modules of the aggregator (as in Figure 1), called processing modules from now on. The data processed by these modules are, accordingly, send to the optimization module.

4.4.1.1 Owner Interface module

A set of parking lots is controlled by one aggregator agent. Determining the proper number of parking lots per aggregator depends on various factors and is beyond the scope of this research. Hence, it is assumed that only one aggregator controls parking lots demand and manages the DR program. Each parking lot (PL_i) is equipped with a set of chargers (Chr_j) represented by specific identities (ID_j) and only one PEV is connected per charger. An integrated battery and charger model is used here, where for the Lithium-ion (Li-ion) batteries; variation of SOC over time is a nominal function of battery capacity, as in (4-1), where, (P_{Chr}) is the charging power of the battery over time τ[102].

$$SOC_{\tau+1} = SOC_{\tau} + f_{\tau}\left(SOC_{\tau}, P_{Chr_{\tau}}\right).T_s \quad (4\text{-}1)$$

Upon plugging in the PEV, the owner delivers the required data to the aggregator through a smart dashboard, which is recognized by ID_j. These data cover the battery status including initial and required SOCs ($SOC_{in,j}$ and $SOC_{req,j}$, respectively), as well as the battery capacity (Bat_{Cap}). Moreover, the owner announces the expected departure time (t_{dep}).

As the aggregator receives PEV data, it determines the corresponding required energy (E_{req}) and the required charging time (t_{ch}), as in (2). Accordingly, PEVs are classified based on a criteria factor, called the comfort criterion (CC) here, which compares the departure time (t_{dep}) and the required charging time (t_{ch}). The aggregator then offers owners three charging options, called ($DChrg_{class}$), ($FlxChrg_{class}$), and ($Chrg_{class}$) from now on. By choosing $DChrg_{class}$ offer, the owner agrees to receive a discount through discharging the battery. Similarly, the owner who accepts the $FlxChrg_{class}$ offer receives discounts._However, the latter discount is based on accepting flexible charging by shifting the battery charging process to lower tariff intervals. No tariff reduction goes for owners who accept the $Chrg_{class}$, and their battery receives charging power immediately. The PEVs' CC factor is expressed by (4-3). Of course, offers differ in number and content for PEVs. For a PEV with (t_{ch}) less than (t_{dep}), the owner is offered all three options, while for (t_{ch}) more than (t_{dep}), only $Chrg_{class}$ is offered by the aggregator. $Chr_{cap-rat}$ is power ratings of charger facilities in kW and η_{BAT} is the efficiency of the battery charging process.

$$t_{ch} = \frac{(SOC_{req} - SOC_{in}) \times Bat_{Cap}}{\eta_{BAT}\ Chr_{Cap-rat}} \quad (4\text{-}2)$$

$$CC = \begin{cases} DChrg|\ FlxChrg|\ Chrg & \forall\ t_{ch} < t_{dep} \\ Chrg & \forall t_{ch} > t_{dep} \end{cases} \quad (4\text{-}3)$$

4.4.1.2 Grid interface module

The grid interface module receives information from the SCADA system about the grid status. Moreover, it receives information from the grid operator regarding energy pricing and ancillary services requirements. The Independent Electricity System Operator (IESO) in Ontario offers a number of wholesale Real Time Pricing (RTP) payments for large consumers, including businesses and the public sector [103]. For business consumers with internal meters, payments are based on the Hourly Ontario Energy Price (HOEP) scheme, which is the basis in this study.

4.4.1.3 PEV prediction module

The PEV prediction module includes two prediction tasks: number of future vehicle arrivals and their corresponding charging/discharging options.

4.4.1.3.1 Number of prospective arrivals

Decision results are prone to significant change due to energy demands of PEVs that will arrive later at the parking lot. Historical data are required to build a prediction model of PEV arrivals. In this study, annual historical data of the Toronto Parking Authority (TPA) is employed to build and train an artificial neural network (ANN) for an hourly-regression forecast model of future arrivals. Applications of ANN in power system planning and operation are not new. They have been successfully utilized, in transmission and distribution sectors, for short-term load forecasting since the 1990s [104, 105]. Recently, several studies have examined the capability of ANN, in PEV-related research, including trip model development [106], charging management and demand forecast [107, 108], as well as battery state of health estimation [109].

Similar to [83], this study assumes owners drive PEVs ICEs-similarly. Thus, historical data on parking lot hourly transactions is valid for building the regression model for PEVs hourly transactions. Fig (4-2) demonstrates average hourly parked vehicles in a parking for a weekday in downtown Toronto, and indicates that, with respect to RTP tariffs, a correlation exists between typical commercial electric load patterns and parking lot transactions. Since this parking lot is located downtown, the aggregator's decision making on PEVs would significantly reshape the load. Let the number of PEV arrivals to the parking lot at $(\tau + 1)$ time frame be a function of all previous interval arrivals $[1, 2, \dots, \tau]$ as represented in (4-4). Therefore, the structure of the ANN as demonstrated in Fig (4-3), includes a τ-dimension input vector and one output, corresponding, respectively, to 1st till τ^{th} PEV arrivals, and next arrival at $(\tau + 1)$, as in (4-5).

$$Arv_p^{\tau+1} = f(Arv_p^1, Arv_p^2, Arv_p^3, \dots, Arv_p^{\tau}) \tag{4-4}$$

$$inputs: \left\langle \begin{matrix} Arv_p^1 \\ \vdots \\ Arv_p^{\tau} \end{matrix} \right\rangle \qquad output: \langle Arv_p^{\tau+1} \rangle \tag{4-5}$$

After several tests, the ANN structure in this study is a feed-forward multilayer perceptron (MLP), accompanied with a Levenberg-Marquardt back-propagation training algorithm (LMA, which uses a Jacobian based on the mean squared errors during its calculations [110]. Table (4-1) summarises the characteristics of the final-trained ANN, trained off-line to generalize nonlinear relationships between the inputs and the corresponding output. The PEV prediction module uses the adopted ANN in every decision making interval (τ).

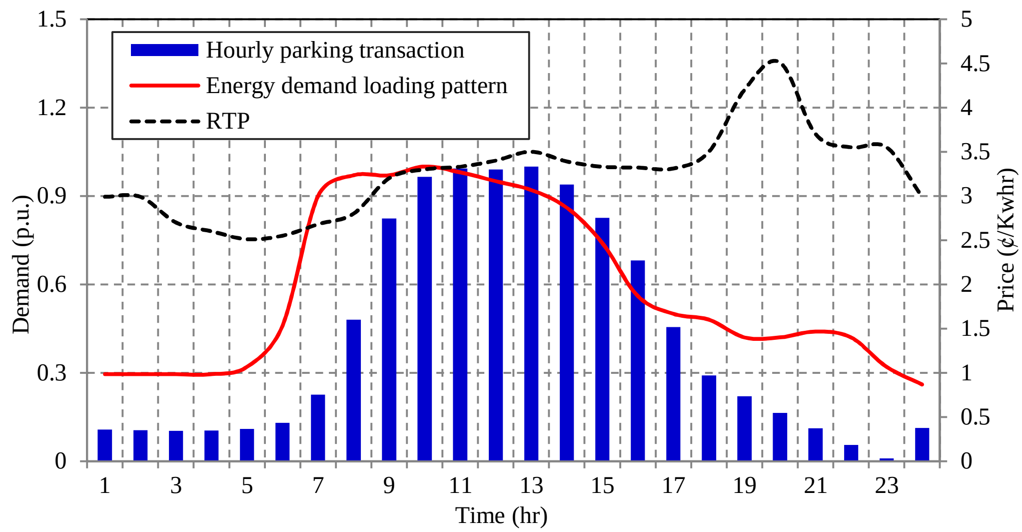


Figure 4-2 Average hourly parked vehicles of a parking lot

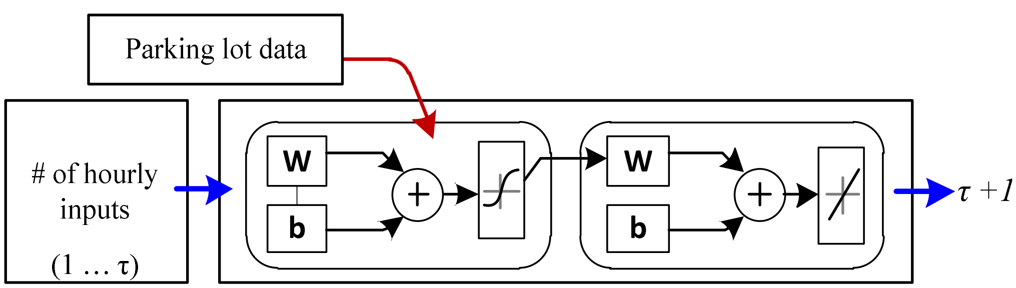


Figure 4-3 Architecture of the ANN model

Table 4-1 CHARACTERISTICS OF THE ANN BUILD FOR PEV PREDICTION

ANN Type	Multi-Layer Perceptron		
Number of Neurons	Input Layer	Hidden Layer	Output Layer
	τ at interval $\tau+1$	15	1
Training algorithm	LMA back-propagation		
Performance	Mean Squared Error (MSE)		

4.4.1.3.2 Expected Charging/discharging options

The ANN regression model deals only with estimating PEV numbers arriving at the parking lot within next decision intervals. Still, it is important for the aggregator to have an estimation of in-coming PEVs' charge/discharge status. One solution is assuming the extreme case, which only considers requests for charging in future estimation [94]. However, it is more realistic to employ various scenarios that include charging and discharging, rather than the charge-only extreme case.

This paper takes advantage of a stochastic solution based on the Markov Chain model (MC), which, in general, is a memory-less random process to represent the following state of an event based only on the current state. MC is employed in some recent studies of load modelling and demand management, especially where the stochastic nature of human interactions is involved. Munkhammar *et al.* use MC for modeling the flexibility of the energy consumption habits of householders [111, 112]. Similarly, in [113], user-activity profiles are synthesized regarding electrical appliance usage. Here, PEV owners' likely preferences to aggregator offers are modelled through the MC process. The idea is based on the fact that there is a close similarity between the patterns of PEVs using one particular parking lot within a specific time interval. Let S^{τ}denotes a state of an offer made by the aggregator. At the decision-making instance (τ), each owner, is offered one the three options of "S^{τ}_{Chrg}", "$S^{\tau}_{FlxChrg}$", and "S^{τ}_{V2G}". Upon the owner's response to an offer, a state transition occurs ($S^{\tau} \rightarrow S^{\tau+1}_{*}$) with the transition probability of $P^{\tau+1}_{S \rightarrow S^{*}} = P(S^{\tau+1}_{*}|S^{\tau})$, as in (4-6). Transit probabilities from state (S^{τ}) to any possible states of ($S^{\tau+1}_{*,i}, \forall i \in S_{*}$) should satisfy (4-7). Thus, the transition matrix (*TM*) among the states and the distribution over the states can be, respectively, written as (4-8) and (4-9). Figure (4-4) shows the mechanism by which owners' responses are predicted. Collaboration between the ANN outputs and the MC probabilities complete the PEV prediction module in the aggregator.

