

# Power Grid Planning for Vehicular Demand: Forecasting and Decentralized Control

By

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## Abstract

Temporal and spatial distribution of incoming vehicular charging demand is a significant challenge for the future planning of power systems. In this thesis the vehicular loading issue is categorized into two classes of stationary and mobile; they are then addressed in two phases.

The mobile vehicular load is investigated first; a location-based forecasting algorithm for the charging demand of plug-in electric vehicles at potential off-home charging stations is proposed and implemented for real-world case-studies. The result of this part of the research is essential to realize the scale of fortification required for a power grid to handle vehicular charging demand at public charging stations.

In the second phase of the thesis, a novel decentralized control strategy for scheduling vehicular charging demand at residential distribution networks is developed. The performance of the proposed algorithm is then evaluated on a sample test feeder employing real-world driving data. The proposed charging scheduling algorithm will significantly postpone the necessity for upgrading the assets of the network while effectively fulfilling customers' transportation requirements and preferences.

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# Dedication

To my beloved family Fatemeh, Noorali, Goli, and Pouya.

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# List of Symbols

<i>AD</i>	Aggregated demand (forecasted)
<i>B</i>	Base-Load
<i>CA</i>	Customer agent
<i>CH</i>	Desired charge
<i>CP</i>	Critical point
<i>DA</i>	Database agent
<i>DG</i>	Distributed generation
<i>DTH</i>	Distance to home
<i>E</i>	Drawn charging energy from the grid
<i>EC</i>	Effective desired charge
<i>EV</i>	Electric vehicle
<i>FD</i>	Flexibility degree
<i>HEV</i>	Hybrid electric vehicle
<i>L</i>	Length of charging interval
<i>MOL</i>	Maximum over-load
<i>N</i>	Number of customers
<i>N<sub>o</sub></i>	Number of over-loaded customers
<i>NRC</i>	Summation of negative <i>RC</i>
<i>OL</i>	Over-load
<i>P</i>	Charging demand
<i>PD</i>	Parking duration
<i>PEV</i>	Plug-in electric vehicle
<i>PHEV</i>	Plug-in hybrid electric vehicle
<i>POL</i>	Permitted over-load
<i>RC</i>	Remaining capacity
<i>RD</i>	Risk degree

<i>RE</i>	Remaining energy
<i>SM</i>	Security margin
SOC	State of charge
<i>T</i>	Number of charging interval
<i>TD</i>	Total demand of a customer (actual)
<i>T<sub>l</sub></i>	Number of intervals eligible for overloading
<i>T<sub>o</sub></i>	Number of intervals with negative <i>RC</i>
<i>T<sub>u</sub></i>	Number of intervals with positive <i>RC</i>
UA	Utility agent
<i>UL</i>	Under-load
V2G	Vehicle to grid

# Chapter 1

## Introduction

### 1.1 Background

Electrification of transportation in recent years has attracted a great deal of attention because of its tremendous environmental and economic benefits for the society as a whole. With an urgent necessity to reduce greenhouse gas emissions, employment of renewable energy sources in generation of electricity and using electric vehicles (EV) have been promoted by various means such as international agreements, government incentives, media, etc. Currently, the majority of on-road vehicles consume gasoline as the primary fuel for their propulsion systems and this has been pointed out as the main reason for air pollution. Therefore, gradual substitution of gasoline with electricity not only significantly diminishes the adverse effects of transportation on the environment, but also promises a sustainable fuel for the future vehicular industry [1]-[4].

However, lower performance of commercial EVs as well as their higher prices in comparison with conventional internal combustion engine (ICE) vehicles has hindered

the rate of penetration of EVs in the market [5]. As a result, hybrid electric vehicles (HEVs) have been proposed and manufactured as an interim solution for cost and performance obstacles of EVs. Indeed, in the transitional period while EV technologies such as battery storage and electrical engines are still at the development stages, the combination of the two energy sources in the propulsion system of a vehicle seems to be the most-suited possible option. This combination can be accomplished in various ways (e.g., series, parallel, series-parallel, and complex) aiming to employ advantages of both energy sources [5], [6].

Unlike initial models of EVs, HEVs could provide longer driving range. In order to maximize the overall efficiency and performance of the vehicle, different control strategies can be applied in HEVs. Managing the energy flow between two sources and battery sizing have been the main issues regarding HEVs [5].

Plug-in hybrid electric vehicles (PHEV) followed by plug-in all-electric vehicles are the latest achievements of vehicular industries. PHEVs have the capability to operate in electric mode over a significant distance, so they have battery storages with higher capacity and smaller ICEs in comparison to HEVs. Moreover, adding an on-board charger in plug-in electric vehicles (PEVs<sup>1</sup>) has made the recharging of battery storage much more convenient as its ideal aim is to have the possibility of charging wherever a plug of the electrical grid is accessible. All of these improvements have led to a positive reaction of the market to some commercial models of PEVs in recent years [1], [2], [5].

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<sup>1</sup> “PEV” stands for both plug-in hybrid and plug-in all-electric vehicles



However, the fast penetration rate of PEVs, as well as unique characteristics of load demand of their corresponding battery storages, have spun some new and challenging issues in the power system area. The charging demand of PEVs is presently considered as one of the problematic concerns for planning of the electrical network. Currently operating electrical networks are mostly designed without taking in to account a fast rate of growth for vehicular charging load and might be inadequate to supply and properly operate in many nodes of the system [3], [4], [6], [10].

Convenience of charging is an important factor for commercializing PEVs. It should be fast, efficient, and cost-effective. To do so, battery chargers are designed to draw maximum power for considerably long periods from the available outlet in order to charge the battery as fast as possible. Therefore, battery storages of PEVs present much larger loads in comparison to other household loads. For example, for a regular outlet with household ratings of 120V/15A (North-American standard) a maximum power of 1.8 kW may be drawn by chargers of PEVs.

The duration of the charging demand depends on various factors. Most importantly the driving profile of the vehicle determines the required energy and also potential time for charging. Furthermore, personal preference on capacity of battery storage (all-electric range of the vehicle), and the vehicle technology are other influential aspects.

Mobility of PEVs adds another uncertainty factor to the positioning of charging demand in the distribution network. This is much more difficult in the low level of penetration of PEVs due to the challenge of accurately estimating the driving behavior and charging habits of the majority of electric vehicle drivers; moreover, information about market acceptance of various kinds of PEVs with different all-electric capabilities cannot

be obtained easily. These all make it difficult to identify the place and the amount of the required or demanded charging load.

Therefore, vehicular loading on power systems is a multifaceted issue, which initially deals with vehicle technology, transportation network, electrical power network as well as human (drivers) interactions with all of these technological entities.

## 1.2 Potential Impacts and Possible Solutions

The electrical power system in its different voltage levels namely generation, transmission, and distribution will be affected by unforeseen vehicular charging load. Among these different levels of the electrical network, the assets of the distribution system (e.g. transformers, feeders), which are not only the closest infrastructures to customers, but also have the lowest capacities, are more vulnerable to the adverse effects of excessive charging demand. Indeed, at a low penetration level of PEVs, studies have shown that generation and transmission levels of the grid are sufficiently capable of handling the incoming charging load and their reserve margins and regular upgrading pace are adequate to meet the anticipated penetration rate of PEVs; on the other hand, at the distribution level with low reserved capacity of assets, coincidental charging of even a small number of PEVs, energised from the same low-voltage feeder, might lead to overloading of assets [7]-[12]. This is mainly due to the fact that PEVs are not going to be uniformly distributed among the area of interest and therefore, there will be some hot-spots in the power network where charging demand is higher than the present capacity of the grid. Identification of such locations in advance will not be an easy task. This is due to the fact that

this issue deals with an excessively large number of low-rating nodes of the distribution system as well as their associated customers' transportation preferences and electrical energy usage habits. As a result, many potential issues might arise in the power system environment such as lower longevity of network elements as well as power quality and reliability concerns.

Upgrading assets of the distribution network at problematic locations is an obvious but least-favoured solution for the PEV loading issue due to its cost. The distribution level is the most expensive part of the power network due to its high number of elements; hence, upgrading of the assets especially at low penetration levels must be considered as the last solution. Therefore, maximizing the utilization of the current capacity of the network has been considered as the main solution for the vehicular loading issue in order to postpone the need for upgrading.

The block diagram of Figure 1-1 illustrates major approaches that have been taken by researchers mostly in the last five years striving firstly to enlighten the status of the present power systems and potential charging patterns of PEVs; secondly to assess possible impacts of charging demands on the system; and ultimately to investigate viable solutions to effectively address planning and operating concerns of the network. Handling these upcoming issues by employing facilities enabled in the future smart grid environment such as customer/demand-side responses and intelligent control schemes, has been the dominant approach in various studies. The main aim of such studies has been to find out an optimal charging profile meeting both the utility's and customers' objectives.

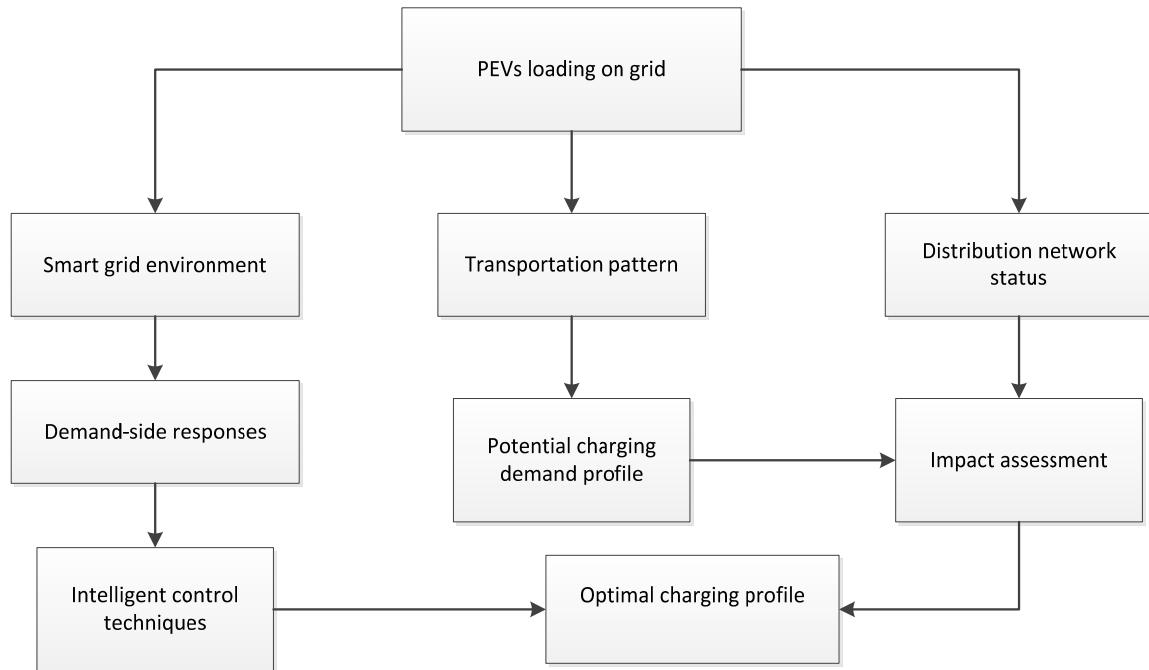


Figure 1-1 Dominant areas of research on vehicular loading.

### 1.2.1 Impact assessment

Firstly to deal with the vehicular loading issue, the present capacity of the power grid and its capability to feed incoming charging demand must be investigated. Data on current demand, load growth and generation as well as rating of assets are part of the required information to determine the status of a distribution network [12], [13].

Planning of the electric grid requires reliable estimation of the load demand on all nodes of the network. In fact, all subsequent actions, such as determining the rating of assets, managing the power distribution and so forth, depend on the accuracy of this essential and critical stage. Poor quality and waste of capital money are the adverse impacts of underestimation and overestimation of load demand, respectively [13], [14]. Therefore, having a proper picture of spatial and temporal features of charging demand is the initial

and main step of the planning for upcoming vehicular load in the power system and performances of all following preventive measures depend on its validity.

The main challenge in this regard is the lack of historical data for charging patterns of PEVs. Therefore, to address this problem, studies have been conducted to estimate potential patterns for recharging PEVs storages within power systems [8]-[12]. Features such as location, starting time, duration, and amount of demand are essential for a comprehensive assessment of adverse effects of unsupervised (or uncontrolled) charging on the power network.

Due to the uncertainties involved in the traits of vehicular demand in terms of vehicle specifications, driving cycles (patterns), and drivers' preferences, there is not an exact and perfect approach to resolve this issue. As a result, researchers have examined different approaches including deterministic and stochastic (by employment of real-world driving data) to characterize the vehicular demand.

In stochastic approaches, by means of analysis of real-world driving data, essential features of vehicular load, which vary stochastically, are estimated [15]-[22]. In fact, in light of the lack of historical records of actual charging behavior of majority of drivers, local driving patterns of conventional vehicles can provide a realistic picture of potential starting time and duration for charging as well as daily mileage and its associated amount of energy consumption. Demographic and geographic attributes of the area of interest are also reflected properly in such data. However, it should be noted that driving pattern of a specific location might not always be a good representative of all jurisdictions. Therefore, availability of reliable and informative data restricts the application of such approaches of vehicular load feature realization.

In deterministic approaches, different probable scenarios for charging period (e.g. peak or off-peak) are considered. The amount of required charge is also specified according to the average mileage of vehicles and their specific energy consumptions [8], [25], [26].

Locations of charging are commonly defined deterministically as well. In this determination, accessibility of a plug as well as convenience in terms of availability of adequate time and cost of charging plays a critical role. Home, work, and public charging stations are the main potential locations considered for recharging battery storages of PEVs. Due to the undeniable convenience of the home charging mode, it is often identified as the dominant location for upcoming vehicular demand, and therefore many studies have focused on efficient management of demand at residential areas [21]-[31].

Moreover, charging rate of battery storages of PEVs is an influential element, which greatly affects the drawn power from the grid and may change the level of adversity of the impacts. Depending on the assumed available charging infrastructure, charging rate can be regular or fast (ac or dc).

### 1.2.2 Scheduling charging demand

Studies about vehicular loading on power systems have pointed out the effect of uncontrolled charging is excessive especially on the assets of the residential or domestic load class of the distribution network. As a result, a significant share of the existing research is focused on alternative charging scenarios aiming to content both utility and customers [5]-[30]. Different terms such as coordinated, controlled and smart charging have been used in the literature for a supervised mode of charging, necessitating demand or custom-

er side management in order to enhance satisfaction degree of utility service and customers in presence of vehicular load.

*1) Customers' objectives /Utility's objectives*

From the customers' point of view, a charging pattern with the least possible cost while fulfilling all of their transportation requirements is the most favorable one. Note that customers' or drivers' prior objective in this case is a convenient driving experience; then, minimizing the cost comes into the picture.

From the utility's point of view, the vehicular load is initially considered as an additional unforeseen load and thus a potential threat for the normal operation of the system. This is due to the fact that the unsupervised mode of charging, especially if it takes place during the present peak demand, causes overloading of assets and thus operational problems for the overall system. Therefore, the main criterion is preserving the peak demand; of course this cannot be accomplished without systematic cooperation from the customers' side.

After overcoming the danger of additional unplanned demand, utilities' second objective can be shifting the additional load to periods of low demand to improve load factor of assets (valley filling of the aggregated load curve). In other words, charging demands with flexibility in time can be employed to enhance the overall utilization of elements of the power distribution network [32], [33].

The power system is affected by the customers' dominant criteria of driving features and the utility can only influence the customers' later objective of cost. In fact, utility services can enact proper pricing scenarios or designate incentives (according to the system performance objectives) in order to make it beneficial for customers to follow the de-

sired charging pattern. However, in every planning method, upgrading is inevitable after some level of penetration of PEVs in the system when charging management schemes become incapable of meeting the desired criteria.

### *2) Smart grid environment*

In the future smart grid environment, PEVs are going to play a more significant and interactive role. Besides their strong potential to serve as a flexible demand, they can also be considered as auxiliary distributed small scale generation assisting the main generation during critical periods.

The vehicle-to-grid (V2G) concept has been investigated by various researchers to augment the performance of the power system in different ways such as voltage stability, frequency regulation, etc. [33]-[38]. The main idea is using batteries of PEVs as distributed small storages in the system. They are supposed to be charged in off-peak period (ideally while renewable energy sources are generating power); then supply their stored energy during the peak power demand or when a quick reaction to an unexpected incident such as fluctuation or failure is required. Therefore, PEVs' battery technologies and their capacities are integral factors to enable V2G power exchange.

One of the unique attributes of a smart grid is engagement of the customer-side responses in the planning procedure to improve efficiency [32], [33]. Indeed, having intelligent communication between the utility and the customer will give a modern active role to the customer side of the grid rather than its conventional passive role. In the scheduling techniques for PEVs charging demand, customers' actions and responses to the changes in the interaction environment (e.g. variation in electricity tariff) play significant roles.



The degree of reliance on demand-side responses and customers' cooperation depends on the fundamentals and objectives of the scheduling strategy.

3) *Centralized strategies versus decentralized strategies:*

Generally, explored methods for supervised charging patterns in the smart grid environment are categorized as centralized and decentralized (or distributed) control strategies. In the centralized approach, the charging profile of all distributed PEVs in the system is determined by the central intelligence of the utility aiming to achieve an optimal aggregated charging profile. On the other hand, in the decentralized approaches, charging patterns of distributed PEVs are decided locally aiming to fulfill individual's desires and thus a decentralized strategy is not necessarily perusing the objective of overall system's optimal operation [40]-[43].

Indeed, in a centralized strategy, system performance criteria have priority over customers' preferences; however, customers can still define their strict and inflexible objectives. On the one hand, having comprehensive awareness of the whole system status can lead to higher utilization of assets. On the other hand, as all decisions are made centrally, information on a large number of PEVs must be gathered and command signals must be sent back. Firstly, this requires a complicated computational procedure. Secondly, a comprehensive and reliable communication infrastructure is necessary to handle transferring data between distributed PEVs and the central decision maker. At the same time, many security and privacy concerns might arise (and need to be addressed) due to huge amounts of communicated personal data.

Several studies have been conducted in recent years on developing decentralized strategies, which better suit the modern power system environment by emphasizing on

individual PEVs' unique objectives [40]-[43]. Generally, distributed scheduling of the charging demand requires less communicational expenses and computational complexity. Local control also provides faster responses to a change in the status of the power system. Furthermore, adding a new PEV to the system is handled simply in decentralized approaches, so they have much better scalability than centralized approaches.