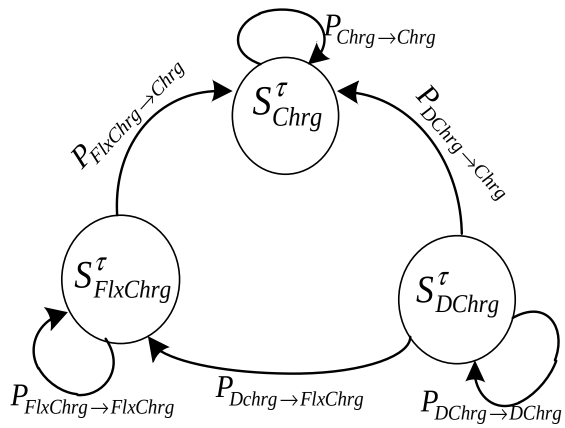


Figure 4-4 MC-based presentation of the responses and the state transitions

$$P^{\tau+1}_{S \to S^*} = \frac{No. of\ PEVs\ that\ offered\ and\ choose\ S^*}{Total\ No. of\ PEVs\ offered\ S} \tag{4-6}$$

$$\sum P_{s \to s^*} = \sum_{*} P(S^{\tau+1}_{*} | S^{\tau}) = 1 \tag{4-7}$$

$$TM = \begin{pmatrix} P_{Chrg \to Chrg} & 0 & 0 \\ P_{Flx \to Chrg} & P_{Flx \to Flx} & 0 \\ P_{DChrg \to Chrg} & P_{DChrg \to Flx} & P_{DChrg \to DChrg} \end{pmatrix} \tag{4-8}$$

$$S^{\tau+1} = S^{\tau} \times TM \tag{4-9}$$

4.4.2 Decision Optimization Module

All information from other modules is utilized by the optimization module to allocate charging/discharging decision actions to PEVs in parking lots under the aggregator's administration area. The above-mentioned offers classify PEVs as those that should charge immediately and those that can either hold/shift charging or discharge for a discount price. Therefore, the proposed optimization is designed to satisfy different objectives: maximizing delivered energy and minimizing the cost of energy. It solves a multi-stage non-linear optimization to satisfy PEVs in all offer classes. The first stage maximizes the delivered energy to $Chrg_{class}$. The charging decisions of $Chrg_{class}$ are not subject to change in the following stages. Conversely, the second stage is intended to optimize resource utilization and minimize cost while satisfying other PEVs needs (i.e., $FlxChrg_{class}$ and $DChrg_{class}$). However, due to the fact that the grid was not originally designed to accommodate the extra load imposed by the PEV charging, satisfying the required charging energy levels for these classes may not be possible without violating the system technical constraints.

Thus, the second stage attempts to determine the maximum possible energy that can be delivered for each vehicle, subject to the required charging energy by the customers and the grid technical limits, according to the distribution system code of the Ontario Energy Board [114]. This stage will usually result in a maximum delivered energy equal to the required energy, as long as there is no violation for the grid technical limits (this stage is redundant if the grid is designed to accommodate large penetration of PEVs with proper diversity factor). The third stage aims at minimizing the charging cost while maintaining the maximum delivered energy for each vehicle from second stage. Fig (4-5) shows data flow inside the optimization module.

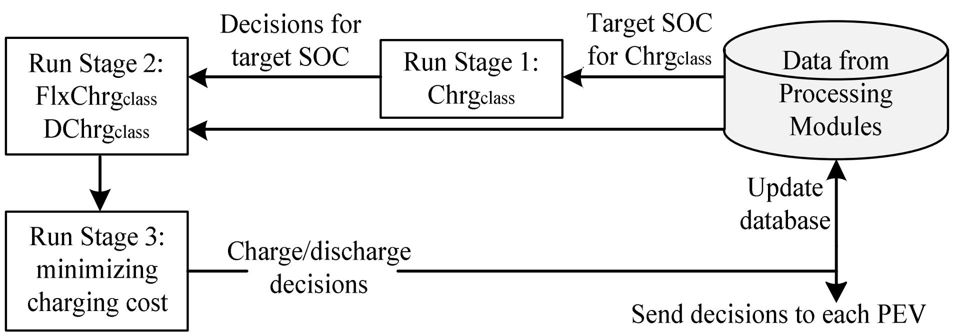


Figure 4-5 Structure of the proposed decision optimization module

4.4.2.1 Stage 1: $\mathrm{Chrg}_{\mathrm{class}}$ energy maximization

The objective of this stage is to maximize energy delivered to $Chrg_{class}$-batteries in response to their required SOC. At time instant τ_{t+1}, energy delivered to the n^{th} PEV ($PEV_{n,Chrg}$) plugged in to the j^{th} charger in the i^{th} parking lot ($Chr_{(j)} \in PL_i$) is dependent on the decision taken over the decision making window τ_t, ($E_{del(j,\tau_{t+1})}$). Accordingly, the objective function of this stage can be described as in (4-10):

$$\underset{X}{Max} \sum_{i\in\Gamma} \sum_{\tau} \sum_{j\in Chrg} \varpi(\tau)\ .\ E_{del(j,\ \tau)} \tag{4-10}$$

Where, X is the power exchange rate for $Chr_j \in PL_i$ of bus Γ of the system, and $\varpi(\tau)$ is a time-weighting factor that gives priority to earlier time slots (i.e., PEVs that plug in earlier). The objective function is subject to a number of constraints, including the active and reactive power at each bus, which is controlled by the voltage magnitudes and angles, represented as power flow constraints in

(4-11, 4-12). Moreover, the voltage and thermal loading limits of the system feeders expose the objective function to additional constraints, as in (4-13, 4-14).

$\forall i \in \Gamma, \tau$:

$$P_{G_{i,\tau}} - P_{L_{i,\tau}} - P_{PEV_{i,\tau}} = \sum_{i'} \{V_{i,\tau} V_{i',\tau} Y_{i,i'} \cos(\theta_{i,i'} + \delta_{i'} - \delta_i)\} \quad (4\text{-}11)$$

$$Q_{G_{i,\tau}} - Q_{L_{i,\tau}} = -\sum_{i'} \{V_{i,\tau} V_{i',\tau} Y_{i,i'} \sin(\theta_{i,i'} + \delta_{i'} - \delta_i)\} \quad (4\text{-}12)$$

$$V_{min} \le V_{i,\tau} \le V_{max} \quad \forall i \in \Gamma, \tau \quad (4\text{-}13)$$

$$I_{i,i',\tau} \le I_{max} \quad \forall i, i' \in \Gamma, \tau \quad (4\text{-}14)$$

where P_G, Q_G denote active and reactive generated powers, and P_L, Q_L denote active and reactive load powers, respectively. $I_{i,i',\tau}$ represents the per-unit current through the line between buses i and i' at time τ. The demand at each bus is the summation of both the normal load and the PEV demands (P_{PEV}), which depend on the charging decision (X), charger capacity, and the charger efficiency (η_{Chr}), as in (4-15).

$$P_{PEV_{i,\tau}} = \sum_{j} \frac{Chr_{cap_{i,\tau}} \times X_{i,\tau}}{\eta_{Chr_i}} \quad \forall i \in \Gamma, \tau \quad (4\text{-}15)$$

The energy delivered to a PEV battery can also be represented by the battery final reaching its desired SOC (SOC_{fnl}), as shown in (4-16), where Bat_{Cap_j} is the battery capacity in kWh of the PEV connected to the charger (j). The final SOC needs to be controlled by the required SOC that has been announced in advanced by the owner, as in (4-17). Accordingly, at the end of each decision making window, the SOC of a PEV is updated based on (4-18).

$$E_{del_j} = Bat_{Cap_j} \sum_{\tau} \{SOC_{fnl_j} - SOC_{in_j}\} \quad (4\text{-}16)$$

$$SOC_{fnl_j} \le SOC_{req_j}, \quad \forall j \in PL_i \quad (4\text{-}17)$$

$$SOC_{fnl_{j,\ \tau+1}} = SOC_{fnl_{j,\ \tau}} + \frac{X_{j,\tau} \times Chr_{cap_j}}{\eta_{BAT}\ Bat_{cap_j}} \quad , \forall i \in \Gamma, \tau \quad (4\text{-}18)$$

Thus, the objective function of the charge-only stage (i.e., equation (4-10)) is subject to all constraints of (4-11)-(4-18), where:

$$X \in [0, 1] \quad (4\text{-}19)$$

4.4.2.2 Stage 2: $FlxChrg_{class}$ and $DChrg_{class}$ energy maximization

In this stage, the aggregator optimally maximizes the energy delivered to both the $FlxChrg_{class}$ and $DChrg_{class}$ classes of PEVs without any consideration to the charging price. In other words, the aggregator attempts to serve all PEVs through this stage up to the grid technical constraints, and vehicle owner requirements, as in (4-20, 4-21). This stage has a structure similar to as stage one's. However, positive and negative charging decisions are allowed according to the class, $X' \in [-1, 1]$, indicate charging and discharging, respectively. Moreover, the maximum delivered energy to $Chrg_{class}$ from stage 1 is maintained as a hard constraint, as in (4-22). The power delivered (P_{del}) or consumed (P_{cns}) by each charger is then given by (4-23). During discharge of the PEV batteries, no power is allowed to be delivered to the grid; therefore, the total parking lot power (P_{prk}) always needs to be positive, as in (4-24).

$$P_{L_{i,\tau}} \le \rho_{max_{i,\tau}}, \quad \forall i \in \Gamma, \tau \tag{4-20}$$

$$\underset{X,X'}{Max} \sum_{i \in \Gamma} \sum_{\tau} \Big(\sum_{j \in Flx} E_{del_{FlxChrg_\tau}} + \sum_{k \in DChrg} E_{del_{DChrg_\tau}} \Big) \tag{4-21}$$

$$E_{del_{Chrg}} \Big|_{Stage\ 1} = E_{del_{Chrg}} \Big|_{Stage\ 2} \tag{4-22}$$

$$\begin{aligned} P_{cns_{j,\tau}} &= \frac{X_{j,\tau} \times Chr_{cap_j}}{\eta_j} \qquad \forall X'_{j,\tau} \ge 0 \\ P_{del_{j,\tau}} &= X_{j,\tau} \times Chr_{cap_j} \times \eta_j \qquad \forall X'_{j,\tau} \le 0 \end{aligned} \tag{4-23}$$

$$P_{prk_{i,\tau}} \ge 0, \quad \forall i \in \Gamma, \tau \tag{4-24}$$

4.4.2.3 Stage 3: $FlxChrg_{class}$ and $DChrg_{class}$ cost minimization

In this stage, the charging costs for *$FlxChrg_{class}$ and $DChrg_{class}$* are minimized, as in (4-25) while the maximum delivered energies for all classes from stage 1 and stage 2 are maintained as hard constraints, as in (4-26).

$$\begin{aligned} &Sub_{Stg_{(2-2)}}: \\ &\underset{X,X'}{min} \sum_{i \in \Gamma} \sum_{\tau} \Big(\sum_{j \in Flx} Prc(\tau) \times E_{del_{FlxChrg_\tau}} + \sum_{k \in DChrg} Prc(\tau) \times E_{del_{DChrg_\tau}} \Big) \end{aligned} \tag{4-25}$$

$$\forall\, class \in Chrg, FlxChrg, DChrg :$$
$$E_{del_{Stage\,1}} = E_{del_{Stage\,2}} \tag{4-26}$$

4.5 Implementation

As in Chapter 3, the performance of the proposed method is comprehensively studied for a 38-bus distribution system. Further details of the system specifications and loading demand and types can be found in [98]. The test system, including two candidate parking lots, connected to buses 25 and 33, is displayed in Fig (4-6). The parking data for these parking lots are provided by TPA. Different PEVs, already available on the market, are selected to employ their battery capacity data for the simulation. They vary between 17-85kWh, for the TeslaS and Chevrolet Volt, respectively. Chargers are assumed to be Level-II AC with a rating size of either 3.3 or 7 KW.

The MATLAB® software environment is used to model the system under study. To implement the aggregator's different modules the General Algebraic Modeling System (GAMS) is employed in accordance with MATLAB, where the PEVs' battery data, the offers, and the system data measurement as well as future PEV prediction are modeled in MATLAB and, accordingly, the decision optimization is executed in GAMS. Charging/discharging decisions are sent back from GAMS to MATLAB to update the PEVs' status for the next decision-making window. The simulation covers 24 hr of a weekday.