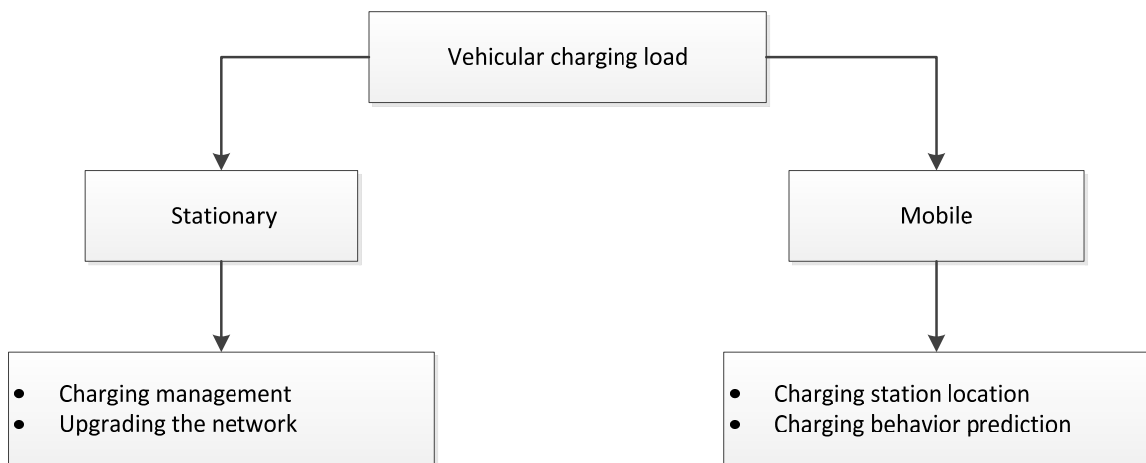
Multi-agent systems possess all the means required to implement a comprehensive decentralized control strategy. Agent-based systems have been developed throughout the years in different disciplines prior to attracting power engineers and thus they are in a mature shape and are well-defined to be employed. In [44], applications of multi-agent systems in the power system field are discussed. Unique characteristics of agents that make them different from conventional supervisory facilities (e.g. protection relays) are also clarified. Three main features are associated to an intelligent agent: 1) reactivity, to react in a timely manner according to the change of its predefined environment, 2) proactiveness, to have a goal-directed behavior and be able to take imitative and 3) social ability, to collaboratively communicate with other intelligent agents. Flexibility in taking one of many possible actions and extensibility, as adding or modifying a functionality without need to re-implement the existing functionality, are other important traits of a multi-agent system [44].

In an ideal smart distribution network, which is comprehensively controlled by a multi-agent system (comprising a utility agent, distributed generation agents, customer agents, and a database agent) and real-time communication is enabled among agents, scheduling of charging demand can be carried out by individuals in a way that every agent pursues its own goal.

## 1.3 Motivations, Objectives, and Outline

### 1.3.1 Motivations

In this thesis, vehicular loading issue on the power system, from a planning point of view, is categorized into two classes. They are stationary and mobile vehicular charging demand. This categorization is done based on the location where charging occurs. Figure 1-2 demonstrates this categorization and their associated challenges.



**Figure 1-2 Categorization of vehicular charging load based on location of demand in the power network**

#### *1) Stationary vehicular demand*

Charging of PEVs during home parking is one of the common logical assumptions among most scenarios mainly because of its convenience in terms of available time and expense. In fact, it is highly expected that a major portion of the required charge of a PEV is demanded at the home of its owner. Therefore from the planning point of view, in

this case, vehicular charging load is a “stationary” demand similar to other household loads. As it is elaborated in Section 1.2.2, the main challenges of handling vehicular load at residential areas are initially the efficient management of charging patterns and, eventually, upgrading endangered or incapable assets.

#### *2) Mobile vehicular demand*

Any charging demand of PEVs away from home is considered as a “mobile” charging demand. This class of vehicular load is directly affected by the mobility of PEVs; mobile charging load can potentially take place in any possible charging location, based on the charge requirement and driver’s will; therefore, from the planning point of view, it cannot be predicted in a similar fashion to the stationary demand.

Although PEVs have the potential to be charged through any available plug of the electric network, in reality charging of PEVs are restricted to only accessible plugs. In other words, besides home and in some rare cases work, other charging stations are defined deterministically. As are result, in planning the power systems for mobile charging demand, first, potential suitable charging locations within the area of interest must be identified. Of course, the number of parking events and their corresponding length at such locations must be adequately high. Utility service needs to be convinced that installation of the new charging infrastructure will be beneficial in terms of returning the capital money and encouraging society to switch to green transportation with more confidence.

The PEV drivers’ charging behaviors at off-home stations must also be investigated to predict the potential amount of demand at a specific location to decide on the capacity of the charging facilities.

### 1.3.2 Objectives and outline

This thesis is divided into two phases. In the first part, the focus of the study is on the mobile portion of the vehicular demand. In Chapter 2, an overview of traditional load forecasting in power systems and vehicular load forecasting considerations is presented first; then an algorithm is developed to predict the charging behavior of PEV owners at off-home parking locations and forecast the potential demand. Moreover, owing to the fact that several local factors, such as characteristics of the present grid and driving patterns, contribute to PEVs charging demand on a specific power system, this study emphasizes the importance of employing real-world data as far as they are available. To do so, in Chapter 3 the proposed location-based vehicular load forecasting is applied to real-world data of two potential charging stations at major shopping centers.

The second part of this work is dedicated to scheduling charging demand at residential distribution network. In Chapter 4, an overview of flexible demand management at the customer side and decentralized control scheme is presented first; then, a distributed control strategy, which can be implemented by a multi-agent system, is developed. Chapter 5 presents specifications of a case-study followed by its corresponding simulation results to demonstrate the performance of the proposed distributed charge scheduling technique.

Finally, in Chapter 6, conclusions and contributions of the accomplished study are stated and some future trends for continuation of this work are suggested.

## Chapter 2

# Location-Based Forecasting of Vehicular Charging Demand

### 2.1 Introduction

In order to investigate the significance of the potential issues due to addition of vehicular demand, a reliable prediction of the profile of the charging demand on the distribution network is essential. Conventional load forecasting methods in power systems for different time horizons employ various statistical and artificial intelligence techniques (e.g. time series, multiple regression, expert systems, fuzzy logic, neural network, etc.) [13], [14], [45]-[49]. These methods mostly use historical data along with influential parameters on the demand profile (e.g., climatic conditions, day-type, land usage, etc.). However, due to lack of actual comprehensive historical data, efforts for prediction of the charging demand of the upcoming vehicular load have been mostly done through defining op-

timal charging scenarios from the points of view of both the utility and the customers [25]-[29].

Generally, realizing the temporal and the spatial behavior of the charging demand on the power system depends on such factors as the convenience and cost of charging, adequate parking time, availability of charging stations and their rating, and most importantly the charging need of PEVs [19], [50]. It is also reasonable to assume that the society will not develop radically different transportation habits based on the charging requirements of the PEVs. In fact, the PEV technologies and the utility planners may aim to capture the existing driving traits of the society and enhance their services in that direction.

Therefore, in the absence of actual measured data of the charging demand, use of real-world driving data in the area of interest provides a realistic picture of driving habits and characteristics of drivers of PEVs [15]-[23]. Layout of roads and traffic patterns influence not only the driving traits, but also vehicular energy consumption. These together contribute to the timing and the distribution of charging demand. Local driving data also provide information about potential parking locations where future PEVs may be connected to the network for charging.

For as long as PEVs are not widely adopted in a given jurisdiction, it is reasonable to assume that home plugging will be the dominant (or in most cases perhaps the only) mode of charging [51]. As the penetration-level of PEVs increases, additional off-home charging stations should be gradually assigned in strategic locations in order to fulfill the charging demand of on-road PEVs. Places where a large number of parking events occur (e.g. shopping centers) will obviously be more subjected to vehicular charging, so they

can be considered as main candidates for future charging stations and necessary fortifications of the network.

This chapter investigates the potential charging demand in such high-density off-home parking locations, while considering home charging as the most favorable charging mode. In Sections 2.2 and 2.3, a location-based fuzzy decision-making algorithm is developed to predict the probability of charging for a given parking event. Model sensitivity is then analyzed in Section 2.4 followed by conclusions. In the next chapter the developed forecasting procedure is implemented on real-world case studies.

## 2.2 An overview of location-based vehicular load prediction

A location-based study of vehicular load aims to predict the potential load demand due to PEV charging at off-home parking locations. Whether or not drivers decide to charge their vehicles in a specific place depends on various parameters; however, a person's decision making process for cases like this often does not involve precise computations or analyses. Indeed, drivers usually evaluate the situation using their own experience, convenience, and other factors, perhaps most importantly economic considerations.

The essence of a fuzzy inference engine is to quantify a complex process, e.g. charging decision making, through reasonable assumptions that capture the experience of the expert (i.e., the driver). A fuzzy inference system was proposed in [52] to simulate a driver's decision-making process for PEV charging. It used the present state-of-charge (SOC) and parking duration (PD) as its inputs to predict the probability of charging, in-



dependently of the actual place of parking. However, in the location-based prediction method presented in this chapter, the actual driving distance to home (DTH) is also used as an additional input. This is done as it seems natural that most drivers would prefer to charge their vehicles at home rather than at other locations. Several factors contribute to this preference including longer duration of vehicle down-time at home (e.g. overnight), and potentially less expensive electricity. The developed fuzzy inference system takes this preference into account but also includes provisions for the case when there is doubt whether the current state of charge of the battery is adequate or not for the drive to home. This is done through definition of proper fuzzy rules.

Figure 2-1 illustrates the block diagram of the proposed procedure for location-based vehicular load prediction. This procedure starts with an analysis of a real-world driving dataset for the area of interest, and extracts characteristics of recorded parking events. Then, a fuzzy decision-making engine uses the extracted statistical results to determine the average probability of charging for every hour at the location of interest. This, together with local parking characteristics and market information, determines the expected charging demand. The following sections present details of the procedure.

## 2.3 Location-based fuzzy decision making unit

The three input parameters of SOC, PD, and DTH need to be expressed with linguistic terms and their corresponding membership functions. Once the inputs are fuzzified, the rules of the fuzzy system are applied to generate the respective outputs. The outputs are then combined and defuzzified to yield the output of the fuzzy inference engine, which is

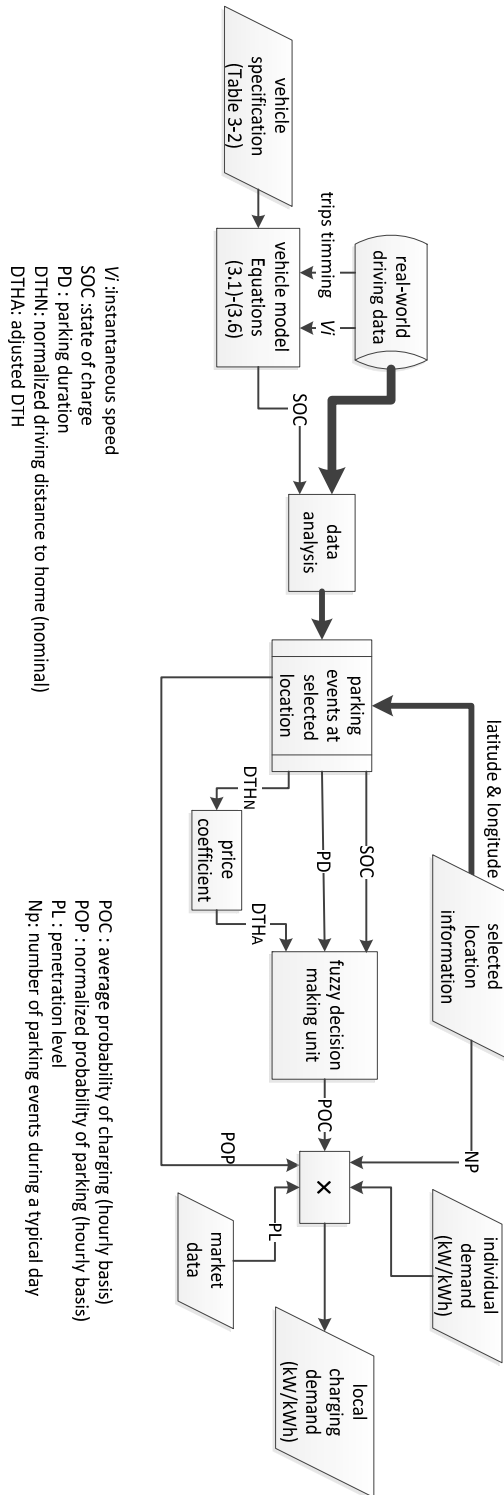


Figure 2-1 Block diagram of the location-based vehicular charging load forecasting procedure

the probability of charging. The following subsections present details of the membership functions assigned to each input and output variable [53], [54].

### 2.3.1 State of charge (SOC)

The SOC is the most readily available input to the driver. It indicates the amount of stored electrical energy that is presently available. Figure 2-2(a) shows membership functions created for the SOC. Three linguistic terms, i.e. Low, Medium, and High, are defined to cover the whole working area of the battery storage. The on-board vehicle controller only operates the battery within lower and upper bounds, to ensure its longevity. In the study presented here a range of [15,85]% is considered (corresponding to a 70% depth of discharge); that is why the Low and High membership functions shown in Figure 2-2(a) attain a value of 1.0 below 15% and over 85% SOC, respectively.

### 2.3.2 Parking duration (PD)

Parking duration is a variable that represents the anticipated length of the parking event. Note that most drivers do not have an exact length of time for parking at the onset of a parking event. Therefore, it is assumed that they express the parking duration with three linguistic terms (Short, Average, Long) as shown in Figure 2-2(b). For example, the membership function labeled 'Average' fully encompasses (degree of membership = 1.0) all parking events ranging from around 45 minutes to around 3 hours. Therefore, any parking with a duration in this interval will be treated equally; this makes the model less

sensitive to the deviation between the actual length of the parking event and its anticipated duration by the driver.

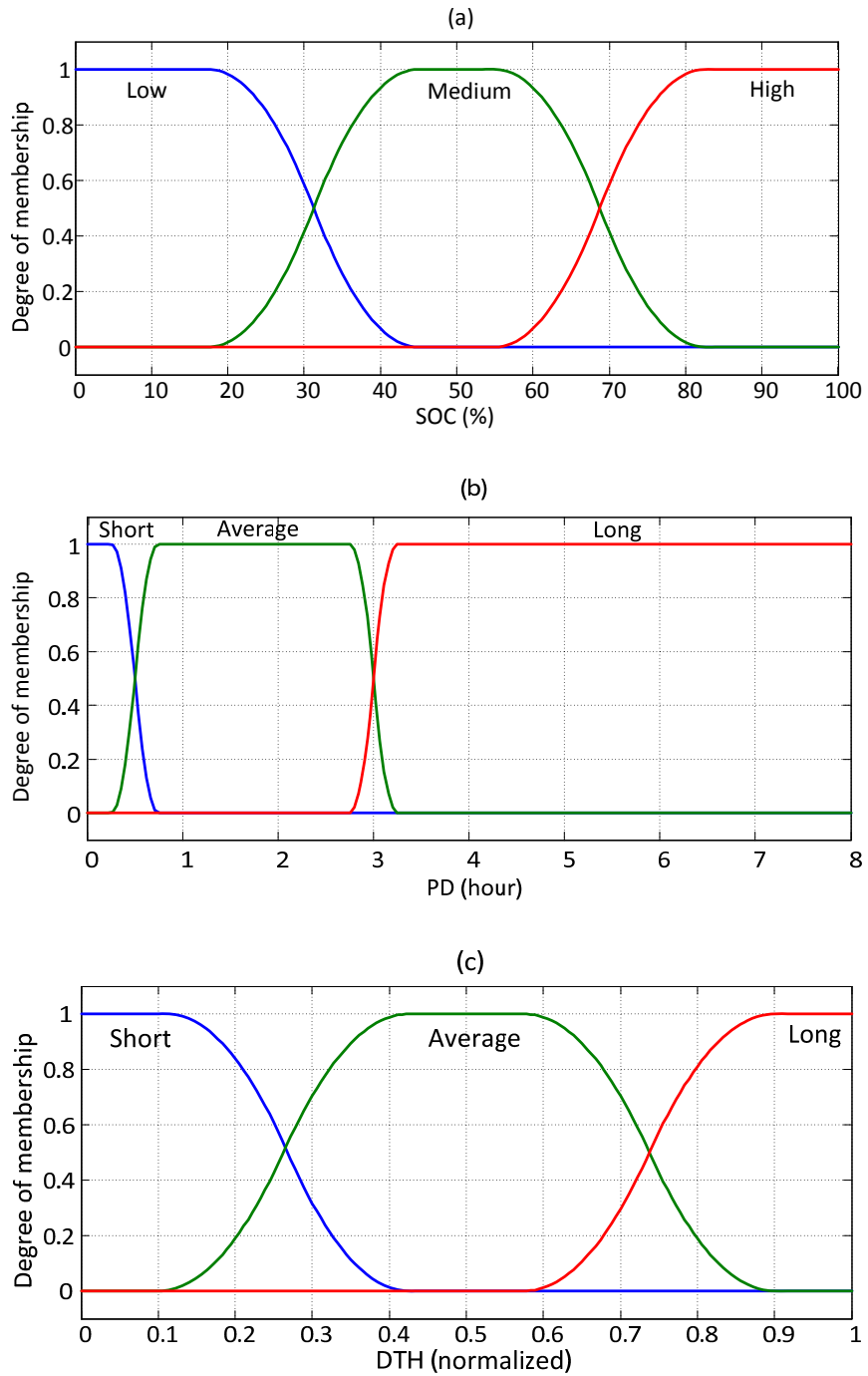


Figure 2-2 Membership functions of the input variables: a) state-of-charge (SOC); b) parking duration (PD); c) normalized driving distance to home (DTH).

The linguistic terms for the PD input are highly affected by the available level of charging. This is because the amount of charge that can be replenished over the period of charging is directly determined by ratings of the charger. For example a parking event whose duration may be considered ‘Short’ (and hence not worthwhile) for regular charging may indeed be considered ‘Average’ if fast-charging facilities exist. The membership functions in Figure 2-2(b) are designed with the assumption of level-1 charging (120-V, 15-A).

### 2.3.3 Actual driving distance to home (DTH)

By experience a prudent driver of a plug-in vehicle may have a reasonable estimation of how much SOC is required to drive the vehicle to a convenient charging location, i.e. home in this study. However, knowledge of the required SOC may be a higher-than-normal expectation for an average driver and involves several uncertainties. On the other hand, an estimate of the driving distance to home is doable for most drivers. Therefore, in the fuzzy inference system described here the actual driving distance to home is used as a representative of the required SOC to drive home.

The DTH assigned to a parking event includes the mileage of all the subsequent trips during the day before arriving home for overnight parking. Indeed, the DTH is a factor that enhances the precision of the charging behavior prediction significantly: it shows the experience of the driver about daily trips, and their timing and mileage (i.e. the expert knowledge). It also considers the location of each parking event, thereby making the decision-making process location-specific.

The DTH input is categorized under three linguistic terms of Short, Average, and Long (Figure 2-2(c)). Note that the battery capacity plays an important role in the definition of the range for these linguistic terms. A battery with a higher capacity allows a longer all-electric range. To avoid development of membership functions for the DTH for vehicles with different battery capacities, a normalized figure (based on the maximum all-electric range) for the DTH is used.

In reality the all-electric range of a vehicle will depend on such factors as the age of the battery, driving patterns of the driver, and traffic, among other things (see Section 2.3.5 for further discussion); thus the actual all-electric range will likely be less than nominal.

#### 2.3.4 Rule table and defuzzification

A set of 25 rules for charging decision-making are developed for a Mamdani-type fuzzy model [54] as shown in Table 2-1. These rules act on the three inputs of the fuzzy system to produce outputs that are then aggregated and defuzzified to yield the probability of charging for a specific parking event. Before defuzzification, the probability of charging is described using seven linguistic terms as shown in Figure 2-3. The fuzzy ‘AND’ is implemented using the ‘min’ operator, and the center-of-mass (centroid) method is used for defuzzification.

The design of the rules in this fuzzy system is done with a view to maintain reasonability of the assumption from a prudent driver’s point-of-view. The main consideration in the design of the rule table is that if the SOC of the battery is less than the driver’s estimation

of the required SOC to drive the vehicle home (based on the DTH), the probability of charging increases with respect to the parking duration.