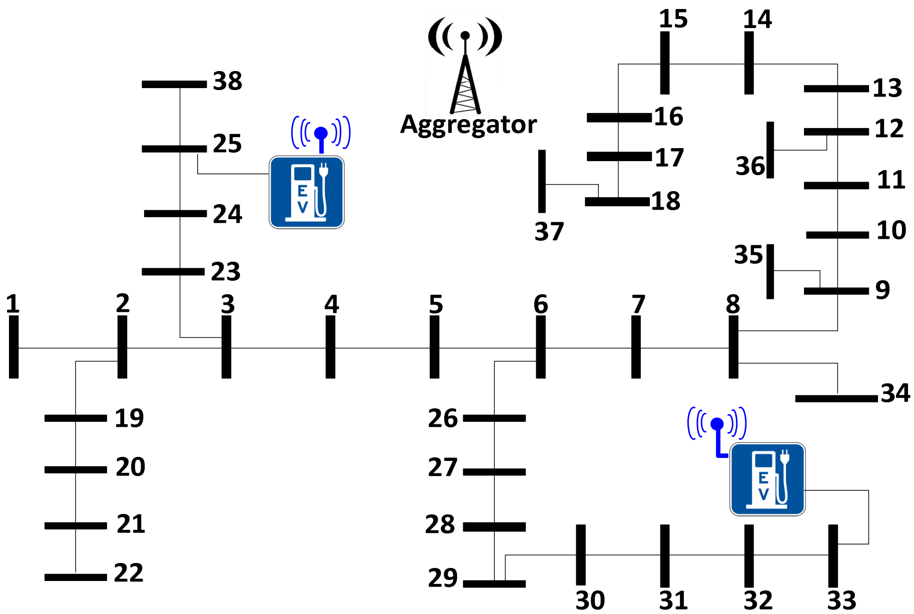


Figure 4-6 The 38-bus test system with parking lots

The performance of the trained model is verified through regression calculations over a typical weekday. Fig (4-7) demonstrates the hourly goodness of fit (R-value) for training, validating, and testing sets. PEV-arrival prediction is executed every hour for the next hour. Fig (4-8) compares the actual PEV arrival rates versus the predicted arrival results for both lots (The maximum number of charger outlets are 1069 and 249, respectively, for parking lot 25 and 33). The flowchart represented in Fig (4-9) summarized how the aggregator's modules cooperate in every decision-making window.

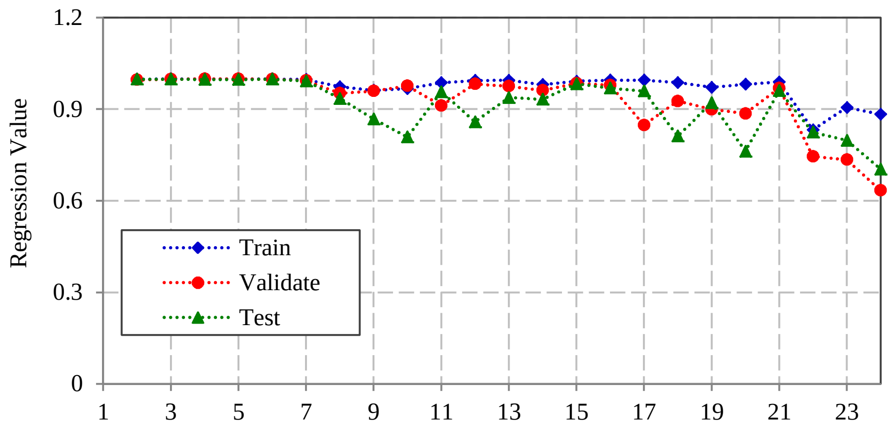


Figure 4-7 R-values for training, validating, and testing set

4.6 Results and Discussions

Three case studies are examined on the 38-bus test system to better evaluate the proposed method performance in reshaping demand. The first two set of analysis compares charging PEVs through the conventional first-come-first-serve (FCFS) method, with charge-only scenario (i.e. two charging options). The third case study investigates the proposed charging and discharging solution with three charging options. Maximum parking lot loading is 30% of the total system loading. Figure 10 shows the pattern of PEVs corresponding to the offers in lots.

4.6.1 Case (1): First come first serve (FCFS)

Here, charging is based on allocating high priority to PEVs that arrive earlier (i.e., FCFS) and no flexible-charge option is available. The demand pattern of the parking lot is illustrated in Figure (4-11).

4.6.2 Case (2): Charge-only

This case provides charge-only scenario, where the aggregator offers only two charge options (i.e., $Chrg_{class}$ and $FlxChrg_{class}$). Figure (4-12) compares parking demands with charge-only scenario to when it offers that of first case study. Although both cases results in relatively similar demand patterns, Case (2) shows some shifts as the RTP varies. Particularly, when the RTP increases, the charge-only case attempts to decline the demand and shifts it to the lower tariff intervals.

4.6.3 Case (3): Charge and discharge

To assess the effects of all offers, parking demand is illustrated in Figure (4-13), in which $Chrg_{class}$, $FlxChrg_{class}$, and $DChrg_{class}$ provides the aggregator with more flexibility in decision making. Consequently, the demand drops more as RTP rises. All discharge (i.e. $DChrg_{class}$) occurs within two RTP peaks; between 10 am-2 pm and 7-10 pm, where most energy saving is achieved. Comparison case study (2) and (3) reveals that although the charge-only scenario helps reshape the RTP-based load, the charge-discharge scenario (i.e., case 3) outperforms in demand reduction at peak tariff hours.