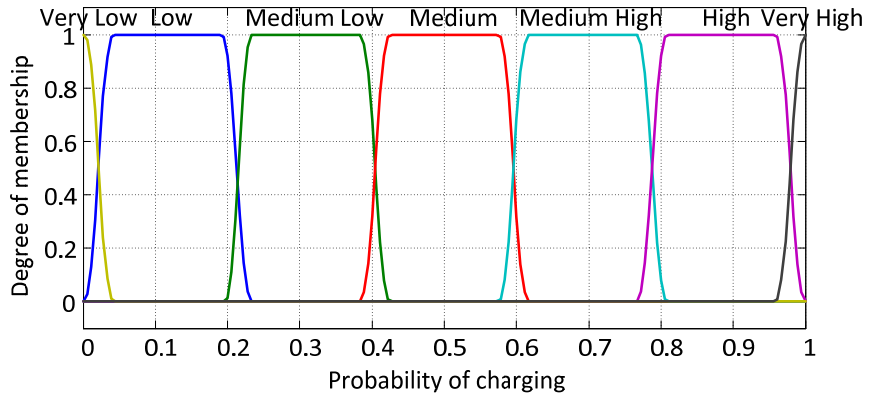


Figure 2-3 Probability of charging (output of fuzzy system)

Table 2-1 Rules of the fuzzy system

if <i>SOC</i> is	AND <i>PD</i> is	AND <i>DTH</i> is	then <i>Probability of Charging</i> is
Low	Short	Short	Very Low
Low	Short	Average	Low
Low	Short	Long	Medium Low
Low	Average	Short	Low
Low	Average	Average	Medium High
Low	Average	Long	High
Low	Long	Short	Medium Low
Low	Long	Average	High
Low	Long	Long	Very High
Medium	Short	Short	Very Low
Medium	Short	Average	Low
Medium	Short	Long	Medium Low
Medium	Average	Short	Low
Medium	Average	Average	Medium
Medium	Average	Long	High
Medium	Long	Short	Low
Medium	Long	Average	Medium
Medium	Long	Long	Very High
High	Short	Average	Low
High	Short	Long	Medium Low
High	Average	Average	Low
High	Average	Long	Medium
High	Long	Average	Medium Low
High	Long	Long	Medium High
High	-	Short	Very Low

It should further be noted that when the DTH is ‘Long’ both the ‘Medium’ and ‘Low’ SOC are treated similarly; this reflects the fact that a ‘Long’ DTH most likely represents a parking event in the earlier hours, and from a driver’s point-of-view foreseeing all future trips throughout the rest of the day might not be possible; therefore an increased chance of charging is given to the ‘Medium’ SOC range.

### 2.3.5 Additional factors

#### *1) Climatic conditions and aging*

It must be noted that other factors than the ones considered here may impact a driver’s decision to plug in for charging. Severe climatic conditions (e.g. extreme heat or cold, humidity, etc.) not only affect the driver’s decision making, but may also affect the three considered inputs. For example, temperature variations do impact the chemical reactions within a battery and hence its SOC, its total capacity (affecting the DTH) and the required heating/cooling energy. Although there are studies that aim to approximate such variations [55]-[56], the level of detail and complexity required by these methods renders them infeasible for aggregated long-term vehicular load forecasting, which also involves a large number of storage units with different properties. Therefore, instead of attempting to augment the model to directly include such auxiliary effects, this work investigates the sensitivity of predicted probability of charging (output of the fuzzy model) as well as final forecasted load (for the presented case study) to uncertainties in its input variables collectively caused by such factors as seasonal temperature variations, humidity, aging, measurement errors, etc. These analyses are shown in Sections 2.4 (for the model) and 3.4.2 (for the presented case study).



### 2) *Utility tariffs*

The DTH input, which is the preference-factor for the location of charging, accounts for the driver's desire for the least expensive transportation and convenience of charging. In the design of the fuzzy rule table two cost effectiveness objectives are considered as follows:

- a) consumption of electricity has preference over gas because of the lower cost of electricity;
- b) home-charging has preference over off-home charging because of lower cost (as well as convenience);

Although the convenience of charging is not directly quantifiable, it is possible to include the effect of electricity cost variation by only modifying the DTH input without any further change in the kernel of the developed model. A favorable charging rate at the time of parking will entice the driver to charge at an off-home location, and this can be captured by suitably increasing the DTH input. Conversely a decrease in the DTH resembles an unfavorable charging rate, and hence a driver's inclination to charge at home. For example, these can be due to a utility's time-variant tariffs for peak and off-peak hours, and/or incentives offered for off-home charging. However, it should be noted that as long as the two said cost objectives of the model are valid the change in the DTH is expected to be small; i.e., when the price increases but stays below the equivalent gas price, or when the price decreases but remains more expensive than the convenience threshold over which a driver prefers to charge at home.

The investigation of the effect of price variation is mostly useful when a more accurate short term forecast of charging demand is required, and then exact charging costs in each location and for different time (during a day) are available.

## 2.4 Model performance assessment

The developed fuzzy model is designed to capture the driver's decision making process through a reasonable set of rules acting on the three inputs. The adopted membership functions and rules will certainly have an impact on the output of the fuzzy system, i.e. the predicted probability of charging.

Figure 2-4 shows the probability of charging for three representative values of the PD input (30 min, 120 min, and 240 min), while the SOC and the DTH vary within their respective ranges. In all three surfaces, the probability of charging increases gradually starting from maximum SOC and minimum DTH. Furthermore, the figures show an increasing probability of charging as the PD increases, as noted by the top left corner of each figure where the probability of charging increases from 60% for PD = 30 min to essentially 100% for PD = 240 min. These are reasonable expectations, which are satisfied through the selection and composition of the rules.

In order to assess the performance of the fuzzy model, an analysis of the sensitivity of its output is undertaken with respect to variations of the inputs. This analysis quantifies the expected deviation of the output when inevitable uncertainties occur in the estimation of the inputs. These uncertainties may arise due to factors such as the ones discussed in Section 2.3.5.

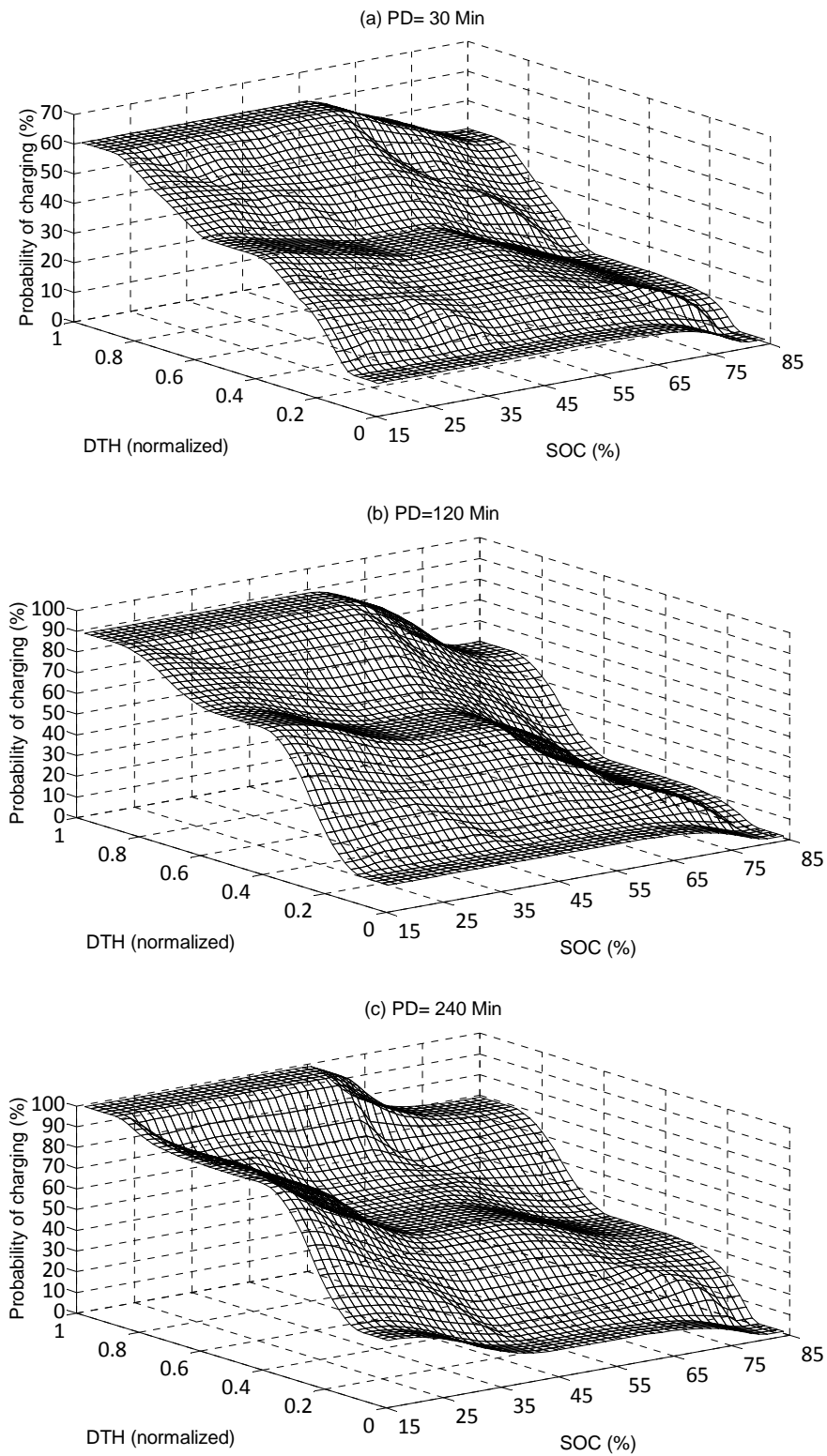


Figure 2-4 Fuzzy decision making surfaces for three representative PDs

Table 2-2 presents the results of sensitivity analysis for individual variations of  $\pm 20\%$  in each input. For example the table shows that the average change in the probability of charging (predicted by the fuzzy model) is  $+5.70\%$  when the SOC input decreases by  $20\%$ . To calculate these statistical quantities, 100 equally-spaced samples are selected for each of the three input variables (PD over  $[0,4]$ , SOC over  $[15,85]\%$ , and DTH over  $[0,1]$ ). Perturbations of  $\pm 20\%$  are introduced in each sample while keeping the remaining two constant, and the probability of charging is calculated using the fuzzy inference engine. The difference between the results of the perturbed values and the nominal value are then calculated and recorded. This is repeated for all samples, which results in  $100^3$  values for each of the  $+20\%$  and  $-20\%$  perturbations and for each input variable. The average and the standard deviation are then calculated as per Table 2-2.

The table shows that the output is most sensitive to the DTH input, which encapsulates cost effectiveness and convenience of charging (home preference factor). The SOC, which captures the available charge factor, is the second most influential input; and the least sensitivity belongs to the PD input, which quantifies the worthiness of the available parking time for charging.

**Table 2-2 Sensitivity analysis results of the fuzzy model**

	Mean +20%	St. dev. +20%	Mean -20%	St. dev. -20%
SOC	-4.67%	4.24%	5.70%	5.12%
DTH	5.55%	5.64%	-7.65%	6.80%
PD	1.49%	2.40%	-2.21%	2.91%

## 2.5 Closing remarks

In this chapter a location-based forecasting algorithm for vehicular charging load was developed. It uses a fuzzy inference system with three real-world inputs to emulate a driver's decision to charge at an off-home charging location. The main advantage of this approach is that it incorporates the driver's experience factor to the decision making process.

Moreover, sensitivity of the output probability of charging to the input variable was investigated. This analysis showed that the combination of the membership functions and the rules do indeed, and as intended, make the probability of charging more responsive to the inputs considered to be more important, i.e. the DTH and the SOC. It further suggests a certain robustness of the fuzzy model's output to the variations of the inputs. The sensitivity of the fuzzy inference engine to the shape of the deployed membership functions and also to the particular implementation of the fuzzy operations is not considered, although it may be an additional topic of investigation.

In Chapter 3, the method developed in this chapter is examined by considering real-world case studies. The corresponding results and complementary conclusions are presented.

## Chapter 3

# Implementation of Location-Based Forecasting and Simulation Results

### 3.1 Introduction

In this chapter a real-world application of the location-based algorithm of forecasting charging demand of upcoming PEVs at off-home charging stations is presented.

In the following sections, firstly a set of real-world driving data (for the city of Winnipeg) is introduced (in Section 3.2) and for the selected case studies of two major shopping centers partaking events are characterized. Section 3.3 is dedicated to specification of the vehicular model used in the simulations. The results of probability of charging as well as forecasted vehicular load are presented in Section 3.4 followed with conclusions in Section 3.5.

## 3.2 Recorded driving data

A set of real-world driving data collected from 74 conventional internal combustion engine (ICE) vehicles in Winnipeg [57] is used in the analyses shown in this chapter. This data-set includes participants from different areas of the city with diverse demographic characteristics (income, education, gender, etc.). Instantaneous latitude, longitude, and speed of the vehicle in each trip as well as their time and date were recorded.

This data-set is fairly small and may not include an adequate number of participants to satisfactorily demonstrate all the driving traits of the entire population of the area of interest; however, its use in this study is important firstly because it does comprise of real-world measurements of actual driving profiles, and secondly because it only serves to enable a demonstration of the proposed location-based forecasting algorithm in Chapter 2. If a larger and more comprehensive data-set is available, the numerical results on the proposed algorithm become more trustable as indicators of the actual charging load; this however will not adversely impact the essence of the proposed algorithm.

Two major shopping centers in Winnipeg are considered as the case studies. All recorded parking events in these two locations are extracted from the data-set and their statistical characteristics (e.g., parking time, duration, number, etc.) are extracted and used as attributes of parking events in these shopping centers. The large number of parking events recorded (from different participants with the said demographic characteristics) in each of the two locations provides reasonable confidence about the parking trends in these two locations [58].

Weekday and weekend data are analyzed separately as their corresponding driving patterns are different [15], which in turn will lead to a different expected charging load during weekdays and weekends.

Figures 3-1 and 3-2 illustrate the probability distribution of parking time at the two shopping centers. The results demonstrate strong similarity for both locations. However, the curves for shopping center 1, which has a larger sample size, are somewhat smoother than those for shopping center 2.

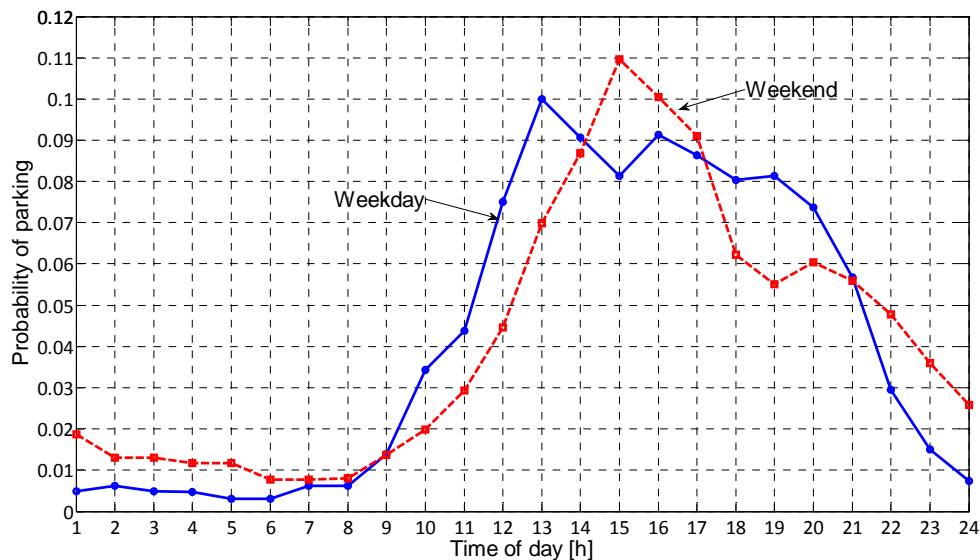


Figure 3-1 Probability of parking for shopping center 1 for weekday and weekend

Moreover, Table 3-1 provides the cumulative probabilities of short duration parking events (considered to be up to 2 hours) at these malls. The results indicate that short-duration parking events occur more frequently on weekdays than on weekends; however, most parking incidents on both weekdays and weekends tend to last less than 2 hours.



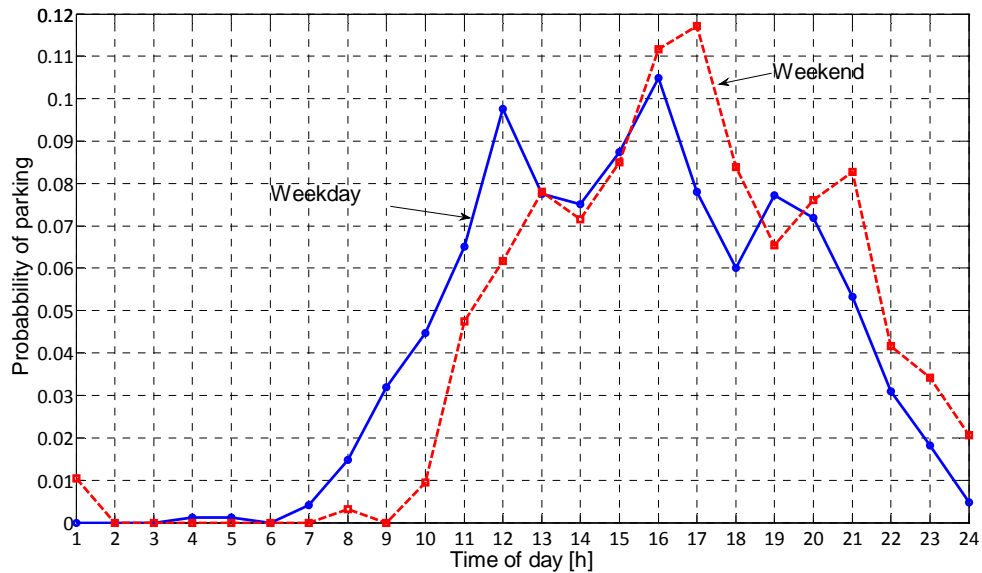


Figure 3-2 Probability of parking for shopping center 2 for weekday and weekend

Table 3-1 Cumulative probability of the short duration parking at shopping center 1 (top) and shopping center 2 (bottom)

Day type	Duration		
	≤ 30 min	≤ 1 hour	≤ 2 hours
weekday	39%	60%	84%
weekend	30%	56%	80%

Day type	Duration		
	≤ 30 min	≤ 1 hour	≤ 2 hours
weekday	45%	69%	93%
weekend	32%	60%	82%

### 3.3 Vehicle subsystem models

A backward vehicular model [6] is developed to calculate the mechanical energy ( $E_m$  in Joules) used by the vehicle in each trip (defined as the distance travelled between any two

consecutive stops). This model is based on Newton's second law of motion and is shown in (3.1)-(3.4) below.

$$E_m = \int_{t_0}^{t_{end}} P_m \cdot dt \quad (3.1)$$

$$P_m = F_p \cdot v \quad (3.2)$$

$$F_p = m_v \frac{dv}{dt} + F_a + F_{roll} + F_g \quad (3.3)$$

and

$$\begin{cases} F_a = \frac{1}{2} \rho \cdot A_f \cdot C_D (v - v_w)^2 \\ F_{roll} = 0.01(1 + \frac{v}{100}) \cdot m_v \cdot g \cdot \cos \theta \\ F_g = m_v \cdot g \cdot \sin \theta \end{cases} \quad (3.4)$$

where,  $P_m$ ,  $v$ , and  $F_p$  are the instantaneous mechanical power (W), speed (m/s), and propulsion force (N), respectively.  $F_a$ ,  $F_{roll}$ , and  $F_g$  (all in N) are the aerodynamic drag, rolling force, and grading resistance, respectively.  $\rho$  is the air density ( $\text{kg/m}^3$ ),  $A_f$  is the frontal area of the vehicle ( $\text{m}^2$ ),  $C_D$  is the aerodynamic drag coefficient,  $v_w$  is the tailwind speed (m/s),  $\theta$  is the road grade, and  $m_v$  is the vehicle mass (kg). In the simulations presented in section 3.4, the road grade and the wind speed are set to zero.

The total required electrical energy from the battery can be calculated using the consumed mechanical energy, the contribution of regenerative braking, and the efficiencies of different drive train components, as shown in (3.5).

$$E_e = \frac{E_m}{\eta_T \cdot \eta_M} - E_{reg} \cdot \eta_G \cdot \eta_{reg} + E_{H/C}(T) \quad (3.5)$$

where  $E_e$  is the total electrical energy (from the battery) and  $E_{reg}$  is the total regenerative energy (mechanical) during a trip.  $\eta_T$ ,  $\eta_G$ ,  $\eta_M$ , and  $\eta_{reg}$  are efficiencies of the vehicle transmission system, generator, motor, and regenerative braking system respectively.  $E_{H/C}(T)$  is the amount of energy consumed for heating or cooling (air-conditioning load) the vehicle cabin in a trip, which will depend, at least partly, on the ambient temperature  $T$ . Note that other factors such as a driver's choice and the action of the vehicle controller may impact the amount of heating/cooling power consumed.

The change in the electrical energy manifests itself as a variation of the SOC of the battery. It is, therefore, necessary to determine the battery SOC given the electrical energy transactions. A simplified expression [59] for calculating the SOC is given in (3.6).

$$SOC = SOC_0 - \frac{100}{3600 \times C_b \times V_b} \cdot E_e \quad (3.6)$$

where  $SOC_0$  is the state of charge at the beginning of the trip,  $V_b$  is the nominal terminal voltage of the battery (V), and  $C_b$  is the capacity of battery (Ah). To account for the losses that occur during grid charging (ac-dc converter, plug, etc.) an efficiency figure of 90% is applied to the drawn power.

## 3.4 Simulation results

The simulation results in this section show the probability of charging for both weekday and weekend in the two shopping centers. As an example of the load forecasting procedure shown in Figure 2-1, the expected vehicular load in one of the locations is shown. The simulation results also include level-1 and level-2 charging scenarios.

### 3.4.1 Simulation setup and vehicle specifications

In the simulations presented it is assumed that vehicles leave home fully charged (with SOC = 85%). This is because the typically long overnight downtime of the vehicle is adequate to fully charge its battery. It also conforms to the underlying assumption that home is the preferred location for charging. During daily trips, the SOC of the battery may decline down to a minimum of 15%. Although charging may be available to some PEV owners at other places (such as work place) to create the worst-case scenario no charging is considered in other off-home locations prior to arriving in the locations of interest.

Equations (3.1)-(3.5) show that specifications of a vehicle have a significant effect on its required energy. In relation with the required energy, the battery capacity determines the variations of the SOC. The battery capacity also directly impacts the all-electric range, which is a determining factor in the DTH input to the fuzzy system.

In this study three types of plug-in vehicles, namely the Toyota Prius plug-in hybrid, the Chevrolet Volt and the Nissan Leaf, are considered. The Prius and the Volt are representatives of PHEVs with light-duty and heavy-duty battery storage, respectively. Nissan Leaf represents EVs with higher capacity of battery storage (in comparison with PHEVs, which have the option of switching to gas).

Some adjustments to the developed decision making procedure are required to meet the special conditions of Nissan Leaf (or other battery electric vehicles, if considered); i.e., it is assumed that if there is doubt whether or not the remaining SOC is adequate to

drive the vehicle home, the driver will have to charge the battery. This primarily affects conditions when the SOC is ‘Low’ or ‘Medium’ and the DTH is ‘Long’.

Table 3-2 shows the specifications of the three vehicles considered in the simulation, as well as the efficiencies for drive train components. Although the efficiency of drive train components do vary depending to the operating conditions, an assumption of constant efficiency figures is commonly made in high-level vehicular studies [60]-[61], and is therefore adopted here as well.

A constant value of 500 W is used to approximately represent the heating/cooling power or additional electrical loads onboard. Note that an accurate characterization of the actual heating/cooling power requires data that is not reliably quantifiable, and also that the  $E_{H/C}$  is only a small portion of the consumed energy during a trip and hence the impact of its *variations* on the SOC are small. The analysis in Section 2.4 showed that the probability of charging has only modest sensitivity to SOC variations, and hence the use of a constant value will not be detrimental to the validity of the results shown.

**Table 3-2 Vehicle and drivetrain specifications**

Parameter	Prius	Volt	Leaf
Curb mass (kg)	1436	1715	1535
Frontal area (m <sup>2</sup> )	2.23	2.13	2.27
Drag coefficient	0.26	0.29	0.29
Battery capacity (kWh)	4.4	16.5	24
All-electric range (km)	18	61	117
Efficiencies of drivetrain components			
Generator	Motor	Transmission	Reg. braking
0.8	0.8	0.85	0.7

### 3.4.2 Weekday/weekend probability of charging and load

The SOC, PD and DTH attributes for every parking event at the selected shopping centers are given to the fuzzy system to generate a probability of charging. The value of probability for each parking event contributes to the average probability for the hour the parking occurs. If parking continues to the next hour(s), the same probability of charging will be carried to the next hour(s) as long as the battery is not fully charged.

Figures 3-3 and 3-4 show the predicted average probability of charging in every hour for the two locations during a typical weekday and weekend, respectively. The value of probability in each hour indicates the percentage of the vehicles that are parked during the given hour and will charge. It is calculated by taking the average of all charging probabilities associated with the recorded samples during every hour. As can be seen in Figures 3-1 and 3-2 the probability of parking during the early morning and late night hours is small. This implies that negligible charging is expected during these hours. Therefore, in the calculation of the probability of charging (Figures 3-3 and 3-4) an average probability of zero is assigned to them.

As shown in Figures 3-3 and 3-4, the value of probability is mostly dependent on the type of vehicle (i.e., the capacity of their battery storage). The probability of charging for light-duty battery storage (e.g., Prius plug-in) is much higher than the other two. It is due to the fact that in most cases such vehicles arrive with nearly depleted battery. The substantially lower probability of charging for the Volt and Leaf at these off-home locations is an indication that the daily mileage of these large-capacity vehicles (prior to arriving in the shopping centers) is likely to be much less than their all-electric range; this implies

that these vehicles will likely receive the main part of their charging demand during home plugging.

Apart from the probability for charging, in order to predict the potential peak load (kW) and energy demand (kWh), the number of parking events that occur during the day, their duration, and distribution among different hours must also be known (Figures 3-1 and 3-2).

As an example of the prediction process, the potential peak load is calculated at shopping center 1 for both weekday and weekend. This example shows how the probability of charging curves in Figures 3-3 and 3-4 enable calculation of the peak load for any given number of parking events, types of vehicles, and market penetration levels of PEVs. In particular, with an assumption of 20% penetration level of PEVs, and an average daily number of parking events in shopping center 1 equal to 10,000 it is expected that 2,000 PEVs will arrive and park in this shopping center each day. As seen in Figure 3-1, at 4 PM, the probability of parking is equal to 9% for a weekday, implying that  $2,000 \times 0.09 = 180$  of the PEVs are expected to be parked at this particular hour. It is further assumed that of the PEVs, 35% are light-duty (similar to Prius), 35% are heavy-duty (similar to Volt) and 30% are all-electric (similar to Leaf). The number of PEV types as per the assumed breakdown will therefore be 63 Priuses, 63 Volts and 54 Leafs. The probabilities of charging at 4 PM for each PEV type is then read from Figure 3-3(a) as 47% for the Prius, 20% for the Volt and 13% for the Leaf. With a nominal power of 1.8 kW for level-1 charging (with unity power factor), this results in an expected charging load of  $(63 \times 0.47 + 63 \times 0.20 + 54 \times 0.13) \times 1.8 \text{ kW} = 88.61 \text{ kW}$ . Similar calculations can be repeated for other hours.

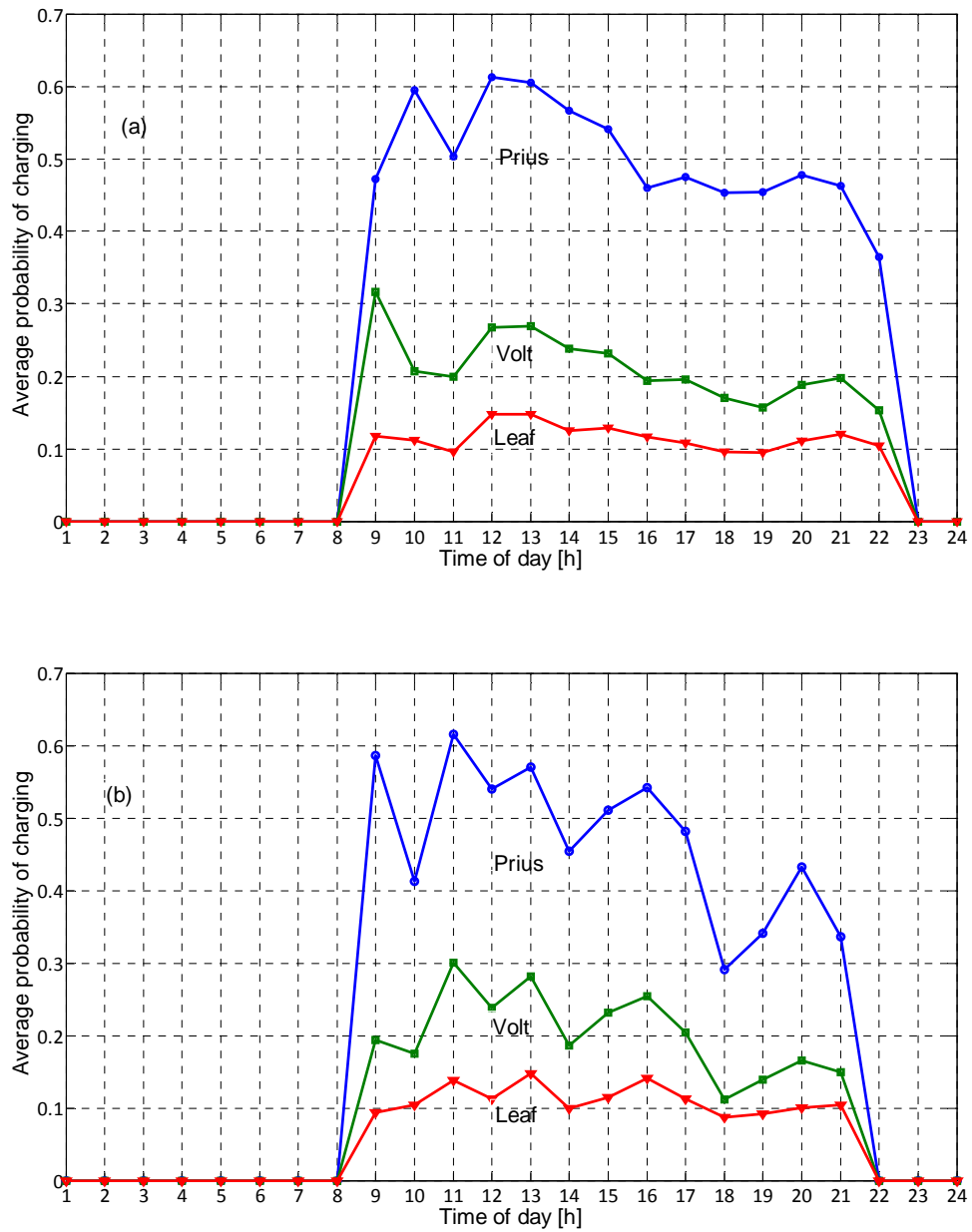


Figure 3-3 Average charging probability for weekday (level 1) a) shopping center 1, b) shopping center 2.



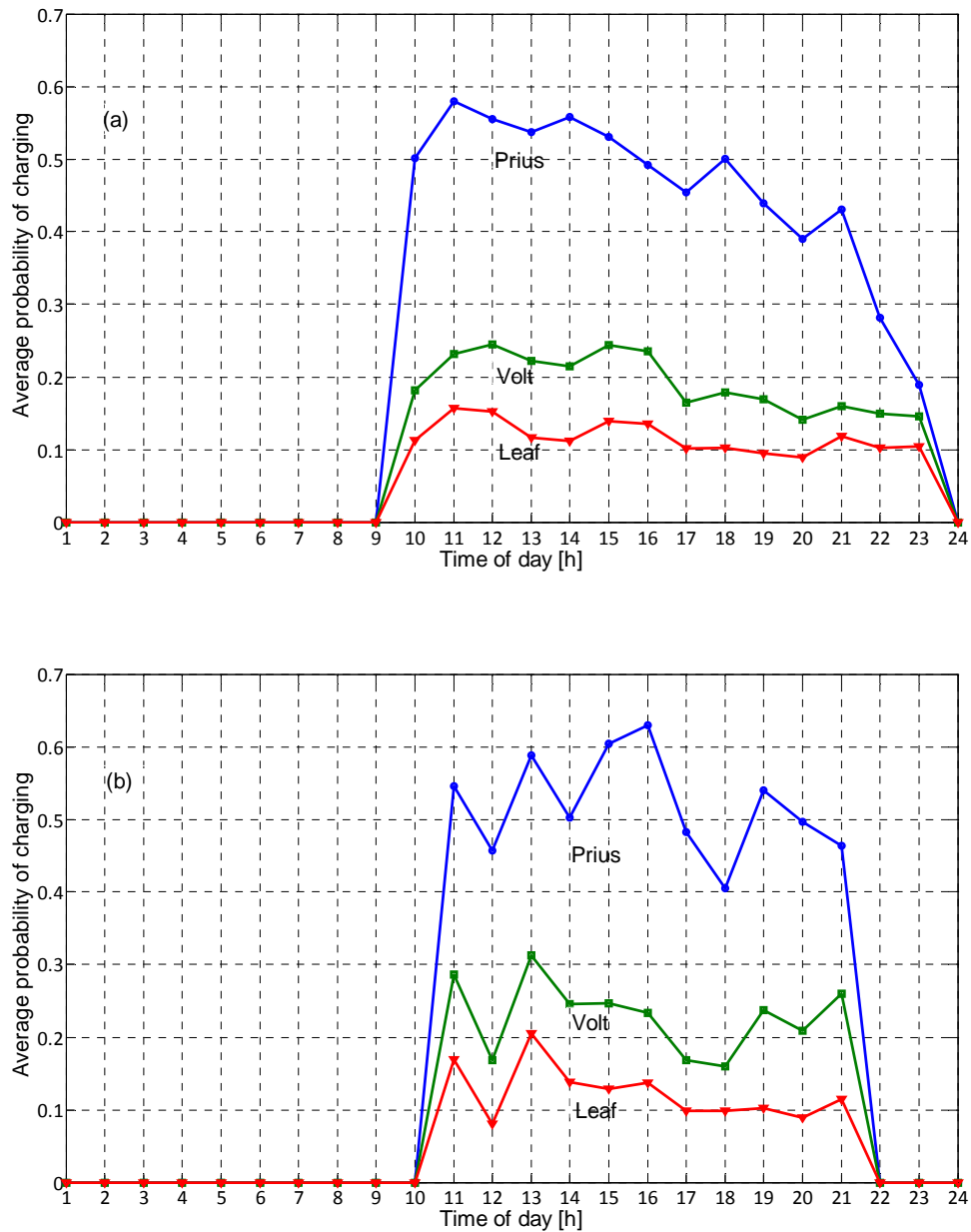


Figure 3-4 Average charging probability for weekend (level 1) a) shopping center 1, b) shopping center 2.

The expected peak charging power, as a function of time, for shopping center 1 for both weekday and weekends are shown in Figures 3-5 and 3-6 (the traces labeled ‘expected’) for the assumed penetration level and breakdown of PEV types. The procedure

can be easily used to consider other PEVs, other penetration levels or other composition of PEV types according to market acceptance of specific vehicle types in different jurisdictions. The procedure can also be adopted to analyze the charging load for each individual day of the week if adequate samples are available.

Figures 3-5 and 3-6 each also show two additional traces labeled as ‘lower’ and ‘upper’ around the ‘expected’ peak power. These curves show the average upper and lower bands of the expected charging power for a given level of uncertainty in the input parameters. As mentioned in Sections 2.3.5 and 2.4 factors such as temperature variations, aging, measurement error, etc. may contribute to uncertainty in the inputs to the fuzzy engine and thereby impact the predicated charging load. In this section simultaneous random variations in the inputs around their nominal values for each parking event are considered and their collective impact on the charging load is evaluated. In particular, for every parking event a randomly selected change (of up to 20%) is applied to each input with a directional consideration for the SOC and DTH inputs. In particular two sets of experiments are conducted; the first set considers random changes in the positive direction for the SOC and negative direction for the DTH input (e.g., resulting from a chance of charging before or after the event), yielding the ‘lower’ probability of charging. A second set of experiments is done with negative changes in the SOC and positive changes in the DTH (e.g., due to severely cold temperatures), leading to the ‘upper’ probability of charging. Each experiment consists of 1000 number of randomly and directionally changed samples of each parking event involved. The relatively tight placement of the two bands around the ‘expected’ trace is an indication of the model robustness to inevitable variations of the inputs.

The predicted vehicular charging power must be added to the present load profile to obtain the total peak power at the location of interest. This will be necessary for planning of the distribution network to decide about augmentation of network assets to prepare for the potential vehicular charging demand.

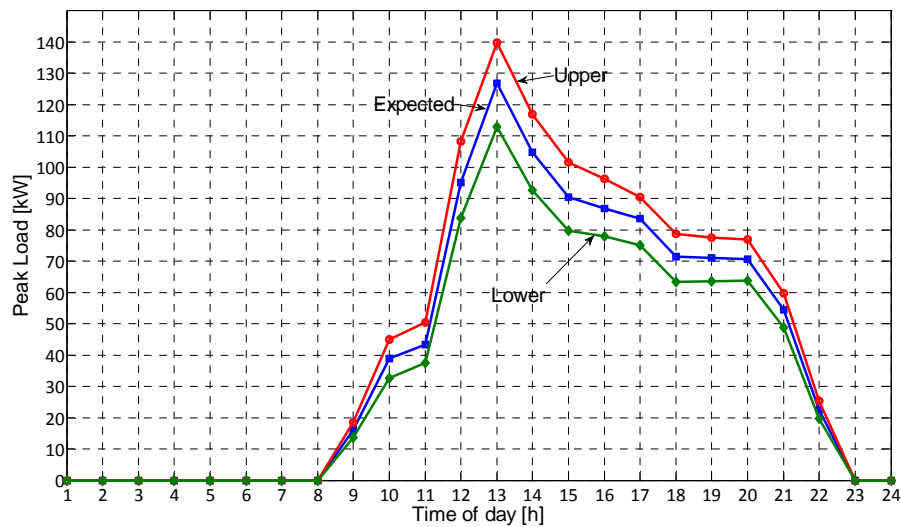


Figure 3-5 Peak power at shopping center 1 during a weekday (level 1 charging) for 2000 PEVs.

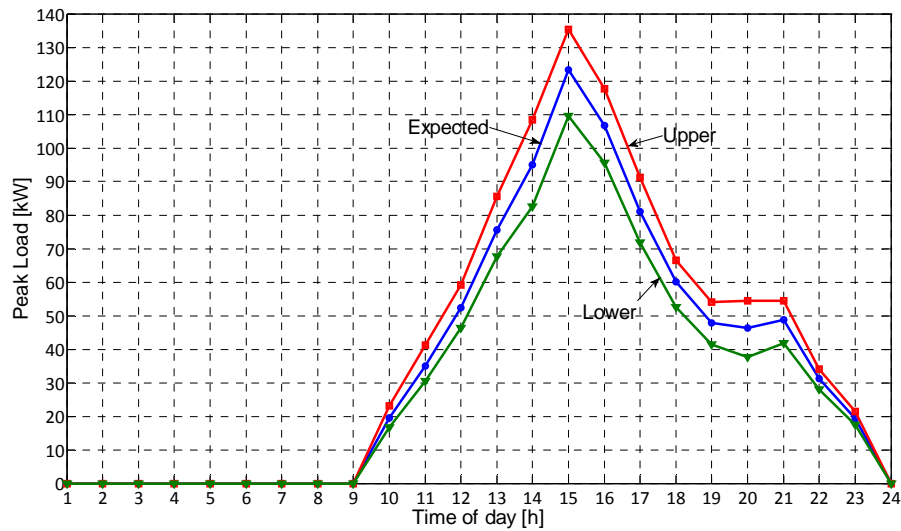


Figure 3-6 Peak power at shopping center 1 during a weekend (level 1 charging) for 2000 PEVs.