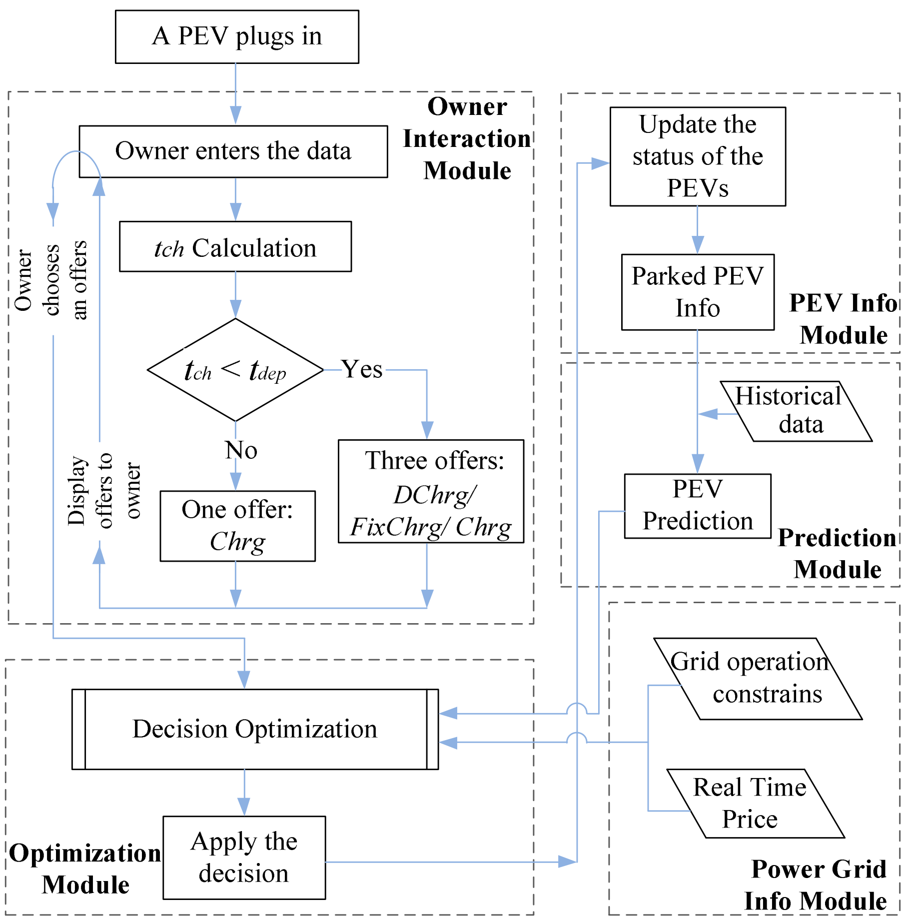


Figure 4-8 Flowchart of the aggregator modules' collaboration in decision making

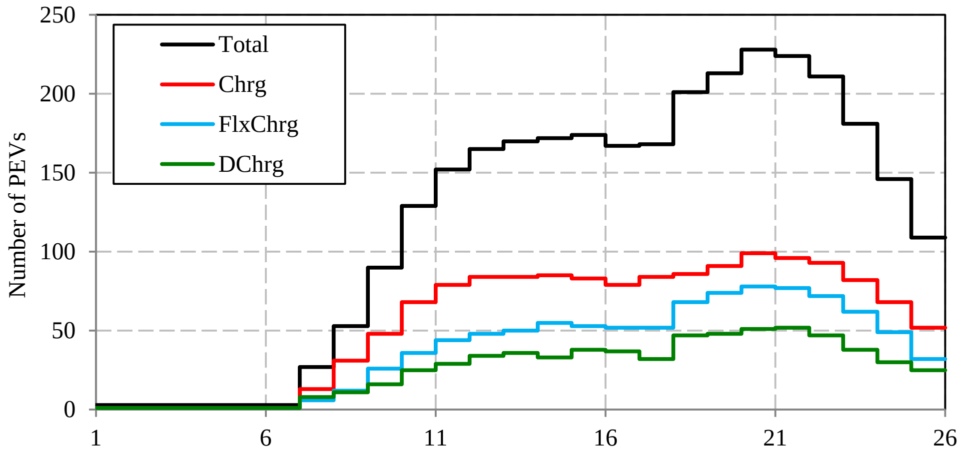


Figure 4-9 Patterns of plugged PEVs based on offers in lots

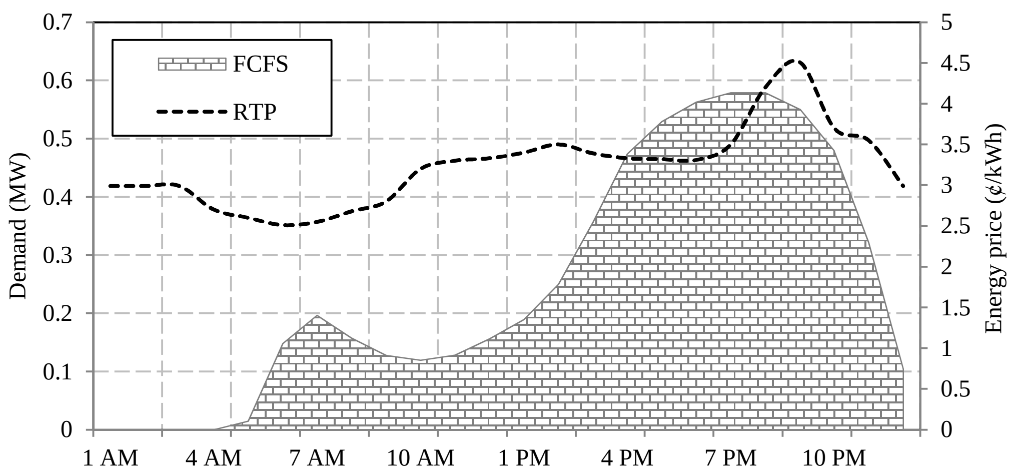


Figure 4-10 Demand pattern of the parking lot through FCFS charging regime

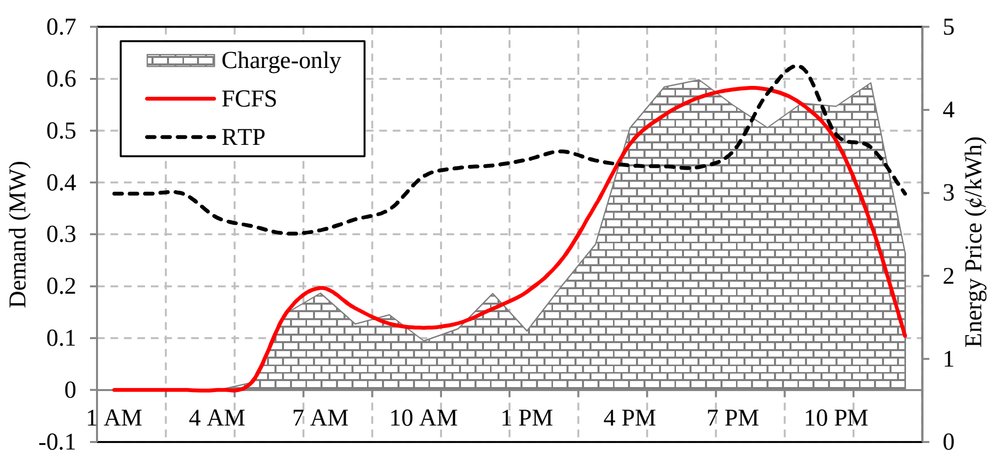


Figure 4-11 Demand pattern of the parking lot through Charge-only regime

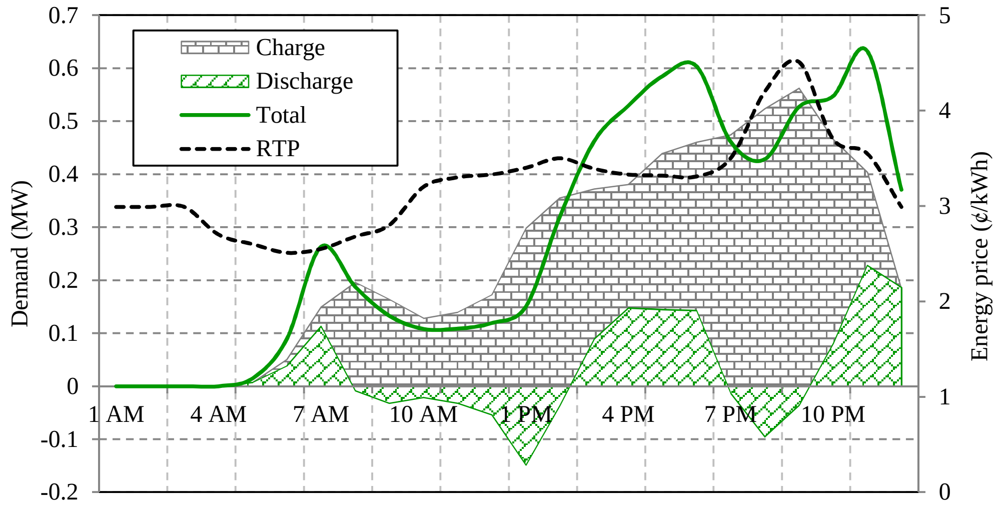


Figure 4-12 Demand pattern of parking lot through Charge/discharge regime

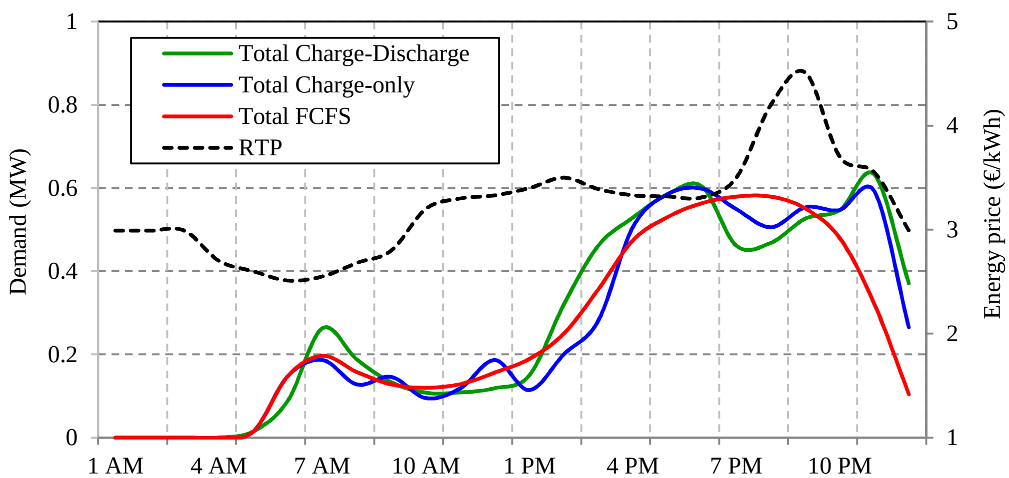


Figure 4-13 Demand pattern of parking lot comparing the case studies

4.6.4 Discussion

Further to energy management and load reshaping, the proposed method is evaluated in terms of vehicle owner fulfillment, in which the deficiencies of the case studies are compared by calculating the energy-not-supplied (ENS) using the mean square deviation (MSD) between the delivered energy and the required energy, as in (4-27). MSD is frequently used to measure the differences between values predicted by a model and those actually observed (i.e., the delivered energy and required energy, respectively, represented by $Enrg_{MSD}$ in (4-27).

$$ENRG_{MSD} = \frac{1}{j}\sum_{j}(E_{req,j} - E_{del,j})^2 \quad (4\text{-}27)$$

Table (4-2) demonstrates the energy required (E_{req}) and the energy delivered (E_{del}) in each case study. The results of E_{del}/E_{req} ratio indicate that the third case study better satisfies the customers. Table (4-2) also summarizes the energy-not-supplied, including the average, the maximum, and the standard deviation (SD) of the ENS. The maximum ENS happens in case 1 (i.e., FCFS), followed by charge-only scenario (i.e., case 2), and the charge/discharge scenario (i.e., case 3), respectively with 26.7, 16.73, and 2.94 kWh. The S.D. values illustrate a range of 0.46-4.88 kWh margin of error in the significance analysis, belonging respectively to case study 3 and 1. On average, the proposed charge/discharge solution results in ENS by 36% less than the conventional FCFS strategy (0.54 kWh versus 1.46 kWh). Moreover, Table (4-2) indicates that the total charging cost is considerably lower in case (3) compared to the other charging regimes, which reflects the effectiveness of shifting charging in time to achieve cheaper tariffs for the vehicle owners. Looking at total system losses reveals that the second case results in higher operational cost for the distribution grid.

Further analysis compares the average ENS of each class of offer in both parking lots (Fig (4-15)). In both lot 25 and 33, ENS due to the proposed charge/discharge solution (i.e. case (3)) is less than 1 kWh. However, there are significant ENS in lot 33 due to case (1) and case (2) (more than 3.5 kWh). One interesting finding is that, overall, all case studies result in lower ENS in lot 25 than in lot 33, which could be interpreted as the outperformance of the proposed method in larger lots with more vehicle transactions and consequently with more decision making flexibility. Additional analysis is needed to confirm this.

Table 4-2 ENS comparison of the case studies

Case studies	**E_{req} (MWh)**	**E_{del} (MWh)**	**ENS (kWh)** AVR.	**ENS (kWh)** MAX	**ENS (kWh)** S.D.	**E_{del}/E_{req} (%)**
Case (1)	7.82	6.27	1.46	26.7	4.88	82
Case (2)		7.15	0.64	16.73	2.95	91
Case (3)		7.24	0.54	2.94	0.46	95

Price ratio over FCFS	**Case (1)**	**Case (2)**	**Case (3)**
Total Loss	100%	116%	94%
Charging	100%	93%	81%

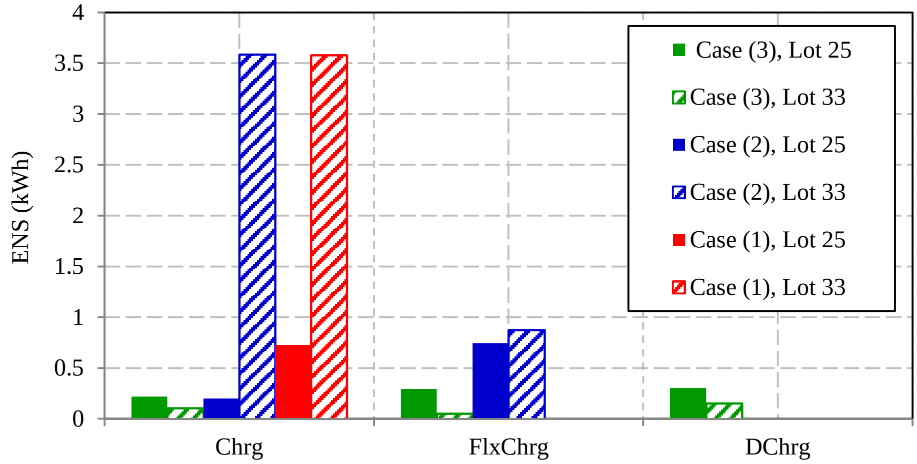


Figure 4-14 ENS comparison based on class of offers

4.7 Summary

Deployment of grid-able PEVs holds the promise of using their batteries for DR without imposing the additional costs associated with domestic storage systems. However, new studies debate that the conventional approach–PEV drivers signing pre-specified contracts in return for annual cash back– is unlikely to appeal to drivers. Thus, the present study was an interactive approach to realize DR programs by incorporating aggregated PEVs into public smart parking lots, whereby an aggregator offers various options based on the comfort criteria factor and vehicle owners respond based on preference. The aggregator benefits from five different modules for decision-making. In other renovation, an ANN-regression and a Markov Chain model collaborate to include the effect of future PEV arrivals in the decision results.

Case study simulations of a 38-bus distribution system indicate the effectiveness of real-time interaction with vehicle owners in DR. Case-study comparisons ascertain that the conventional charging regimes are not efficient and the results of this study supports the idea of appreciating smart charging solutions in our smart grids. Although the most promising performance seen in larger parking lots with more vehicle transactions. Yet, the proposed solution can be applied in any size of lots [115, 116].

Chapter 5
Managing Demand for Plug-in Electric Vehicles in Unbalanced Low Voltage (LV) Systems

5.1 Introduction

This chapter addresses how smart charging can be used to support more efficient energy delivery and phase unbalance control, while improving demand response (DR) contributions by plug-in electric vehicle (PEV) owners. The DR concept, introduced in Chapter 4, was extended to include an investigation of the impact of PEVs in three-phase LV distribution systems. The potential of PEVs and the application of V2G with respect to mitigating phase unbalance are also explored. As explained in Chapter 4, real-time interaction between the aggregator and the owners has been applied. To provide clarification of the unbalance condition, photovoltaic (PV) units have also been included in the analysis.

The problem statement and the framework of the proposed method are described in sections 5-2 and 5-3. Section 5-4 then provides a brief explanation of the additional modeling features required for incorporating consideration of unbalance, as well as the PV unit specifications needed for the problem formulation. The results of the case studies are presented in section 5-5, followed by a discussion of the findings.

5.2 Problem statement

While the future impact of PEVs on distribution grids is disputed, all parties agree that mass operation of PEVs with uncontrolled charging regimes will dramatically affect overall load profiles and electric grid assets. The large-scale penetration of domestic energy storage systems into the edges of LV grids, such as that arising from rooftop PV units, is also introducing increasing amounts of customer-generated electricity. Unlike transmission networks, a distribution grid is an inherently unbalanced network that tends to become even more unbalanced with the uneven spread of PV units and PEVs. An additional factor is that the majority of residential areas are equipped with a single-phase power supply, and only large households have three-phase connections. In general, the reasons for conducting unbalance studies are (1) to ascertain that the voltage unbalance is within established limits, (2) to determine how to maintain load balance, and (3) to reduce grid losses [117].

Certainly, collaboration of PEVs and local generators could provide dynamic voltage support for the distribution network, which may allow their increasing of penetration of smart grids. This chapter extends the interactive EMS proposed in chapter four in which PEV owners receive offers for various charging options. Through this method owners can immediately choose whether they want to discharge their battery back into the grid. This interactive structure not only provides owners with a flexible scheme for contributing to DR while avoiding the inconvenience of long-term contracts, but also ensures that the existing three-phase infrastructure distribution grid operates within acceptable voltage unbalance limits. This part of the thesis contributes in the following areas:

- Analysis of the ways in which under a charging low and high penetration of PEVs affect voltage unbalance;
- Examination of how the incorporation of PEVs and solar panels could mitigate unbalance issues.

5.3 Framework of the Proposed Method

Modules similar to those in chapter 4 are used here for decision making, as shown in Figure (5-1). One module for receiving PV panel information is added. Data corresponding to energy pricing, PV output power and system operation data are all fed to the Grid Interface module. When owners respond, the aggregator optimizes the decision making and sends charging/discharging signals to individual chargers. Obviously, decisions are subject to continuous change, as all input data are updated in every decision-making window.