### 3.4.3 Probability of charging and demand for fast charging

To examine the impact of fast charging on the potential load demand, the feasibility of level-2 charging (240 V, up to 30 A) is also considered at shopping center 1. The membership functions for the PD variable of the fuzzy decision making unit (section 2.3.2) need to be modified, as the linguistic terms Short, Average, and Long are defined based on the charge that can be received by the battery in a certain time interval. This increases significantly with a level-2 charger over the same period of time. All other parts for calculating the probability of charging remain unaffected.

Figure 3-7 displays the probability of charging using a level-2 charger at shopping center 1. The general shape of these probability curves are not drastically different from those for level-1 shown in Figure 3-3(a), despite the effective change in the PD. This is due to the fact that the charging decision is mainly dependent on the two other factors (i.e., DTH, and SOC), which remain unchanged. The implications of level-2 charging on the peak power, however, are significant as seen in Figure 3-8, which shows the peak charging load under the same conditions as in Figure 3-5. As seen, the ‘expected’ peak power steeply rises to 620 kW (as opposed to just under 130 kW in level-1 charging). The power remains significantly higher than level-1 charging for the entire duration of time. ‘Upper’ and ‘lower’ bands similar to the ones in Figure 3-5 are also shown.

Figure 3-9 demonstrates the hourly “average” load demand curves for the two levels of charging for shopping center 1 and for the considered composition of PEVs. They are obtained by considering the duration of each parking event for as long as charging continues. These curves are indicators of the expected energy demand for every hour. For

example, the curve for level-2 charging shows an average load of around 400 kW at 1 PM. This indicates that the charging vehicles between 12 noon and 1:00 PM are expected to receive 400 kWh of energy.

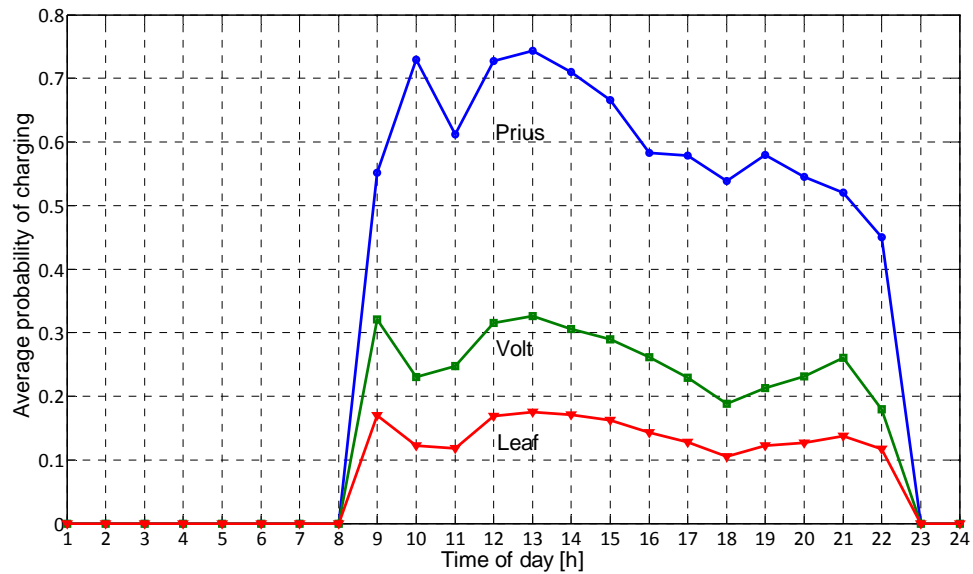


Figure 3-7 Average probability of charging (weekday, shopping center 1, level-2).

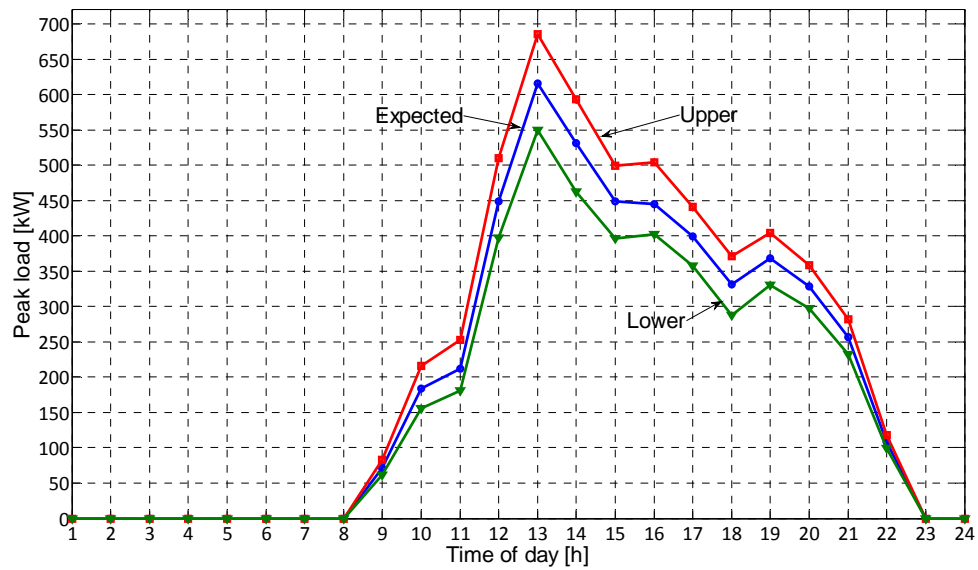


Figure 3-8 Peak power at shopping center 1 (weekday, level 2) for 2000 PEVs.

It is observed from Figure 3-9 that the expected energy demand for level-2 charging will be much higher. Additionally, it is seen that its variations are much steeper. This is due to the fact that PEVs connected to a level-2 charger will draw large amounts of power over a short period of time and disconnect when fully charged, which suddenly drops their power demand by a large amount. This is particularly true for light-capacity PEVs (such as the Prius) whose battery can be charged from a level-2 charger in less than half an hour.

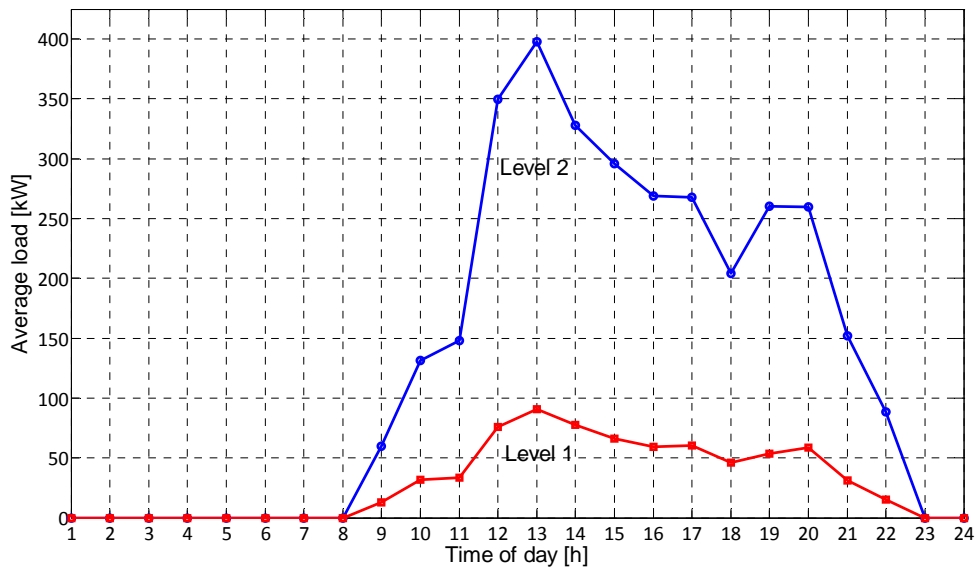


Figure 3-9 Average load demand in shopping center 1 for level-1 and level-2 charging (weekday) for 2000 PEVs.

A quick analysis of the parking events in shopping center 1 (Table 3-1) shows a large number of short-duration parking events (lasting less than 1 hour). While level-1 charging may not provide a substantial amount of charge for such parking events, level-2 charging is appreciably more beneficial. The large amount of energy received from a level-2 charger will alleviate part of the PEVs' needs when these vehicles arrive home

and are plugged in overnight. This may in fact assist in reducing the impact of coincidental charging on the distribution network in residential areas.

The foregoing analysis of level-2 charging is done with the assumption that the cost of charging is not affected significantly by the charging level. In reality level-2 charging is likely more expensive than level-1 charging. As it was explained in Section 2.3.5, it is possible to include the effect of the price of charging in prediction of the probability of charging by adjusting the DTH input. Despite this, the given analysis is still valid because it shows the potential increase of the load should level-2 charging be made available. It can also be used in deciding whether level-2 charging is economically viable, given the revenue that can be obtained from the sale of the extra energy.

## 3.5 Conclusions

Implementation of location-based vehicular load forecasting was carried out in this chapter. The fuzzy system produces an average probability of charging curve (e.g., Figure 3-3), which together with a probability of parking curve (e.g., Figure 3-1) can be used to predict the vehicular charging load due to any perceived combination, number, and type of plug-in vehicles. Central to this is the availability of data for driving and parking that best characterize the local patterns. The general procedure outlined in Figure 2-1 can be easily adopted for any other location, any day-type or season, as long as reasonably reliable driving samples are available.

Note that since plug-in vehicles are still in their early stages of entering the market, there is no large-volume tagged (measured) data pertinent to the charging behavior of

PEV owners. Hence it is not directly possible to fully validate the proposed model and the associated predictions of charging load; however the sensitivity analysis results presented in Chapter 2 demonstrate the ability of the model in realizing the assumptions underlying its design.

Utilities can affect the charging demand by proper coordination of (i) offering fast chargers, which change the effect of the PD input on the received charge, and (ii) regulating tariffs, which in effect change the DTH input. The results such as the ones produced in this chapter (Figures 3-5, 3-6, 3-8 and 3-9) along with other economic and technical considerations can be used in the planning of the scale, location, and type of charging infrastructure, and whether upgrading network assets will be required in providing such service.



## Chapter 4

# Distributed Control of Charging Demand at Residential Areas

### 4.1 Introduction

Residential nodes of the distribution network are the most vulnerable part of the power system to charging demand of upcoming PEVs. On the one hand, home-charging is the dominant mode of charging due to its convenience and (in most cases) cost-effectiveness; on the other hand, power network assets at residential areas have the lowest capacity and highest coincidence factor. Uncertainty in forecasting the charging behavior as well as the penetration level and distribution of PEVs must also be added to the challenges of the vehicular loading issue. Therefore, there is an urgent necessity for comprehensive investigation of the influences of the charging load of PEVs on the distribution network at its residential nodes (i.e. stationary vehicular demand as described in Chapter 1) in advance of the vast adoption of electrified transportation.

Forecasting the temporal behavior of the stationary vehicular demand is the main challenge; unlike the mobile portion of the charging demand, spatial forecasting is not an issue in this case, as it is highly expected that the majority of PEV owners receive all or major portions of their daily battery energy requirement during their home parking.

Generally, from the power system planning point of view, battery storages can be seen as potential time-flexible (or simply flexible hereinafter) loads whose attributes (i.e. intensity and period) depend on each individual customer's commute requirements. Flexible loads play a critical role in modern techniques of load dispatching in future power systems. In [32], some of the main issues regarding real-time demand dispatch for modern power systems are elaborated. In traditional dispatching with conventional generation and old-fashioned systems and loads, to preserve frequency and voltage within their specified bounds, generation is supposed to follow the changes in the load. However, in a modern power grid with an appreciable level of penetration of distributed renewable energy resources, due to uncertainties associated with their availability, rapid commanded changes in generation are not necessarily doable; hence secure performance of the grid requires high amounts of spinning reserve. Therefore, the idea of reversing the dispatching direction comes to the picture wherein the loads follow (at least in part) the generation in order to maintain the stability of the system.

In order to implement this idea, first it is needed to identify potential controllable and flexible loads within the power system. Flexibility of a load means there is flexibility in the timing of its demand because it is not as critical as other loads; therefore, it can be delayed while there is shortage in generation or be demanded with full strength during high generation periods. For example, for a residential customer, lighting and air conditioning

loads are considered as critical loads that cannot be shifted; while clothes dryer loads can be shifted to off-peak hours, and hence might be classified as flexible loads [69], [70].

The controllability attribute of the load is part of the smart grid concept, which strives to make monitoring the states and controlling the power system in different voltage levels more intelligent. In a smarter network, customer-side responses can also be included in the decision making processes towards improvement of the performance of the grid as well as satisfaction of customer's energy requirements. This subject has also attracted several control and stability studies in the micro-grid field [62], [63]; that is, reliable performance of micro-grids, especially during the transient conditions such as loss of the main source, requires controllability of shedding at least part of the non-critical (i.e. flexible) loads.

Charging demand of the battery storages of PEVs are among the most probable flexible loads in future intelligent power systems. As the focus of this chapter is on the charging demand of PEVs on the residential distribution network, it is assumed that battery storage is the only flexible load of each household with a PEV; however, in reality any other load defined by a customer can be added to the class of flexible loads, and this study remains valid for the total predefined flexible load.

In Chapter 1 a general review of studies undertaken by several research groups mainly during the last five years was presented. Indeed, this issue has been approached from different angles with different strategies aiming to address various objectives and concerns of utility services and customers regarding the influence of the PEV charging demand. What the adverse effects of uncontrolled or unsupervised charging of PEVs at home will be, and which profile of charging is the most suited, are the main common

questions all of these research efforts have strived to answer [25]-[30]. These works differ in their control strategies applied to determine PEVs' charging profile, reliable implementation of the suggested methods, and specification of incentive factors (in most cases electricity tariffs) in a way to make abiding by the developed techniques convincingly beneficial.

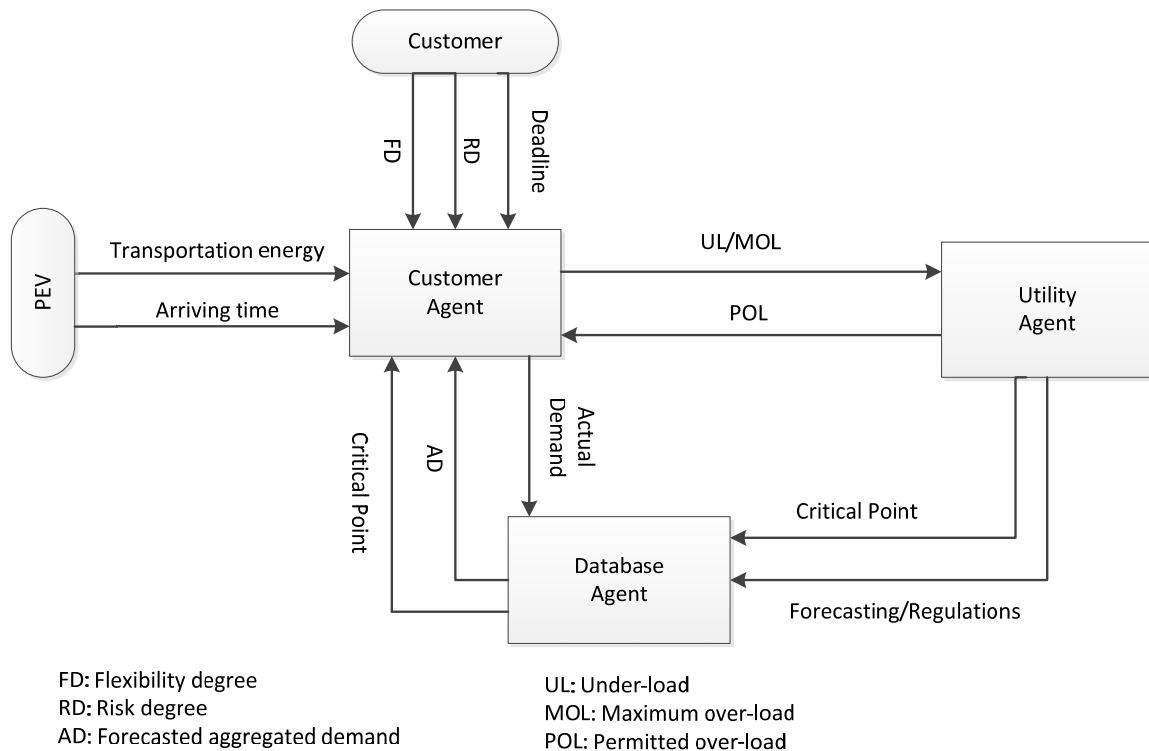
Performance validation of these methods is also accomplished differently in terms of specification of the amount and timing of the vehicular load. Deterministic, stochastic (employing real-world driving data) and custom combinations of the two are approaches deployed by researchers to demonstrate such vehicular load attributes as the charging period, the charging rate, and the amount of charging energy.

All of the efforts for managing the PEV charging load in the power system are aimed to postpone upgrading of the network assets; however, it should be noted that, as any solution for this problem is a planning for the future smart grid, there is not an absolute "best" technique that excels others in all aspects. In fact, the validity of a method at this stage can only be evaluated based on the reasonability of its underlying assumptions as well as sensibility of the results that demonstrate the method's performance.

A comprehensive comparison between two dominant control strategies, namely centralized and decentralized, was also presented in Section 1.2.2. Due to the attractive features of decentralized control schemes and the appropriate compatibilities of multi-agent systems with the future smart grid, the latest focus of research on the vehicular loading issue has been on this approach [40]-[43]. The specification of time-variable tariffs based on the variation of aggregated load and proposing non-cooperative game-based strategies

to realize the equilibrium point for final charging profile are common attributes of corresponding researches [41], [64].

In this chapter a novel decentralized control algorithm is proposed to determine a suitable and realistic charging profile for PEVs in a residential distribution network. The overall goal of this algorithm is to satisfy customers' charging needs while meeting the utility's operating constraints. The algorithm is designed to be implemented by a multi-agent system. In the following sections, the development and rationales of the proposed control algorithm are elaborated. The actual agent-based implementation and its associated considerations [65] such as architecture, communication language, coordination protocols, content language and ontology are not investigated in this thesis.



**Figure 4-1** Block diagram of the developed charging demand scheduling algorithm

Figure 4-1 demonstrates the block-diagram of the proposed control strategy. It should be noted that the control algorithm is performed in two stages with a complex timing manner for input and output parameters. The next section is devoted to elaborate various parts of the algorithm and the logics underlying its design with a comparative approach to other existing methods. In Section 4.3 a detailed account of the algorithm along with a customized example are presented.

The developed algorithm is simulated for a distribution system case-study in Chapter 5, which includes the specifications of the test-case distribution network, attributes of the employed driving data and residential load as well as results and discussion. Complementary clarification of features of the developed algorithm and conclusions are also presented in Chapter 5.

## 4.2 Logics of the proposed algorithm

The main aim of this section is to explain the logics behind different steps of the proposed algorithm in Section 4.3. At the same time some short-comings associated with other counterpart studies are discussed and corresponding improvements to address such short-comings in the proposed method are presented.