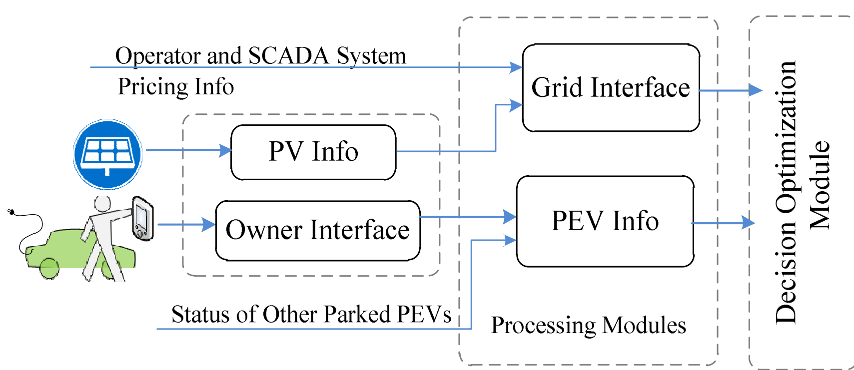


Figure. 5-1 ENS comparison based on class of offers

5.4 Additional Aspects of Modeling

This section introduced the parameters required for generalizing the proposed single-phase model to a three-phase model. Moreover, the model for PV panel output power is briefly explained.

5.4.1 Voltage unbalance constrain

The National Electrical Manufacturers Association (NEMA) and IEEE share one definition for voltage unbalance, called the phase voltage unbalance rate (PVUR). Phase voltages are measured for every bus i voltage at every hour h of the inspection period, and the voltage deviation from the average ($V_{dev}^{i,ph\varphi}$) is calculated as in (5-1).

$$V_{dev}^{i,ph\varphi} = \frac{\left|V^{i,ph\varphi} - V_{avr}^{i}\right|}{V_{avr}^{i}} \times 100 \quad (5\text{-}1)$$

where,

$$V_{avr}^{i} = \frac{\left|V^{i,a}\right| + \left|V^{i,b}\right| + \left|V^{i,c}\right|}{3} \quad (5\text{-}2)$$

$\forall\ \varphi \in \{a, b, c\}$

Accordingly, the PVUR^i % is then calculated for all of the system busses, as in (5-3) [118, 119]. The voltage unbalance should be limited as follows in (5-4).

$$\%\ PVUR^{i} = \max\left\{V_{dev}^{i,a}, V_{dev}^{i,b}, V_{dev}^{i,c}\right\} \quad (5\text{-}3)$$

$$\%\ PVUR^{i} \leq 3\% \quad (5\text{-}4)$$

5.4.2 PV module specifications

The PV-Info module is a measurement unit that sends the output power of the PV panel to the Grid Interface module. The output power of PV panels is stochastic which depends on a number of internal features of the PV cells. The output power of the PV array is a function of the solar irradiance and ambient temperature as well as the characteristics of the array. According to [120], the output power of the panel is calculated as follows in (5-5)-(5-9).The hourly solar irradiance data used here are listed in Table (5-1) [120]. As for the classification of seasons, Figure (5-2) represents the normalized solar irradiances in March, May, September, and December, corresponding respectively to winter, spring, summer, and fall.

$$T_C = T_A + Ir\left(\frac{T_o - 20}{0.8}\right) \quad (5\text{-}5)$$

$$I = Ir\left(I_{sc} + K_i(T_c - 25)\right) \quad (5\text{-}6)$$

$$V = V_{oc} - K_v \times T_c \tag{5-7}$$

$$P_{Ir} = N \times FF \times V \times I \tag{5-8}$$

$$FF = \frac{V_{MPP} \times I_{MPP}}{V_{oc} \times I_{sc}} \tag{5-9}$$

where,

Ir is the solar irradiance (kW/m^2);

T_c is the cell temperature at *Ir* (°C);

T_A is the ambient temperature (°C);

K_i is the current temperature coefficient (A/°C);

K_v is the voltage temperature coefficient (V/°C);

FF is the fill factor;

I_{sc} is the short circuit current (A);

V_{oc} is the open circuit voltage (V);

I_{MPP} is the current at the maximum power point (A);

V_{MPP} is the voltage at the maximum power point (V);

P_{Ir} is the output power of the PV array at *Ir* (kW).

Table 5-1Solar Irradiance Data

Module Characteristics Values	
Watt peak (W)	75.00
Open circuit voltage (V)	21.98
Short circuit current (A)	5.32
Voltage at maximum power (V)	17.32
Current at maximum power (A)	4.76
Voltage temperature coefficient (mV/°C)	14.40
Current temperature coefficient (mA/°C)	1.22
Nominal cell operating temperature (°C)	43.00

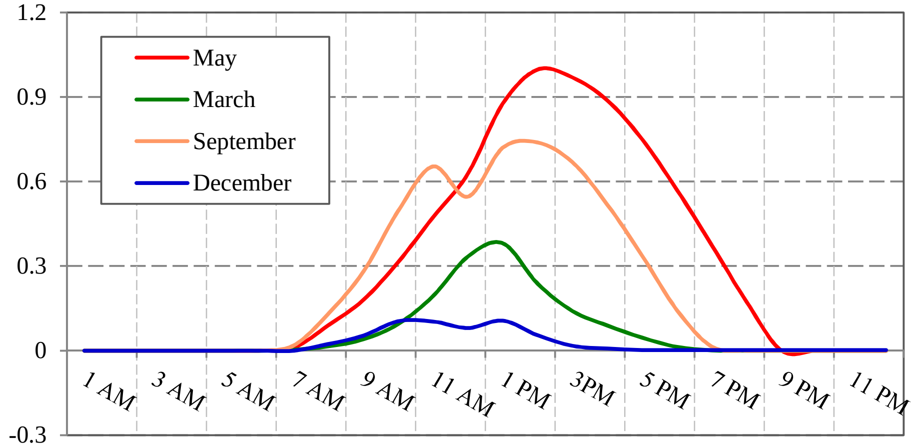


Figure. 5-2 Seasonal PV output

5.5 Extended Problem Formulation

The structure of the decision optimization is designed to satisfy different objectives: maximizing delivered energy and minimizing the cost of energy. As explained in Section (4-4), it solves a multi-stage non-linear optimization to satisfy PEVs in all offer classes. The general form of the objective functions and constraints are summarized as in (5-10)-(5-13). Obviously, these formulations are adopted for three-phase inside the decision-making algorithm. Figure (5-3) shows the overall structure of the decision making-algorithm.

Stage 1: $\text{Chrg}_{\text{class}}$ energy maximization

$$\underset{X}{Max} \sum_{ph \in a,b,c} \sum_{i \in \Gamma} \sum_{\tau} \sum_{j \in Chrg} \varpi(\tau) \,.\, E_{del(j,\ \tau)} \tag{5-10}$$

Stage 2: $\text{FlxChrg}_{\text{class}}$ and $\text{DChrg}_{\text{class}}$ energy maximization

$$\underset{X,X'}{Max} \sum_{ph \in a,b,c} \sum_{i \in \Gamma} \sum_{\tau} \left(\sum_{j \in Flx} E_{del_{FlxChrg_\tau}} + \sum_{k \in DChrg} E_{del_{DChrg_\tau}} \right) \tag{5-11}$$

Stage 3: $\text{FlxChrg}_{\text{class}}$ and $\text{DChrg}_{\text{class}}$ cost minimization

$$\underset{X,X'}{min} \sum_{ph \in a,b,c} \sum_{i \in \Gamma} \sum_{\tau} \left(\sum_{j \in Flx} Prc(\tau) \times E_{del_{FlxChrg_\tau}} + \sum_{k \in DChrg} Prc(\tau) \times E_{del_{DChrg_\tau}} \right) \tag{5-12}$$

Subject to: (5-13)

Eq. (4-11)-(4-20)

Eq. (4-22)-(4-24)

Eq. (4-26)

Eq. (5-4): for phase-balancing

The effects of PV panel output power (P_{PV}) are included in (4-11) and (4-12), and accordingly are modified as in (5-14) and (5-15):

$$P_{G_{i,\tau,a}} + P_{PV_{i,\tau,a}} - P_{L_{i,\tau,a}} - P_{PEV_{i,\tau,a}} = \sum_{\substack{i\prime \\ i\prime \neq i}} \sum_{\varphi=a,b,c} \begin{pmatrix} V_{i,\tau}^{a} V_{i,\tau}^{\varphi} Y_{i,i\prime}^{a,\varphi} \cos(\theta_{i,i\prime}^{a\varphi} + \delta_{i}^{\varphi} - \delta_{i}^{a}) \\ -V_{i,\tau}^{a} V_{i\prime,\tau}^{\varphi} Y_{i,i\prime}^{a,\varphi} \cos(\theta_{i,i\prime}^{a\varphi} + \delta_{i\prime}^{\varphi} - \delta_{i}^{a}) \end{pmatrix} \tag{5-14}$$

$$Q_{G_{i,\tau,a}} - Q_{L_{i,\tau,a}} = -\sum_{\substack{i\prime \\ i\prime \neq i}} \sum_{\varphi=a,b,c} \begin{pmatrix} V_{i,\tau}^{a} V_{i,\tau}^{\varphi} Y_{i,i\prime}^{a,\varphi} \sin\left(\theta_{i,i\prime}^{a\varphi} + \delta_{i}^{\varphi} - \delta_{i}^{a}\right) \\ -V_{i,\tau}^{a} V_{i\prime,\tau}^{\varphi} Y_{i,i\prime}^{a,\varphi} \cos(\theta_{i,i\prime}^{a\varphi} + \delta_{i\prime}^{\varphi} - \delta_{i}^{a}) \end{pmatrix} \tag{5-15}$$

where P_G and P_L denote active generated and load powers, respectively at bus i and at time instant τ.