In the diagram of Figure 4-1 the main participants of the proposed charging scheduling algorithm and their associated actions are depicted. These include:

- 1) Customer agent (CA), serving as the intelligent representative of a customer perusing his/her benefit according to predefined objectives (e.g. receiving the desired charge by the specified deadline and with minimum possible cost) using available data.

2) Utility agent (UA), serving as the representative of the utility service aiming to satisfy the grid's performance criteria (e.g. enhancing the grid's asset utilization to postpone their upgrading) while monitoring the network's actual state in all nodes.

3) Database agent (DA), which might also be considered as a part of the utility, is a data access point for both the UA and all CAs. DA mainly serves as a medium between UA and CAs.

In the following subsections, the underlying logics of the developed algorithm and the function of each agent are presented.

#### 4.2.1 Overall agenda of the proposed scheduling algorithm

In the developed distributed control algorithm, scheduling of charging is accomplished in two independent stages. In the initial stage UA and CAs all pursue their own objectives with reliance on the *forecasted demand* and in the ensuing stage they modify their initial plan according to the *actual status of the demand*.

In order to begin with the explanation, it is essential to firstly define the time intervals in which the scheduling algorithm aims to determine the amount of flexible (charging) power; the 24 hours of a day are divided into a certain number of equal intervals. For example in the simulations of this study (presented partly in this chapter and also in Chapter 5) the interval is selected to be 15 minutes; so there are a total of 96 intervals throughout a day. Therefore, the scheduling problem for an individual customer is to specify the flexible demand during every interval within his/her available charging period.

In the initial stage of scheduling, which is done individually and uniquely for each customer, each CA calculates the initial charging plan of its associated customer accord-

ing to predefined tasks as well as input parameters received from its social environment (i.e. database agent).

As it is shown in Figure 4-1, the customer defines his/her objectives by means of three parameters of (i) deadline, (ii) risk degree (*RD*), and (iii) flexibility degree (*FD*) and delivers them to the CA. The amount of the required charge also depends on customers' transportation energy consumption and can be realized based on the state-of-charge (SOC) of PEV's battery upon arrival. Furthermore, the parameters reflecting the utility's objectives (i.e. forecasted aggregated demand (*AD*) and critical point (*CP*) of demand) are accessible through the database agent. The implication of these parameters is elaborated in detail in Sections 4.2.2 and 4.2.3.

All of the employed load data in this stage of planning are forecasted states of the system obtained from historical data; therefore the initial stage of this study is called the static stage, in order to differentiate it from the ensuing dynamic stage that is carried out in real-time (i.e. every charging interval). The dynamic stage uses information of the actual states of the grid to fortify the static stage; thus the dynamic stage requires active communication between UA and all CAs.

In the dynamic stage of scheduling, the UA which has dominant social intelligence receives signals based on the status of individuals' demands (i.e., *UL/MOL* in Figure 4-1) from all CAs, who are willing to modify their plan for the sake of better satisfaction (i.e. less cost), and sends back signals based on the status of the aggregated demand (*POL* in Figure 4-1) aiming to enhance the target asset's utilization. Section 4.3.3 is dedicated to detailed elaboration of the dynamic stage.



### 4.2.2 Utility service objectives: logics and specifications

Generally, a residential distribution system (e.g. Figure 5-2) starts from a slack bus connected to a step down transformer with a certain capacity and voltage level. This sub-network is designed and planned to feed a certain number of customers mainly with respect to their present peak demand, load growth, and future expansion. Moving downstream in the network and closer to customers, capacities of assets and thus their security margins reduce. For example, the closest transformer to the customer is responsible for a small number of houses, and any deviations from individual estimated load behavior will have more severe effect on the aggregated demand on this lower rating, less tolerant asset. Therefore, after addition of charging load due to PEVs, in most cases, the first constraint will take place at the utility asset that is the closest to customers prior to reflection of its aggregated effect on a higher-level distribution network.

Consequently, in the proposed algorithm, preserving the peak demand (on the most vulnerable asset) as it is currently for the base (i.e. critical, uncontrollable) load, is considered as the utility's main objective. As this peak value is the main criteria for specification of the network assets' capacity, the chosen objective equivalently aims to enhance the load factor ( $LF$ ), defined in (4.1), and utilization of assets. Valley filling techniques follow the same goal as well, aiming to fill the valleys of the demand curve with vehicular charging load.

$$LF = \frac{D_{av}}{D_{max}} \quad (4.1)$$

where  $D_{av}$  and  $D_{max}$  are average and maximum demand on the asset throughout a day respectively.

Moreover, in [25] it is proven that maximizing the load factor is equivalent to minimizing the load variance, and approximately (except in a single line case with all loads at the end of the line for which the exact minimum is achieved) minimizes losses in the distribution network.

From the utility's point of view, a reliable algorithm should be able to utilize maximum capacity of the grid by efficient management of the flexible charging load. At the same time, a complete plan should be capable to reliably detect the necessity for upgrading upon inability of the technique in satisfying the objectives of utility and customers.

Although in most cases having a smooth demand curve throughout 24h is desired by the utility service, shortage of generation in some hours of the day might change the utility's objectives within a period; therefore, the algorithm should have adequate flexibility to meet generation restrictions when it requires the customers to follow a certain load profile at a specific node.

Customer-side responses play a crucial role in the implementation of any planning technique in the future smart grid; moreover, success of all of these planning efforts depends on what extent the aggregated reactions of associated customers is similar to the utility's desires. In other words, the average of individual customer's goals must be in line with the overall utility's goal in order to have a successful plan.

Time-variable tariff is the most commonly used parameter in studies in this area, as an incentive to make following the desired load profile beneficial for customers [41], [43], [64]. In these methods the aggregated demand curve determines the price of elec-

tricity; therefore, demanding the flexible load (PEV charging in this study) during the peak hour will be costly. In fact under conventional time-variable tariff, a customer has to pay more while the majority of people will demand highly, even if his/her own demand is low. This strategy might be considered as the best possible solution now and prior to the time when the power grids become practically more intelligent to monitor every node and customers' behavior; however, when customers' responses are actually included in the control procedure, which is the case in most researches in this field, it will not be fair to penalize one due to others' actions.

The alternative to the incentive factor in the proposed algorithm is assigning an equal share from the target asset's capacity to all customers fed by the same asset of the network. This allocation is named Critical Point (*CP*), and for every time interval it is determined based on the first constraint of the system performance and forecasted aggregated base load. In Section 4.3.2 the details of the calculations involved and other practical issues are elaborated. In order to guarantee that costumers' benefit is in following the *CP* curve, a pricing scenario is designed to have a constant regular tariff for any demand below the *CP*. On the other hand, for demands over *CP*, the tariff will increase with respect to the demand to make excessive over-loading in any interval a costly action. Moreover, another penalty-reward pattern is considered to further encourage customers to demand less during the peak hours; that is, customers who consume less than the assigned *CP* can gather rewards while other customers demand more than the *CP*. These rewards can be utilized for either penalty compensation or total cost reduction. Consequently, a CA mainly strives to preserve its demand less than the appointed *CP* as much

as possible, and depending on the customer's objectives defines its strategy (see Section 4.2.3).

### 4.2.3 Customers objectives: logics and specifications

The main duty of a customer agent is to capture the customer's desires and objectives and satisfy them as far as possible. In the proposed scheme, a customer interacts with his/her agent via three parameters that serve this purpose and are, at the same time, easily comprehensible (Figure 4-1). In this section these input variables as well as the driving profile attributes are explained:

#### *1) Deadline:*

The most critical expectation from a vehicle is its availability upon requirement; it is not acceptable in most cases to delay a trip and wait until charging is completed. Therefore, a user (driver) must specify the deadline he/she wishes the battery to be charged by to a certain *SOC*. This specification can also be more complex; for example, one might want to consider some charge for urgent need by some earlier time, so the deadline specification can be a profile compromising *SOC* targets versus time.

The effect of deadline is significant in the success of the plan: a longer deadline provides more time, so less load may be demanded in each available charging interval. As a result, the utility asset can handle the additional load more easily. Moreover, the total charging cost will be less since the probability that the total demand stays below the assigned *CP* is more.

### 2) Flexibility degree (*FD*):

It indicates the degree of flexibility of a customer in his/her desired objective (i.e. amount of drawn charge by the deadline). *FD* can vary between  $[0,1]$ ; for example, a *FD* of 0.1 implies that for the sake of an overall cheaper charging cost (i.e. transportation expense), the customer agrees to charge less, by up to 10% ( $=0.1$ ) of the desired value (depending on the actual condition of the network's aggregated load). In the scheduling algorithm, if in a charging interval the total demand of a customer is over the *CP*, and the extra demand is charged (monetary) by an incremental tariff, CA takes initiative and applies *FD* to the flexible part of the load to lower the customer's excess demand (Section 4.3.3).

A customer may show flexibility for various reasons mainly for (i) having chance of off-home charging at a work place or a public charging station with cheaper price than the incremental tariff of demand over *CP* or (ii) having a heavy-duty battery storage and no need to fully charge every day if the existing charge is enough for making the next day's trips.

### 3) Risk degree (*RD*):

Every planning technique, involving estimated parameters based on historical data, has a chance of failure due to inconsistency of the actual data with their historical counterparts or error in the estimation. In fact, any vehicular load management technique, which aims to optimize utility's or customers' objectives such as minimizing the cost and maximizing utilization by using the forecasted load, is subject to failure due to this type of error. It should be noted that because the vehicular loading problem deals with assets shared among a limited number of customers (high coincident factor), the uncertainty in the

forecasted aggregated behavior is high as an individual's accidental actions will have a significant effect on the aggregated value.

In the proposed distributed control algorithm, each customer defines the level of his/her trust in the forecasted demand during a charging period, and the CA autonomously reflects it in the decision-making process. In fact, customers define the strategy of their agents by specifying their own risk hoping to achieve less charging cost. This parameter is named Risk Degree ( $RD$ ) and can vary between  $[0,1]$ ;  $RD=0$  (i.e. no confidence in the forecasted demand) implies that flexible demand scheduling is accomplished only based on the customer's own remaining capacity and independently of the forecasted aggregated demand; on the other hand,  $RD=1$  (i.e. complete trust in the forecasted demand) is interpreted as that the charging pattern should follow exactly the predicted aggregated demand in a way that minimum charging is demanded during the peak and vice versa.

$RD$  specification can be done either systematically by employing historical data to find out the optimal risk, or empirically based on one's experience. More detail about the  $RD$  is presented in the algorithm procedure along with its formulations and functions.

#### 4) *Driving profile:*

Transportation requirements of a customer also specify two other influential parameters, namely the arriving time, and the required battery charge (energy) (see Figure 4-1). Indeed, these parameters are entered in the planning procedure indirectly through customers. Besides geographical and demographical situations of the area of interest, for each vehicle the daily mileage, dynamic specification, and accessibility to off-home charging stations are influential factors on the driving profile.

## 4.3 Description of the proposed algorithm

In this section, the procedures of the static and dynamic stages of the proposed algorithm are elaborated. First the problem of scheduling the charging demand is formulated mathematically; then the role and functionality of all variables are described. Agents' actions and reactions in different circumstances are also expressed mathematically. For the sake of better clarification, a single customized case study is developed and presented step by step along with the description of the algorithm. The calculations and results from each step of the algorithm on this case study will be used in the subsequent steps of the algorithm as shown in the following pages.

### 4.3.1 General formulation

The main aim of this algorithm is to determine the demand profile of every individual customer within the time span that time-flexible load is demanded. In general, an individual residential demand has two parts of (i) uncontrollable (base, or critical) load and (ii) controllable (or time-flexible) demand. As the focus of this study is on the control of the vehicular load, in the following formulation only PEV storage will be considered as the flexible part of the demand and all other household loads will be considered as the base load.

Consider there are  $N$  customers sharing a target asset of the network (i.e. a distribution transformer) and their aggregated demand curve,  $AD$ , is predicted for 24 hours (and every interval) using conventional load forecasting techniques (e.g. time series, neural networks, etc.) [45]-[49]. As it is indicated in Section 4.2.2, the utility's main goal is pre-

serving the aggregated demand peak ( $AD_{\max}$ ), which means it can continue to supply the existing demand without having to upgrade any assets. The problem of scheduling, in mathematical form, is defined as follows.

For an individual customer  $n$ , where  $n = 1, \dots, N$ , in an interval  $t$ , where  $t = 1, \dots, T_n$ , and  $T_n$  is the number of possible charging intervals starting from the arriving time of the customer's PEV till the deadline, what is the charging demand,  $P_{n,t}$ , subject to (4.2).

$$P_{n,t} [\text{kW}] \in [0, P_{\max}] \quad (4.2)$$

where  $P_{\max}$  depends on the rating of the available plug enabling regular or fast charging. For the sake of simplicity and since the discussion will continue with a description of a single customer, the subscript  $n$  will be dropped from  $T_n$  from now on.

The amount of energy  $E_{n,t}$  [kWh] drawn from the grid in each interval will be as follows.

$$E_{n,t} = P_{n,t} \cdot L \quad (4.3)$$

where  $L$  is the length of each charging interval (the time-step in hour unit).

**Case study:** Assume that for a specific case the arriving time is at 18h, and the deadline or the intended departure time is at 6h of the next day. If the length of each charging interval is set to 15 minutes, then  $L=0.25\text{h}$ , and there are 4 intervals in each hour. As there are 12 hours available to charge the battery in this example, the total number of charging intervals will be  $T=48$ . ■

Moreover, for every customer  $n$ , the summation of  $E_{n,t}$  by the deadline  $T$  should be equal to desired charge,  $CH_n$ , considering the charger efficiency  $\eta_c$  ((4.4) and (4.5)). It



should be noted that  $EC_n$ , the effective desired charge, is subjected to reduction based on each customer's  $FD$  (see Section 4.3.3).

$$\sum_{t=1}^T E_{n,t} = EC_n \quad (4.4)$$

$$EC_n = \frac{CH_n}{\eta_c} \quad (4.5)$$

The total demand of a customer,  $TD_{n,t}$  [kW] in each interval, consisting of flexible (PEV) load and base (non-PEV) load,  $B_{n,t}$  [kW], in each interval is given as follows.

$$TD_{n,t} = B_{n,t} + P_{n,t} \quad (4.6)$$

The actual aggregated demand curve is the summation of all  $TD_n$  for  $N$  customers, which is different from the forecasted aggregated demand curve ( $AD$ ).

### 4.3.2 Static stage

The static stage of scheduling is done individually for each customer (who possesses a PEV) and begins by their agents at time zero, at the onset of the first charging interval of every customer; only one CA is considered in this section and its associated formulations and actions in different circumstances are presented next. Figure 4-2 demonstrates a flowchart of the static stage of the algorithm.

#### 1) Critical point (CP)

As it is demonstrated in Figure 4-1, besides the customers' objectives and transportation features, the critical point (CP) and forecasted aggregated demand (AD) are the other required inputs to a CA. The utility agent is responsible to provide these pieces of information.

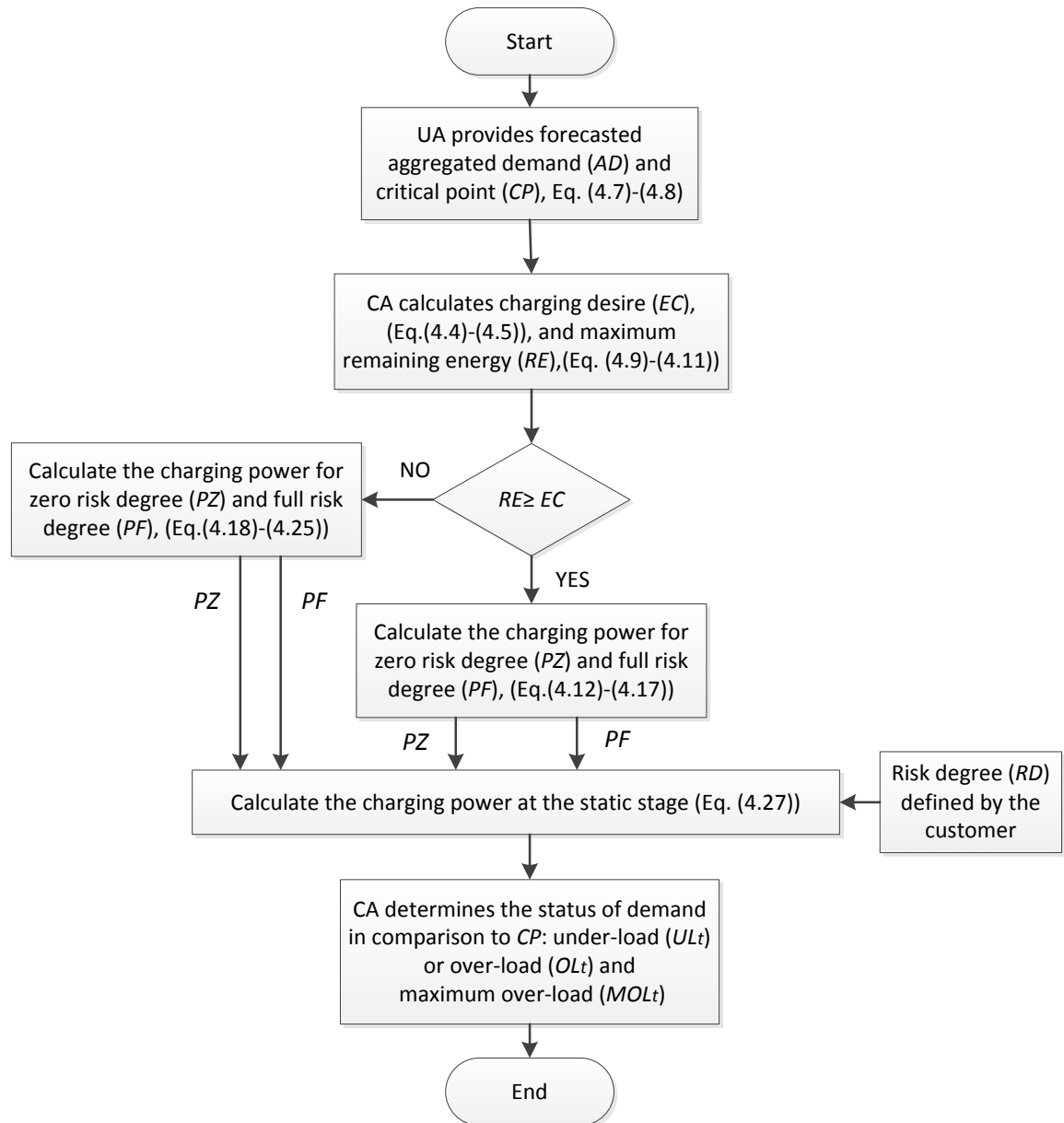


Figure 4-2 Static stage of scheduling

Critical point assigned by the UA is the principal component of scheduling. UA's goal is preserving the peak demand ( $AD_{\max}$ ) based on which the asset capacity is assumed to be selected mainly. Therefore, the utility's intention is to encourage customers to shift

their flexible load to the off-peak hours. According to the proposed strategy of pricing, explained in Section 4.2.2, regulating variable tariffs based on the aggregated demand will not be fair to all customers. Instead, the UA designates an equal share from the target asset's capacity (or aggregated peak demand) to all customers ( $CP$  from (4.7)), and charges (monetary) any demands below the  $CP$  with regular tariff and any demand over the  $CP$  with an incremental tariff. As a result, an individual customer agent can choose its own strategy to compromise between the total cost and the fulfillment of its associated customer's objectives. However, it must be noted that the utility cannot be completely oblivious to the fact that there is always more chance of overloading during peak hours; therefore, besides the pricing scenario in order to have a more secure planning, in the calculation of  $CP$ , the UA considers a security margin in each interval ( $SM_t$ ).  $SM_t$  is calculated based on the ratio of the forecasted demand in the interval  $t$  (i.e.,  $AD_t$ ) to the peak demand ( $AD_{\max}$ ), for which the security margin is maximum ( $SM_{\max}$ ) (4.8).

$$CP_t = \frac{(1 - SM_t) \times AD_{\max}}{N} \quad (4.7)$$

$$SM_t = \frac{AD_t}{AD_{\max}} SM_{\max} \quad (4.8)$$

Effectively the UA considers the fact that the chance of overloading during peak hours is higher; therefore, the critical point is set lower at such periods in order to reduce the likelihood of overloading. A proper  $SM_{\max}$  should be obtained for each node of the network depending on the capacity of the shared asset and the present peak demand as well as the collaboration level of its associated customers.