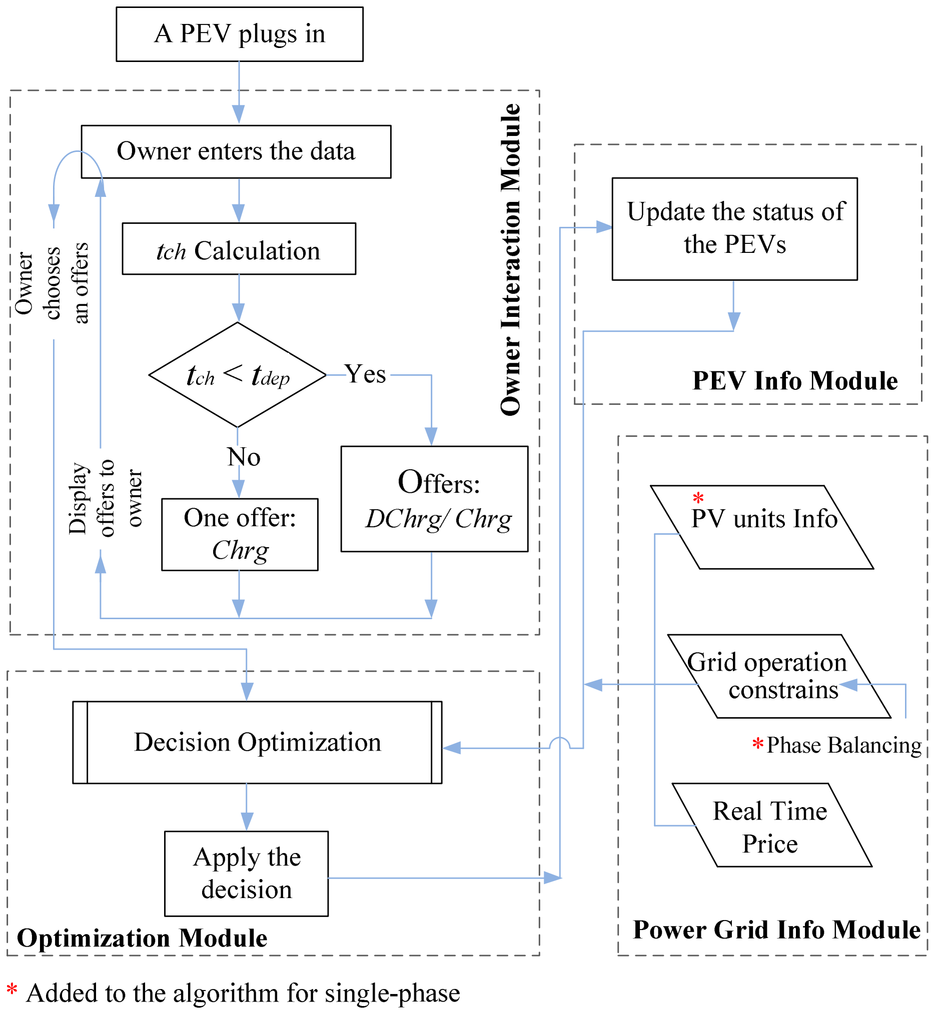


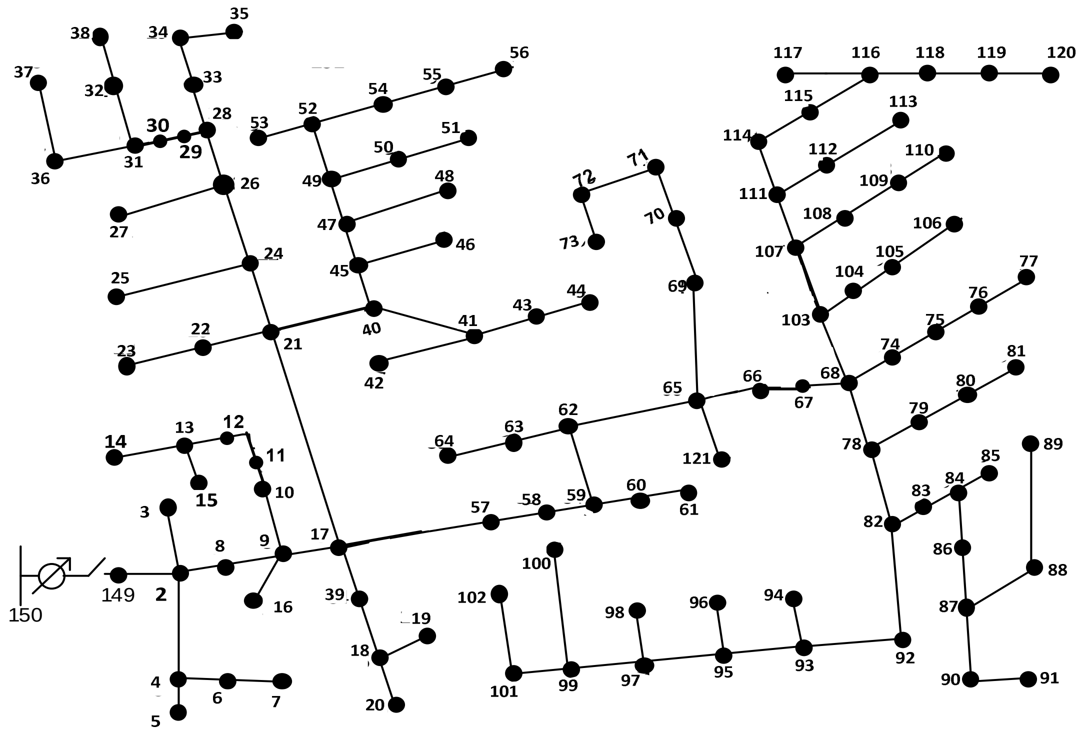
Figure. 5-3 The structure of the decision making algorithm

5.6 Case Studies

A number of case studies are considered to observe the impacts and the potential supports of PEVs regarding phase-unbalance in LV systems. To do so, specific unbalance situations have been created to better illustrate the role of PEVs on such situations. The first set of analyses compares the impact inherent in low and high penetrations of PEV charging in the LV system. Then, unbalance mitigation through V2G application is addressed accordingly in the rest of the case studies with the collaboration of PV panels.

5.6.1 Test system

Figure (5-4) illustrates the IEEE 123-bus distribution system used for this study. It operates at a nominal voltage of 4.16kV from the main substation; the total system load is 10 MVA, and further details of the system specifications and loading demand can be found in [121] and in Appendix B. The typical weekday load pattern for the load-types, available in [98], are used here.



	8, 9, 17, 24, 28, 34, 35, 40, 41, 45, 49, 52, 53, 55, 56, 57, 59, 60, 62, 65, 70, 72, 73, 78, 84, 89, 92, 95, 99, 103, 104, 105, 106, 111, 114
	2, 3, 8, 9, 10, 12, 40, 65, 85, 86, 87, 88, 89, 90, 91, 92, 93, 95, 97, 98, 99, 101

Figure. 5-4 IEEE 123-bus test system

As in chapter 4, battery capacities vary between 17-85kWh and chargers are assumed to be Level-II AC with a rating size of either 3.3 or 7 KW. The maximum output power of the solar units is assumed to be 2kW and 5kW. The buses with PEV chargers or parking lots are illustrated in Fig (5-4) and the number of PEVs/PEVs'chargers per-phase are available in Table (5-2).The test system is a three-phase feeder balanced under the operation of the base load. Figure (5-5) shows the PVUR values over 24 hrs under base load operation. Once a number of PVs are randomly distributed over the system, there is no guarantee that three-phase balance condition will be maintained. A sample of violated

PVUR is illustrated in Figure (5-6), indicating that even small scale roof-top PVs could disturb the voltage.

Table 5-2 **Number of PEVs per-phase in the system buses**

Bus #	Ph-a	Ph-b	Ph-c		Bus #	Ph-a	Ph-b	Ph-c
8	12	17	22		60	12	27	47
9	32	17	27		62	32	42	12
17	17	22	27		65	32	32	47
24	32	22	27		70	22	7	42
28	22	42	2		72	25	2	29
34	2	32	42		73	17	7	27
35	32	2	22		78	42	27	20
40	42	12	17		84	22	2	27
41	17	7	2		89	27	40	2
45	22	32	17		92	2	17	36
49	2	37	17		95	12	42	22
52	12	42	12		99	12	12	32
53	2	22	42		103	42	32	7
55	2	22	37		104	19	32	32
56	17	42	2		105	25	22	42
57	47	12	27		106	22	12	12
59	42	32	12		111	22	42	42
60	12	27	47		114	47	37	37

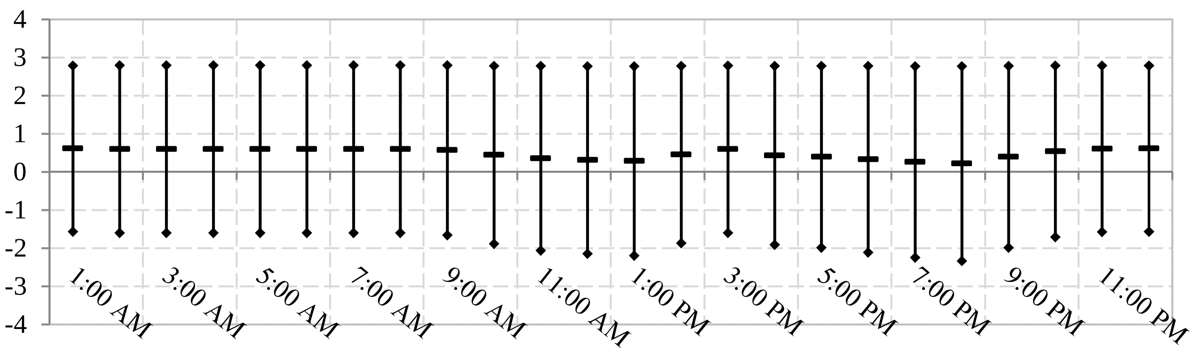


Figure. 5-5 Hourly Max and min PVUR values: system is balanced under normal condition

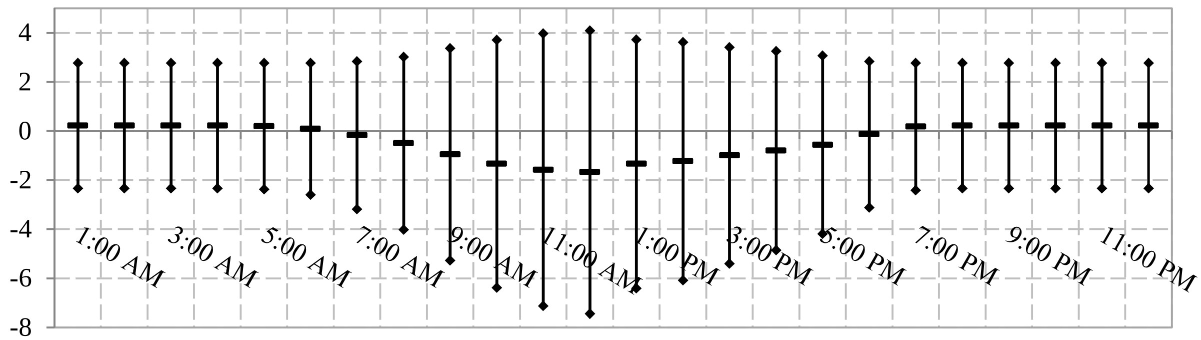


Figure. 5-6 Hourly Max and min PVUR values: System is unbalanced when PVs are added

5.6.2 Case study 1: PEV charge-only (comparison between high/low penetration)

The goal of this case study is to analyze the impact of PEV charging on system unbalance. This case provides a charge-only scenario and no PVs are available. Two penetration levels of PEVs are compared to better illustrate the loading impacts as well. These buses are selected randomly. Respectively, the low and high penetrations include almost 1.9 and 3.7 MW of total system loading.

5.6.2.1 High/Low penetration: no phase-balancing constraints

It is assumed that all PEV owners choose charging, and there is no control over phase-balancing in this case. Figure (5-7) compares total loadings of PEVs for low and high penetrations of chargers in three phases. Apparently, the more PEV charging, the greater the total demand will be. More importantly, significant PVUR violations can be seen in Figures (5-8) and (5-9), from the acceptable threshold. This analysis indicates that random distribution of PEVs in a LV system could result in great phase unbalance, which consequently could increase system losses and transformer degradation.