It should be noted that the  $AD$  curve, prior to the emergence of the charging demand, is forecasted only using historical data on the base-load. With an increase in the penetration of PEVs, the  $AD$  curve will naturally include the charging demand as well. In the calculation of the  $CP$  in (4.7), the role of  $SM_t$  (through adjustment of  $SM_{\max}$ ) is to allow the utility to adapt to the increasing  $AD_{\max}$  while maintain the desired  $CP$ . This is aimed at preserving the peak demand at its value prior to the introduction of the charging load.

**Case study:** Figure 4-3 demonstrates the forecasted aggregated demand for 6 customers ( $N=6$ ) at the same node within 24h. Assume that for this node of the system,  $SM_{\max}=0.1$  is selected by the UA, which takes place during the peak demand of  $AD_{\max}=16.2$  kW and at 18:15h. Figure 4-4 shows the  $CP$  curve for customers on this node, comprising critical points of demand for 96 intervals of a day in this case. For instance, at 2:00h,  $AD_t=6.4234$  kW, and thus from (4.8),  $SM_t=0.0964$ . As a result, from (4.7),  $CP_t=2.5929$  kW. ■

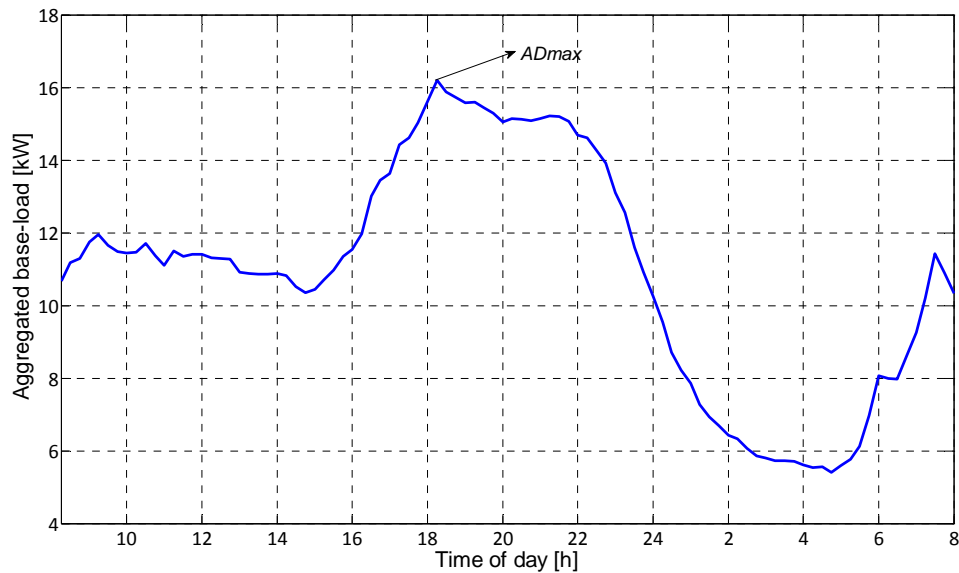


Figure 4-3 Aggregated base-load for 6 residential customers

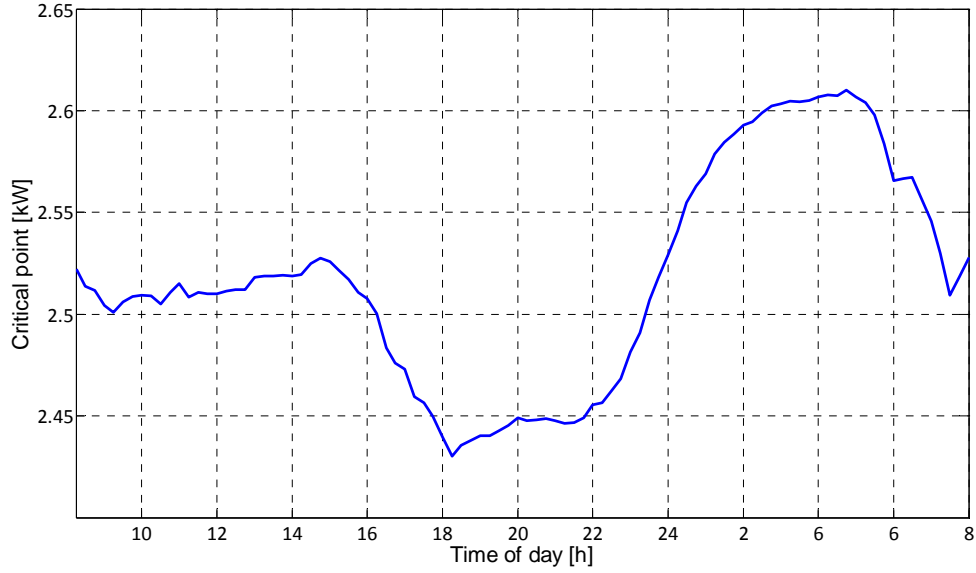


Figure 4-4 Critical points for every interval designated to each single customer

## 2) Remaining capacity (RC)

$CP$  is available at the database agent and is accessible by all CAs upon need to schedule their flexible load. CA is responsible, and the most eligible part of the control system, to estimate the base-load ( $B$  curve) of its own customer.

As a result, the remaining capacity can be obtained from (4.9) for every charging interval. Equation (4.10) gives the maximum energy ( $RE$ ) (in kWh) that can be drawn from the grid by the deadline while preserving the demand below the critical point in all intervals with positive  $RC_t$ .

$$RC_t = CP_t - B_t \quad (4.9)$$

$$RE = \sum_{t \in \mathcal{T}_u} \min(RC_t, P_{\max}) \times L \quad (4.10)$$

where  $\tau_u = \{t : RC_t \geq 0\}$ . Let  $T_u$  be the number of intervals with positive  $RC_t$ . Note that the base-load might be already over the  $CP$  in some intervals, i.e.,  $\tau_o = \{t : RC_t < 0\}$ , and let  $T_o$  indicates the number of such intervals; therefore,

$$T = T_u + T_o \quad (4.11)$$

It should also be noted that as the upper constraint of the flexible power is  $P_{\max}$ , to obtain the effective remaining energy in (4.10), the smaller of  $RC_t$  and  $P_{\max}$  is used in every interval.

**Case study:** Assume Figure 4-5 is the base-load profile of a single residential customer among the 6 mentioned customers.

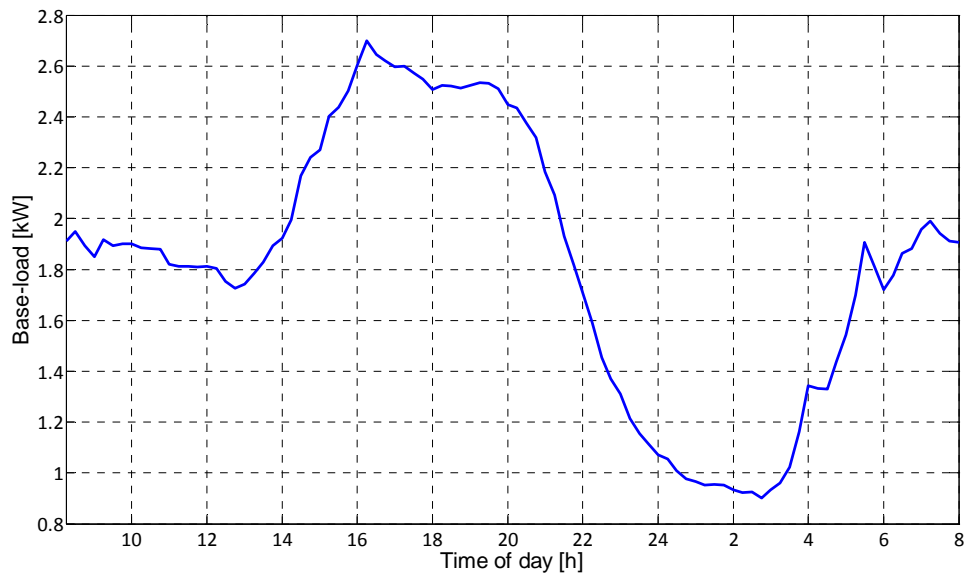


Figure 4-5 Base-load profile of a case study single residential customer

Figure 4-6 shows the  $RC$  curve for this case. For the customized transportation features (i.e. arriving time and deadline),  $RE$  (=11.4465 kWh) is the shaded area and  $T_u$  and

$T_o$  are 41, and 7 respectively. Moreover, it is assumed that  $P_{\max}=1.8$  kW in this case study, which corresponds to a regular charging rating of 120V/15A North American standards plugs.

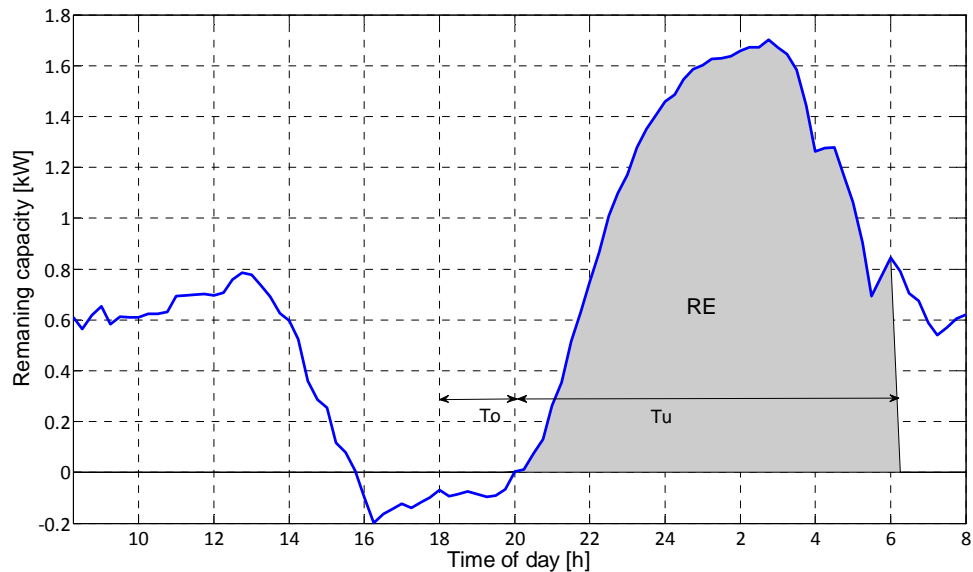


Figure 4-6 Remaining capacity for 24h and remaining energy within the charging period ( $RE$ )

Note that, in reality, the demand curve of one customer often has many sharp variations; however, since an exact prediction of these variations is not possible, a typical profile, obtained from averaging, is usually used instead. ■

### 3) Strategies in different situations:

At this step, based on the comparison between the customers' charging need ( $EC$ ), and remaining energy ( $RE$ ), and for two extreme circumstances of  $RD$  (0 and 1), two different states, namely A and B (each including two sub-states), are defined and explained as follows.

**State A) When  $RE \geq EC$  (the total available energy exceeds the customer's charging need):**

In this condition, the demand of the customer will always be kept below the critical point (exceptions are intervals with negative remaining capacity). In the following description  $UL_t$  stands for the amount of under-load a CA determines for an interval  $t$ , which is then communicated to the UA in the hope of receiving rewards upon other customers' need. Depending on the degree of risk of the customer ( $RD$ ), distribution of the charging (flexible) load among available charging intervals or determination of every  $UL_t$  varies as follows:

A1)  $RD=0$

This is when the customer has no confidence in the forecasted aggregated demand and only relies on his/her own estimated demand, and wishes to have the most secure plan for charging. It should be noted that, in practice, the forecasted base-load is also subjected to uncertainties; however, such uncertainties in the total forecasted demand of a household are inevitable and cannot be quantified in advance. Therefore, when  $RD$  is equal to zero, it is assumed that the chance of error in estimation of the base-load in all charging intervals is the same; thus, the CA treats all intervals equally in a way that, as far as it is possible, a uniform boundary separates the  $CP$  curve and the demand curve. The amount of under-load is calculated as follows.

$$UL_t = \frac{(RE - EC) / L}{T_u} \quad \forall t \in \tau_u \quad (4.12)$$

$PZ_t$ , which is the charging demand with zero risk, can be obtained as follows.



$$PZ_t = \begin{cases} 0 & t \in \tau_o \\ RC_t - UL_t & t \in \tau_u \end{cases} \quad (4.13)$$

A2)  $RD=1$

In this case, one wishes to take risk by fully relying on the forecasted aggregated demand; as a result, the CA should plan in a way that  $UL_{\max}$  is provided during the interval of peak aggregated demand while the chance of over-loading of other customers is the highest, and thus maximum rewards can be achieved. For the rest of the intervals, depending on the ratio of the aggregated demand to the peak, the charging energy is distributed in (4.14).

$$UL_t = \frac{AD_t}{AD_{\max T}} \cdot UL_{\max} \quad \forall t \in \tau_u \quad (4.14)$$

where  $AD_{\max T}$  is the peak aggregated demand within the available charging period ( $T$ ), which might be different from  $AD_{\max}$ .

To calculate  $UL_{\max}$ , the main condition shown in (4.15), should be considered.

$$\sum_{t \in \tau_u}^T UL_t = (RE - EC) / L \quad (4.15)$$

(4.14) and (4.15) together yield the following:

$$UL_{\max} = ((RE - EC) / L) \times \frac{AD_{\max T}}{\left( \sum_{t \in \tau_u}^T AD_t \right)} \quad (4.16)$$

$PF_t$ , which is the charging power with full risk is calculated by (4.17):

$$PF_t = \begin{cases} 0 & t \in \tau_o \\ RC_t - UL_t & t \in \tau_u \end{cases} \quad (4.17)$$

Since  $PZ_t$  and  $PF_t$  must be in  $[0, P_{\max}]$ , a correction to the  $UL_t$  in (4.12) and (4.14) may be necessary to obtain the final demanded power. If  $UL_t > RC_t$  then it will be set as  $UL_t = RC_t$ ; the balance of this will be distributed among other eligible intervals according the defined strategy for  $RD=0$  or  $RD=1$ . For example such correction is reflected in the initial few intervals (between 20h and 21:15h) in Figure 4-7 where the  $UL_t$  is below the constant value of the later intervals.

**Case study:** To simulate the influence of the selected  $RD$ , the  $UL$  curves for risk degrees of 0.0 and 1.0 during the charging time are shown in Figure 4-7, for  $CH=6$  kWh and  $\eta_c=0.9$ ; from (4.5),  $EC=6.67$  kWh, which is less than  $RE (=11.4465$  kWh). The uniform trend of distribution of the blue bars, except for the few initial intervals with the said correction, illustrates the equal treatment of all intervals for  $RD=0$ ; while, for  $RD=1$  the red bars are specified by following the trend of the forecasted aggregated demand. Note that between 18h and 20h the remaining capacity is negative and therefore  $UL = 0$ . ■

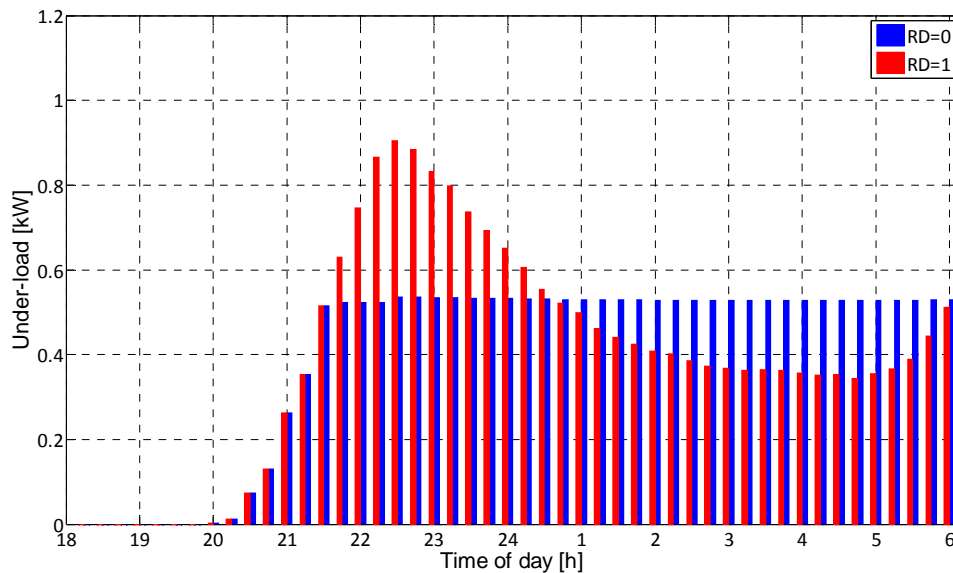


Figure 4-7 Under-load values for every interval:  $RD=0$  and  $RD=1$

**State B) When  $RE < EC$  (the total available energy is less than the customer's charging need):**

In this circumstance, even if the remaining capacities in all charging intervals are used, in order to satisfy the customer's objectives, there is no way but to demand more than the assigned critical point. In this case, the first priority will be to use all the available capacity below the  $CP$  curve; then to schedule for overloading according to the specified  $RD$ .

Two parameters should be introduced before explaining the method for the calculation of  $OL_t$ , which is the amount of over-load in every interval  $t$ . Firstly, the maximum possible  $OL$  in each interval should be defined as the charging power is limited by  $P_{\max}$ . This is denoted as  $MOL_t$ , which also plays a significant role in the dynamic stage (Section 4.3.3). It should be noted that intervals with  $RC_t > P_{\max}$  will be limited to  $P_{\max}$  only, and thus cannot be used for overloading; in the subsequent description  $\tau_l = \{t : RC_t \leq P_{\max}\}$  denotes the intervals that are eligible for overloading; let  $T_l$  be the number of such intervals.

$$MOL_t = \begin{cases} P_{\max} - RC_t & t \in \tau_l \\ 0 & t \notin \tau_l \end{cases} \quad (4.18)$$

Secondly, according to (4.11),  $T_o$  might be greater than zero, meaning that in some intervals the base-load is already above the  $CP$ .  $NRC$  is the summation of negative remaining capacities (4.19).

$$NRC = \sum_{t \in \tau_o} RC_t \quad (4.19)$$

Determination of  $OL_t$  in two extreme risk degrees can be accomplished as follows.

B1)  $RD=0$

When the customer's intention necessitates no risk in the scheduling, CA only relies on its own prediction. Similar to the sub-state A1, the probability of deviation of the actual base-load from the forecasted one is assumed to be equal in all intervals; therefore, CA treats them the same. Moreover, the utility charges demands above the  $CP$  incrementally in all intervals in the same manner, so it is obvious that having a uniform over-demand leads to the minimum cost. This is always true if the trend of pricing for \$/kWh incrementally goes up by the amount of over-load, and the actual pricing curve does not interfere in this deduction.