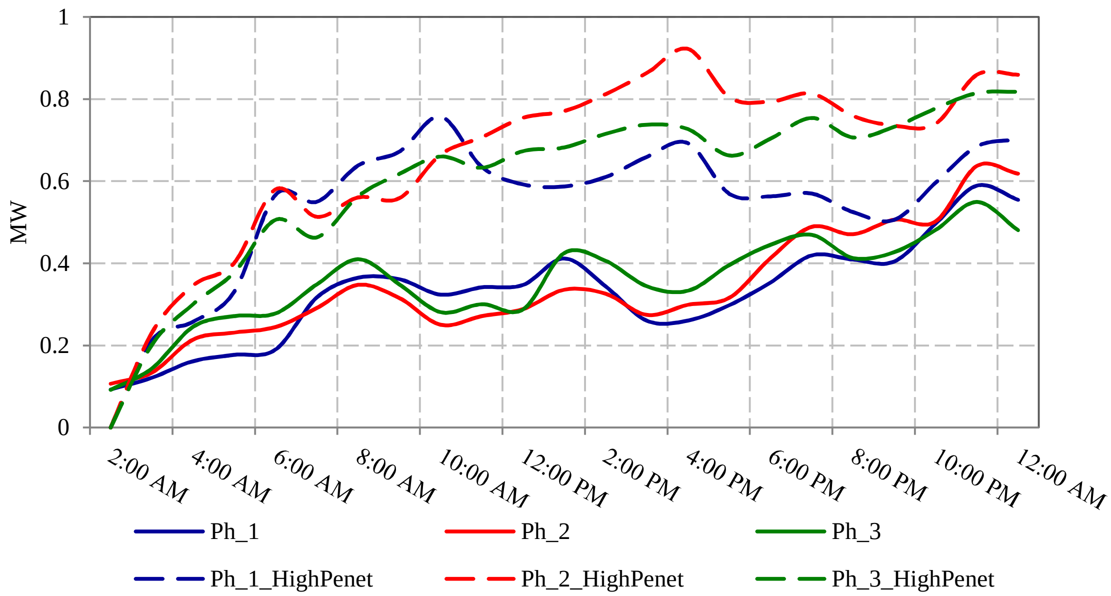


Figure. 5-7 Total loadings of PEVs for low and high penetrations

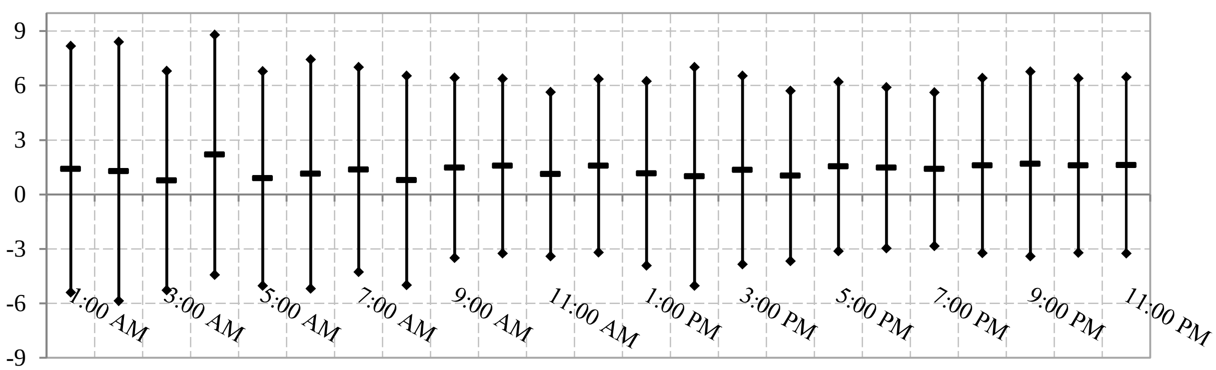


Figure. 5-8 Hourly Max and min PVUR%: for high PEV penetration

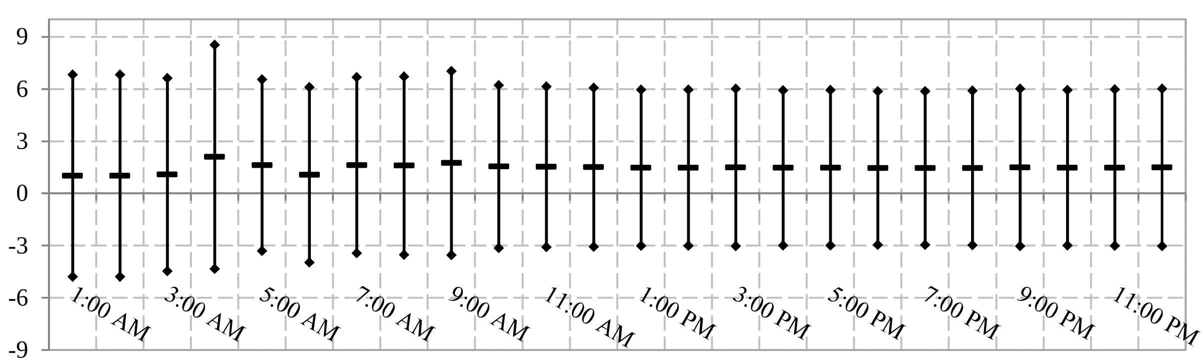


Figure. 5-9 Hourly Max and min PVUR%: for low PEV penetration

5.6.2.2 High/Low penetration: with phase-balancing constrains

Charging schemes are as in Section (5-6-2-1); however, the aggregator controls phase-balancing through an additional constraint, in this case, Eq. (5-4), as illustrated in Figure (5-10). No battery discharging is applied here; therefore, the decision variables are either one or zero, corresponding to charging or holding, respectively. Table (5-3) compares the impact of phase-balancing on total system losses, which with lower PEV penetration results in the total losses dropping by 38.7%. Higher PEV penetration clearly corresponds to greater demand and system losses.

Table 5-3Impact of phase-balancing on total system losses

	Total Charger size (MW)			Penetration (%)			Total Loading (MW)			System Losses (MW)
Phase	**a**	**b**	**c**	**a**	**b**	**c**	**a**	**b**	**c**	
Low Penet. (NPhB/PhB)*	1.88	1.99	2.05	18.8%	19.9%	20.5%	7.60	7.88	8.19	1.388 /0.851
High Penet. (NPhB/PhB)	3.72	4.14	4.25	37.2%	41.4%	42.5%	13.17 /13.33	15.89 /15.98	14.61 /14.66	1.58 /1.475

*NPhB/ PhB: No-Phase-Balancing/ Phase-Balancing

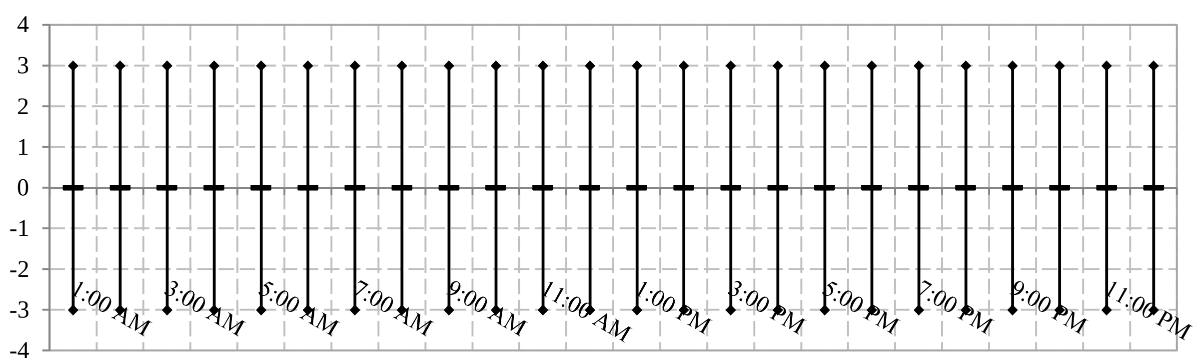


Figure. 5-10 Hourly Max and min PVUR%: adding the constraint for voltage unbalance

5.6.3 Case study 2: PEVs in the presence of PV panels/solar units

The second case employs PEVs in collaboration with the PV panels to determine whether proper decision making in collaboration with end-users results in better utilization of the power grid infrastructure. Based on the aggregator's offers, PEV batteries may be discharged partially. Offers are based on RTP tariff. Hourly output power of the PV panels used here is based on solar irradiance in

May (as in Figure (5-2)). Figure (5-4) also provides busses with solar units, with total installed capacity of almost 1100 KW.

The loading results obtained from case studies (1) and (2) can be compared in Figure (5-11). Obviously, this is the loading seen from the grid-side. The latter case study provides the aggregator with more flexibility in decision making. Consequently, the demand drops more as RTP rises. Extensive discharge (i.e. $DChrg_{class}$) occurs within two RTP peaks; between 10am-2pm and 6-10pm, where most energy saving is achieved. Comparison case study (1) and (2) reveals that the charge-discharge scenario outperforms in demand reduction at peak tariff hours due to local supports of PEVs and PVs. Table (5-4) also indicates that total system losses is reduced trough the 2nd case study, and, as can be seen in Figure (5-12), with phase-balancing constraint the PVUR remained inside the acceptable 3% limits.

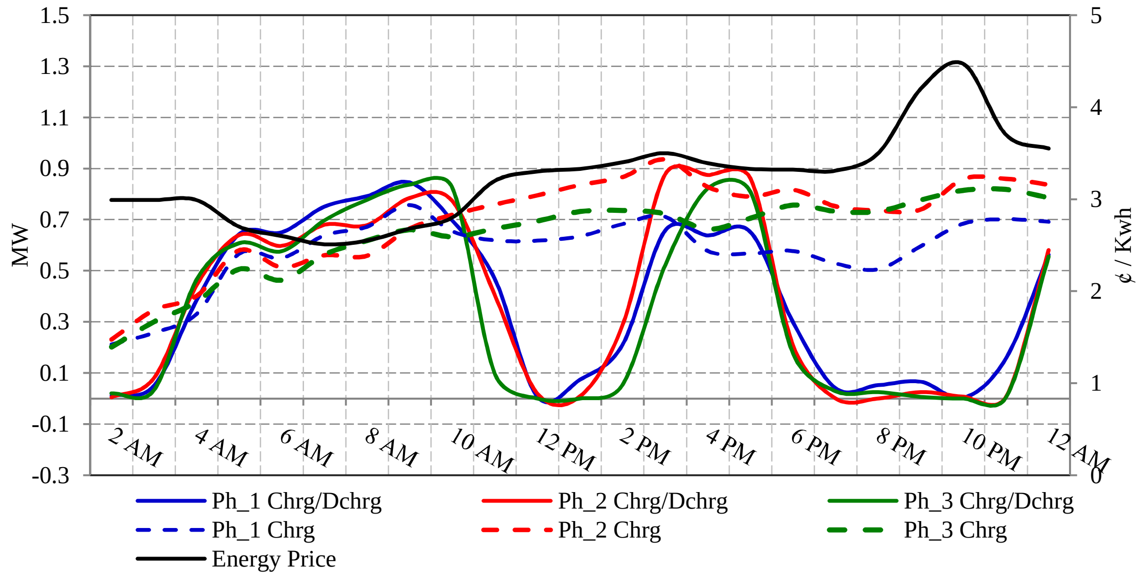


Figure. 5-11 Chrg-only vs Chrg/Dchrg for High Penetration PEVs

Table 5-4 Total System Losses

	Total Charger size (MW)			Penetration (%)			Total Loading (MW)			System Losses (MW)
Phase	**a**	**b**	**c**	**a**	**b**	**c**	**a**	**b**	**c**	
Chrg_only	3.72	4.14	4.25	37.2%	41.4%	42.5%	13.33	15.98	14.66	1.475
Chrg/Dchrg							8.71	8.84	7.94	1.103

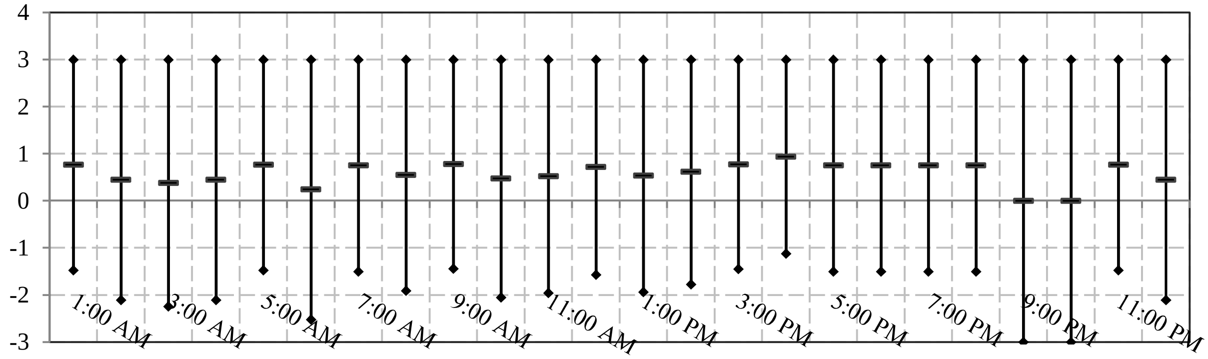


Figure. 5-12 Max and min PVUR%: V2G with PV, including phase-balancing constraint

5.7 Discussion

So far this chapter has revealed that PEVs can support reshaping the load while smart charging acquires phase balancing. This section evaluates the vehicle owner fulfillment by comparing the ENS under different charging schemes and penetration levels of PEVs. Table (5-5) demonstrates the energy required (Ereq) and the energy delivered (E_{del}) in four different charging schemes including charge-only and charge-discharge scenarios for low and high penetrations. Looking at the low penetration case, we observe that there is a small difference in E_{del} when the charge-only scenario (Chrg_Low) is exchanged with the charge-discharge scenario (i.e. 9.53 MWh vs 9.97 MWh). Consequently, the ENS differs only by 0.44 MWh (i.e. 0.79 MWh vs 0.35 MWh).

In contrast, a significant difference exists for Edel under high PEV penetration scenario. The charge-discharge scheme ends in ENS of 2.24 MWh, while the ENS is almost three times greater through charge-only scheme (i.e. 6.88 MWh).

These findings suggest that incorporation of PEVs in short-term power supply, i.e., under V2G application, outperforms more significantly when they highly penetrate the fleet. The results provide further support for the hypothesis that demand response is viable by decentralized collaboration of small smart loads in future smart buildings.

Table 5-5 The energy required vs the energy delivered

	E_{req} (MWh)	**E_{del} (MWh)**	**ENS (MWh)**	**System Losses**
Chrg_Low	10.32	9.53	0.79	130%
Chrg/Dchrg_Low		9.97	0.35	100%
Chrg_High	25.87	18.99	6.88	173%
Chrg/Dchrg _High		23.63	2.24	148%

5.8 Summary

This chapter improved the proposed distributed energy management system (EMS) in chapter 4. It incorporates PEV owners in demand response (DR) through real-time interaction with an aggregator and choosing among various charging options according to personal preference. This interactive-structure not only provides owners with an appropriate scheme for contributing to DR while avoiding the inconvenience of long-term contracts, but also ensures that the three-phase existing infrastructure distribution grid operates within the acceptable voltage unbalance limits. To provide clarification of the unbalanced condition, photovoltaic (PV) units have also been included in the analysis. This study shows how the proposed approach employs PEVs for short-term battery discharging to mitigate phase-unbalance while the PEV owners benefit from their incorporation in DR [122, 123].

Chapter 6
Conclusions

6.1 Thesis Summary

The research presented in this thesis involved the investigation of smart charging for the interconnection of plug-in electric vehicles (PEVs), with the ultimate goal of supporting the growth of greener cities in the near future. A framework has been created that will allow both public parking lots and small residential garages to benefit from smart charging with end-user demand-side management (DSM) and demand response (DR). The work entailed the development of methods that enable an aggregator to handle decision making by interacting with vehicle owners and thus dynamically manage PEV charging in real time. Two real-time interaction levels have been implemented.

The first level, introduced in Chapter 3, is an approach proposed for charging PEVs through a one-round interaction, whereby the owner sends the PEV status data to the aggregator and the aggregator then optimizes the charging actions with respect to other PEVs and the power-grid operating practices. With this technique, a fuzzy-based expert system assigns scores to the PEVs waiting in a charging queue in order to prioritize them and thus determine the order in which they will be charged. The priorities are based on a number of PEV attributes, including the SOC, battery capacity, the maximum charger power rating, and the departure time of the vehicle. The case study simulation results prove the effectiveness of the proposed methodology for dealing with the fast-changing dynamics of PEV charging coordination. The most obvious finding to emerge from this study is that, based on the SCR solution, an aggregator can better address the urgent energy demands of PEVs that have a short parking duration and require a lengthy charging time.

A second approach at a higher interaction level was implemented as explained in Chapter 4 in order to create an energy management system (EMS) based on the incorporation of aggregated PEVs into public, smart parking lot, whereby an aggregator offers a variety of options based on a comfort criterion factor, and vehicle owners respond based on preference. The aggregator employs the input from five different modules for decision making, with an artificial neural network (ANN) regression and a Markov chain model operating together to include the effect of future PEV arrivals in the decision results. Although the most promising performance would be evident in larger parking lots with more numerous vehicle transactions, the proposed solution can be applied for any lot size.

The final research phase, presented in Chapter 5, extends the proposed interactively structured EMS to include single or small garages distributed over a three-phase LV system. This structure offers PEV owners a flexible scheme for contributing to DR while avoiding the inconvenience and limitations of long-term contracts. It also ensures that the existing three-phase infrastructure distribution grid operates within acceptable voltage unbalance limits. The first step in the new structure is an analysis of the voltage-unbalance impact of charging under low and high PEV penetrations. PEVs and solar panels are then employed in combination for phase-unbalance mitigation. The results of this study indicate that significantly greater energy efficiency could be achieved by discharging batteries when the penetration of PEVs in the grid is high.

6.2 Thesis Contributions

The following major contributions of this study have the potential to enhance existing V2G-related initiatives:

- The adoption of an intelligent expert system that meets the dynamics of PEV arrivals/departures and offers a higher level of satisfaction for the owners of PEVs requiring urgent and longer charging times;
- A new multi-stage decision-making approach based on real-time interactions between PEV owners and aggregators, which provides owners with an appropriate scheme for contributing to DR, while avoiding the inconvenience of long-term contracts;
- A new stochastic prediction model of near-future arrivals and their energy demand, which is employed in the decision making, based on the combination of an ANN and a Markov chain; and
- The employment of PEV battery discharging for mitigating phase unbalance in LV distribution systems characterized by high PEV penetration and local single-phase generation such as solar units.

6.3 Prospective Work

As a continuation of this work, the following areas are suggested for future investigation:

- The DR approach could be extended to include future smart buildings in which a variety of interruptible loads, PEVs, and on-site generation can manage building demand through interactive communication.

- A number of performance assessment methods could be developed in order to create guidelines for the future regulation of smart grids. These performance assessment factors would reflect the success of the aggregator with respect to different perspectives: the owners, the utilities, and aggregator fairness/economy.
- The EMS system could be enhanced to include extensive communication between solar panels and public parking lots, which could advance the goal of providing zero-cost PEV charging stations in the future.
- The possibility of the discharging of multiple batteries per parking session and the impacts of battery degradation would be explored through the implementation of further mathematical modeling of economics and incentives.

Appendix A

The 38-bus test system data

Table (A-1)

Test system date

		Line Impedance in p.u.				Loads on to-node (p.u)		
F	T	R p.u.	X p.u.	L	S_L	P	Q	L_T
1	2	0.000574	0.000293	1	4.6	0.1	0.06	R
2	3	0.00307	0.001564	6	4.1	0.09	0.04	I
3	4	0.002279	0.001161	11	2.9	0.12	0.08	C
4	5	0.002373	0.001209	12	2.9	0.06	0.03	R
5	6	0.0051	0.004402	13	2.9	0.06	0.02	I
6	7	0.001166	0.003853	22	1.5	0.2	0.1	C
7	8	0.00443	0.001464	23	1.05	0.2	0.1	C
8	9	0.006413	0.004608	25	1.05	0.06	0.02	I
9	10	0.006501	0.004608	27	1.05	0.06	0.02	C
10	11	0.001224	0.000405	28	1.05	0.045	0.03	C
11	12	0.002331	0.000771	29	1.05	0.06	0.035	R
12	13	0.009141	0.007192	31	0.5	0.06	0.035	C
13	14	0.003372	0.004439	32	0.45	0.12	0.08	R
14	15	0.00368	0.003275	33	0.3	0.06	0.01	C
15	16	0.004647	0.003394	34	0.25	0.06	0.02	I
16	17	0.008026	0.010716	35	0.25	0.06	0.02	C
17	18	0.004558	0.003574	36	0.1	0.09	0.04	I
2	19	0.001021	0.000974	2	0.5	0.09	0.04	R
19	20	0.009366	0.00844	3	0.5	0.09	0.04	C
20	21	0.00255	0.002979	4	0.21	0.09	0.04	I
21	22	0.004414	0.005836	5	0.11	0.09	0.04	R
3	23	0.002809	0.00192	7	1.05	0.09	0.05	C
23	24	0.005592	0.004415	8	1.05	0.42	0.2	C
24	25	0.005579	0.004366	9	0.5	0.42	0.2	C
6	26	0.001264	0.000644	14	1.5	0.06	0.025	C
26	27	0.00177	0.000901	15	1.5	0.06	0.025	I
27	28	0.006594	0.005814	16	1.5	0.06	0.02	C
28	29	0.005007	0.004362	17	1.5	0.12	0.07	C
29	30	0.00316	0.00161	18	1.5	0.2	0.6	C
30	31	0.006067	0.005996	19	0.5	0.15	0.07	R
31	32	0.001933	0.002253	20	0.5	0.21	0.1	R
32	33	0.002123	0.003301	21	0.1	0.06	0.04	C
8	34	0.012453	0.012453	24	0.5	0	0	
9	35	0.012453	0.012453	26	0.5	0	0	
12	36	0.012453	0.012453	30	0.5	0	0	
18	37	0.003113	0.003113	37	0.5	0	0	
25	38	0.003113	0.003113	10	0.1	0	0	

F=From node, T=To node, L=Line number, S_L =Line MVA limit in p.u., P= Real MW load in p.u. ,Q= Reactive MVAr load in p.u., L_T =Load Type, R=Residential, I=Industrial, C=Commercial

Appendix B

The 123-bus test system data

Node F	T	L	Load Model	Ph-1 kW	Ph-1 kVAr	Ph-2 kW	Ph-2 kVAr	Ph-3 kW
1	2	175	Y-PQ	40	20	0	0	0
2			Y-PQ	0	0	20	10	0
4			Y-PR	0	0	0	0	40
5	6	250	Y-I	0	0	0	0	20
6			Y-Z	0	0	0	0	40
7	8	200	Y-PQ	20	10	0	0	0
9	14	425	Y-PQ	40	20	0	0	0
10			Y-I	20	10	0	0	0
11			Y-Z	40	20	0	0	0
12			Y-PQ	0	0	20	10	0
16			Y-PQ	0	0	0	0	40
17			Y-PQ	0	0	0	0	20
19	20	325	Y-PQ	40	20	0	0	0
20			Y-I	40	20	0	0	0
22			Y-Z	0	0	40	20	0
24			Y-PQ	0	0	0	0	40
28	29	300	Y-I	40	20	0	0	0
29	30	350	Y-Z	40	20	0	0	0
30			Y-PQ	0	0	0	0	40
31	32	300	Y-PQ	0	0	0	0	20
32			Y-PQ	0	0	0	0	20
33			Y-I	40	20	0	0	0
34	15	100	Y-Z	0	0	0	0	40
35	40	250	D-PQ	40	20	0	0	0
37			Y-Z	40	20	0	0	0
38	39	325	Y-I	0	0	20	10	0
39			Y-PQ	0	0	20	10	0
41			Y-PQ	0	0	0	0	20
42	43	500	Y-PQ	20	10	0	0	0
43			Y-Z	0	0	40	20	0
45	46	300	Y-I	20	10	0	0	0
46			Y-PQ	20	10	0	0	0
47	48	150	Y-I	35	25	35	25	35
48			Y-Z	70	50	70	50	70
49	50	250	Y-PQ	35	25	70	50	35

50	51	250	Y-PQ	0	0	0	0	40
51	-	500	Y-PQ	20	10	0	0	0
52	53	200	Y-PQ	40	20	0	0	0
53	54	125	Y-PQ	40	20	0	0	0
55	56	275	Y-Z	20	10	0	0	0
56			Y-PQ	0	0	20	10	0
58	59	250	Y-I	0	0	20	10	0
59			Y-PQ	0	0	20	10	0
60	61	550	Y-PQ	20	10	0	0	0
62	63	175	Y-Z	0	0	0	0	40
63	64	350	Y-PQ	40	20	0	0	0
64	65	425	Y-I	0	0	75	35	0
65	66	325	D-Z	35	25	35	25	70
66			Y-PQ	0	0	0	0	75
68	69	275	Y-PQ	20	10	0	0	0
69	70	325	Y-PQ	40	20	0	0	0
70	71	275	Y-PQ	20	10	0	0	0
71			Y-PQ	40	20	0	0	0
73	74	350	Y-PQ	0	0	0	0	40
74	75	400	Y-Z	0	0	0	0	40
75			Y-PQ	0	0	0	0	40
76	77	400	D-I	105	80	70	50	70
77	78	100	Y-PQ	0	0	40	20	0
79			Y-Z	40	20	0	0	0
80	81	475	Y-PQ	0	0	40	20	0
82	83	250	Y-PQ	40	20	0	0	0
83			Y-PQ	0	0	0	0	20
84	85	475	Y-PQ	0	0	0	0	20
85			Y-PQ	0	0	0	0	40
86	87	450	Y-PQ	0	0	20	10	0
87	88	175	Y-PQ	0	0	40	20	0
88			Y-PQ	40	20	0	0	0
90			Y-I	0	0	40	20	0
92			Y-PQ	0	0	0	0	40
94			Y-PQ	40	20	0	0	0
95	96	200	Y-PQ	0	0	20	10	0
96			Y-PQ	0	0	20	10	0
98	99	550	Y-PQ	40	20	0	0	0
99	100	300	Y-PQ	0	0	40	20	0
100	-	800	Y-Z	0	0	0	0	40
102	103	325	Y-PQ	0	0	0	0	20

103	104	700	Y-PQ	0	0	0	0	40
104			Y-PQ	0	0	0	0	40
106	107	575	Y-PQ	0	0	40	20	0
107			Y-PQ	0	0	40	20	0
109	110	300	Y-PQ	40	20	0	0	0
111			Y-PQ	20	10	0	0	0
112	113	525	Y-I	20	10	0	0	0
113	114	325	Y-Z	40	20	0	0	0
114			Y-PQ	20	10	0	0	0
Total				1420	775	915	515	1155

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