Identical  $OL_t$  in all eligible intervals is calculated as in (4.20).

$$OL_t = \frac{(EC - RE)/L + |NRC|}{T_l} \quad \forall t \in \tau_l \quad (4.20)$$

$OL_t$  is limited by its corresponding  $MOL_t$  in all intervals, and if the limit is reached, the balance will be distributed uniformly in all other eligible intervals to obtain the final  $OL_t$ . The charging power ( $PZ_t$ ) for the  $RD=0$  case is then calculated as follows.

$$PZ_t = \begin{cases} RC_t + OL_t & t \in \tau_l \\ P_{\max} & t \notin \tau_l \end{cases} \quad (4.21)$$

B2)  $RD=1$

In this case, a customer wishes to take risk by fully relying on the forecasted aggregated demand assuming that the chance of other customer's consumption to be less than the assigned  $CP$  is highest during the minimum aggregated demand within the available charging period ( $AD_{\min T}$ ); as a result, if one plans to demand his/her maximum over-load during  $AD_{\min T}$  and for the rest of intervals according to (4.22), the overall cost of charging

will be minimized. In fact, due to the adopted pricing scenario, the probability of compensating a major portion or the entire over-load by other customers' under-load will be the highest, which means the corresponding customer has to pay only the penalty (compensating the reward of the providers) and not incrementally by the amount of  $OL_t$ .

$$OL_t = \frac{AD_{\min T}}{AD_t} \times OL_{\max} \forall t \in \tau_l \quad (4.22)$$

$$\sum_{t \in \tau_l}^T OL_t = (EC - RE) / L + |NRC| \quad (4.23)$$

(4.22) and (4.23) together yield the following:

$$OL_{\max} = ((EC - RE) / L + |NRC|) \times \frac{1}{\left( \sum_{t \in \tau_l}^T \frac{AD_{\min T}}{AD_t} \right)} \quad (4.24)$$

Again,  $OL_t$  in each interval must not be above  $MOL_t$ , and if that occurs, the balance will be distributed among other eligible intervals with the full-risk strategy ( $RD=1$ ). The charging power with full-risk,  $PF_t$ , is calculated as in (4.25).

$$PF_t = \begin{cases} RC_t + OL_t & t \in \tau_l \\ P_{\max} & t \notin \tau_l \end{cases} \quad (4.25)$$

Note that in (4.25) (and (4.21) if  $RC_t < 0$  and  $|RC_t| < OL_t$ ,  $PF_t$  (and  $PZ_t$ ) will be set to zero. In this condition the balance should be deducted from the calculated  $OL_t$  (in (4.22) and (4.20)) for the rest of eligible intervals according to the applicable risk strategy (i.e.,  $RD=0$  or  $RD=1$ ). In both cases, the additional part of  $NRC$  will be compensated in the intervals with negative  $RC_t$  as part of the base-load; thus, by the deadline only  $(EC-RE)$  will be the charging energy above the  $CP$  curve.

**Case study:** To illustrate the effect of  $RD$  for scheduling in the overloading situation, it is assumed that  $CH=12$  kWh and  $\eta_c=0.9$ ; thus,  $EC=13.33$  kWh, which is greater than  $RE$  ( $=11.4465$  kWh). Figure 4-8 shows the result for  $OL$  curves for risk degrees of 0.0 and 1.0. As can be seen, when  $RD=1$  the value of  $OL$  in each interval is determined based on the forecasted demand; while, in  $RD=0$ , the  $OL$  is distributed uniformly. Note that outside of the charging period, the  $OL$  and  $UL$  curves are obtained only according to the base-load and thus are not shown in their associated figures. ■

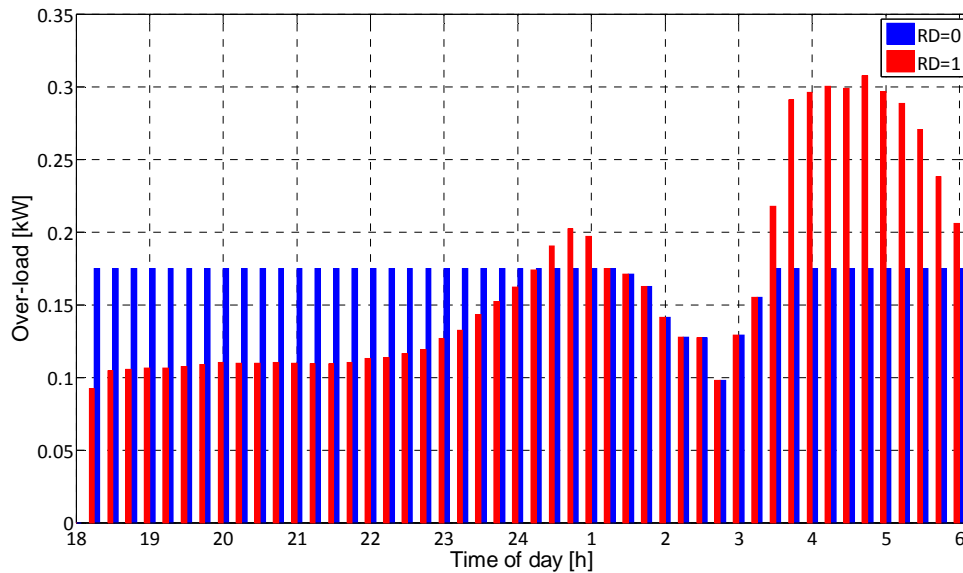


Figure 4-8 Over-load values for every interval:  $RD=0$  and  $RD=1$

#### 4) Ultimate charging (flexible) power:

Up to this point the procedure for computing the charging power scheduling in different conditions with extreme risk degrees of 0.0 and 1.0 has been introduced. However,  $RD$ , depending on a customer's desire and experiments, can have any values within  $[0,1]$ . According to (4.26), it is shown that if in every interval the charging power of  $n^{\text{th}}$  customer

is determined by (4.27), eventually by the deadline the total drawn energy will be equal to the required  $EC$ .

$$\left\{ \begin{array}{l} \sum_{t=0}^T PZ_t = \sum_{t=0}^T PF_t = EC / L \\ \Rightarrow RD \times \sum_{t=0}^T PF_t + (1 - RD) \times \sum_{t=0}^T PZ_t = EC / L \\ \Rightarrow \sum_{t=0}^T (RD \times PF_t) + \sum_{t=0}^T ((1 - RD) \times PZ_t) = EC / L \\ \Rightarrow \sum_{t=0}^T (RD \times PF_t + (1 - RD) \times PZ_t) = EC / L \end{array} \right. \quad (4.26)$$

$$P_{n,t} = RD_n \times PF_{n,t} + (1 - RD_n) \times PZ_{n,t} \quad (4.27)$$

**Case study:** For  $RD=0.7$  and the given over-load and under-load conditions, the scheduling result of the static stage is displayed in Figure 4-9. The total demand including the base and the charging load at the static stage is the summation of Figures 4-4 and 4-8.

To illustrate the benefit of the proposed algorithm in terms of the total cost of charging, a sample pricing scenario is considered for this case. It is assumed that the regular tariff is  $5\phi/\text{kWh}$  (for demands below the  $CP$  curve) and the incremental tariff curve is linear with a  $5\phi/\text{kWh}$  slope beyond  $CP$ . The explained overloading situation with  $EC=13.33$  kWh is considered. In Figure 4-10, charging costs during every interval for two conditions of controlled charging (proposed static-stage of the algorithm) and uncontrolled charging (charging with  $P_{max}=1.8$  kW starting at the arrival time) are shown. The total cost for the controlled charging is  $58.8\phi$ , which is 69% of the cost of  $85.27\phi$  for the uncontrolled case. It should be noted that the result of the static stage may be subjected to change in the dynamic stage, which will further reduce the total cost of charging, depending on the aggregated condition of all CAs. ■

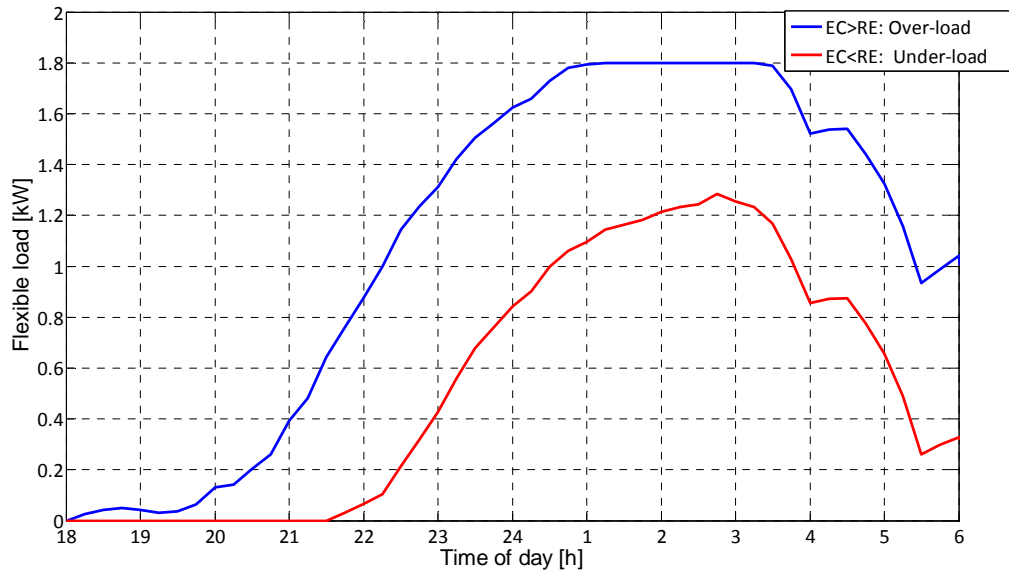


Figure 4-9 Flexible (Charging) profile at the static stage (over-load and under-load classes):  $RD=0.7$

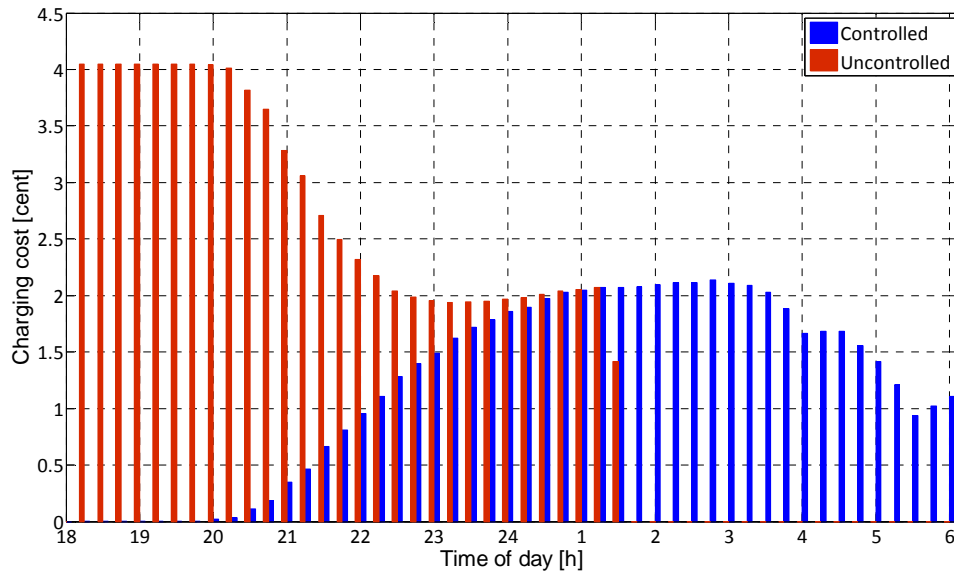


Figure 4-10 Charging cost at every interval for uncontrolled and controlled (the proposed algorithm) charging



Finally, at the end of the static stage, the CA determines the status of its customer's demand by comparing the summation of the customer's base-load and  $P_{n,t}$  with the critical point  $CP$ . The status signifiers are  $UL_t$  (in case of under-load) and  $OL_t$  and  $MOL_t$  (in case of over-load). It should be noted that outside of the charging period (or if a customer does not own a PEV), CAs determine the amount of under-load and over-load only according to their base demand; in this case  $MOL=OL$  as there is no flexible demand involved.

### 4.3.3 Dynamic stage

The dynamic stage of the algorithm follows the flowchart shown in Figure 4-11. In this stage, which is performed in real-time (i.e. every interval), each CA communicates its either  $UL_t$  or  $MOL_t$  to the UA; sending  $UL_t$  signal indicates that the customer's consumption is below the  $CP_t$  and that he/she wishes to receive rewards in return upon other customers' need for overloading. Likewise, sending the  $MOL_t$  signal signifies a customer's potential over-load and his/her wish to use other customers' share upon availability and to pay a penalty in return.

The scheduling scheme is designed deliberately in a way such that the UA has the least interference in CAs' decision making process, and mainly plays a supervisory role; consequently, charging powers are determined by distributed CAs while the UA guides them to modify their plans contributing to better satisfaction of both the utility's and the customers' objectives. Thus, the UA is responsible to receive the status signals from CAs, to calculate the permitted over load  $POL_t$  as in (4.28), and to communicate it back to the CAs.

$$POL_t = \frac{\sum_{n=1}^N UL_{n,t}}{N_o} \quad (4.28)$$

where  $N_o$  is the number of customers sending their  $MOL_t$  (for whom  $UL_t=0$ ) in the interval  $t$ . There is one modification that must be done before sending  $POL_t$  back to the customers of the over-load class. If  $POL_t > MOL_{n,t}$  then obviously this customer cannot consume all the available capacity, so the rest will be again distributed between the remaining members of the over-load class.

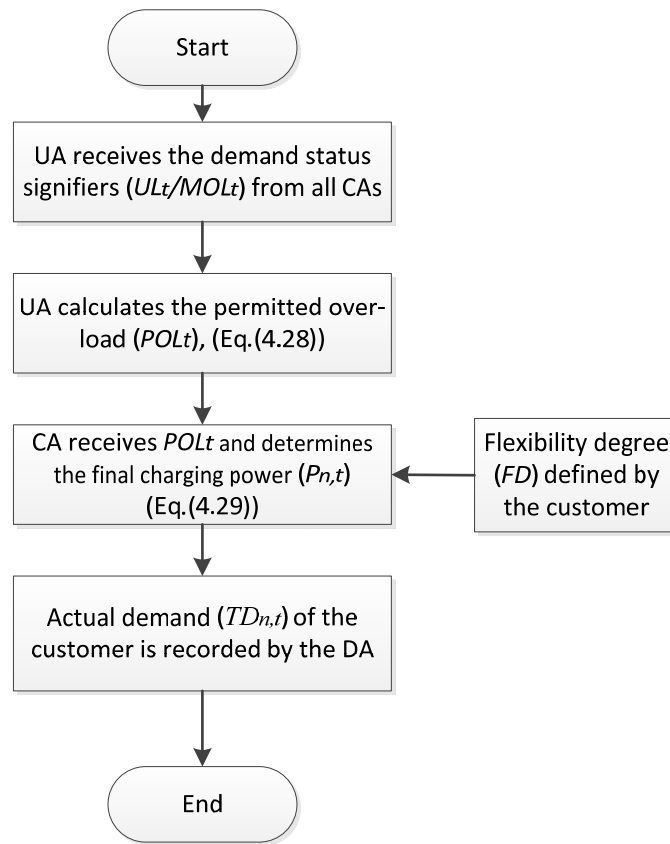


Figure 4-11 Flowchart of the dynamic stage

Then CAs receive  $POL_t$  from the UA, and depending on their objectives, determine the final charging power in the following interval. The flexibility-degree ( $FD$ ), defined by the customer, comes to the picture at this stage aiming to reduce the overall cost of charging required to fulfil the customer's transportation. As it was explained in Section 4.2.3,  $FD$  is only taken into account while over-demand of the customer is in the incremental tariff area; that is,  $POL_t$  is less than  $OL_t$  and the customer's overall benefit is in charging less in that interval.

According to (4.29), there are two options for the CAs and whichever is greater will be the ultimate decision for the members of over-load class. As a result, the total drawn charge by the deadline will be in the desired range of  $[(1 - FD) \times EC, EC]$ .

$$P_{n,t} = \begin{cases} RC_{n,t} + POL_t & (a) \\ (1 - FD_n) \times (RC_{n,t} + OL_{n,t}) & (b) \end{cases} \quad (4.29)$$

There is no change in the charging power (calculated in the static stage) for the customers of the under-load class in this stage; thus the static stage for these customers remains unchanged. The same condition is valid for the CAs who reduced their charging power in the desired range. It should be noted that CAs will keep the summation of any deviation from the static plan, as in the following intervals (up to the deadline) there might be other opportunities to compensate it.

On the other hand, for CAs who modified the charging power to a value more than the planned one, the static stage must be repeated for the updated remaining amount of the required charging in order to find out the charging demand for the next interval.

Finally, the amount of actual consumption of each customer ( $TD_{n,t}$ ) will be recorded by the database agent (DA) for the purpose of calculation of rewards/penalty and energy cost as well as for forecasting procedure.

**Case study:** Assume the customer's  $FD=0.1$  and, according to Figure 4-9, at 4h for the over-load class curve the amount of charging power is  $P=1.5228$  kW; therefore, this power can be diminished up to 10% to 1.3705 kW from (4.29-b). The amount of over-load at the static stage is ( $P-RC$ ), which at 4h is  $OL=1.5228-1.2632=0.2596$  kW ( $RC=1.2632$  kW from Figure 4-6). The amount of maximum possible over-load from (4.18) is  $MOL=1.8-1.2632=0.5368$  kW.

First assume that in this interval  $POL=0.15$  kW. From (4.29-a), a value of 1.4132 kW is obtained, which is greater than (4.29-b) of 1.3705 kW; thus, the ultimate value of  $P=1.4132$  kW is selected and there is no need to repeat the static stage. As another example, consider the case when  $POL=0.3$  kW; as  $POL$  is greater than  $OL$  and still less than  $MOL$ , the final decision of CA will be  $P=POL+RC=0.3+1.2632=1.5632$  kW. As more power is drawn in this interval the static stage will be repeated to find out the next interval's demand. ■

## 4.4 Conclusion

The decentralized scheduling algorithm of charging demand developed in this chapter comprehensively captures both the utility's and the customers' objectives and preferences and thus plans the charging pattern in a realistic manner. This gives authority to the customers in order to prioritize the trend of their charging profile by their own risk while

their privacy is well preserved. Moreover, the utility can be confident that the shared asset is fairly utilized by its associated customers and thus decide for upgrading upon necessity.

The case study presented for various steps of the algorithm in this chapter demonstrates the reflection of an individual customer's defined variables in the scheduling process. In the next chapter the aggregated reflection of distributed customers' charging pattern on the grid's performance is investigated for a test feeder.

# Chapter 5

## Performance Assessment of the Developed Distributed Control Algorithm

### 5.1 Introduction

In this chapter the distributed scheduling algorithm for vehicular load, introduced in Chapter 4, is implemented on a sample small-scale residential distribution network in order to investigate its performance in a real-world application. In the following sections, firstly the necessary elements to build a valid test case-study along with its associated assumptions are specified (Section 5.2); these elements are network topology and characteristics, residential load profile, and PEV charging demand features. Secondly the strategy for analyzing of the performance of the algorithm is described and its corresponding flowchart is presented (Section 5.3). Then, simulation results are classified and presented as a function of the penetration level of PEVs in the system from 0% to 100% and for two

conditions of (i) employing the proposed technique and (ii) unsupervised charging (Section 5.4). The investigated results are both system performance parameters including losses and voltage deviation as well as the algorithm performances indicators including peak demand rise and load factor. Section 5.5 is dedicated to complementary discussions aiming to comprehensively elucidate the aspects of the developed technique. Finally, conclusions and significant remarks are presented.

## 5.2 Test case features and assumptions

In this section all of the employed data in the simulation, their specifications, and corresponding assumptions are introduced in order to clarify for what conditions the subsequent reported results are obtained. It is important to be attentive to the fact that features of the defined conditions in this part shape a customized case study using a combination of real-world data, and deterministic and stochastic approaches; therefore, their associated results are only valid for this case-study, which aims to demonstrate the performance of the scheduling technique.

### 5.2.1 Topology and specifications of the test distribution network

A modified version of the IEEE 13-node radial test feeder [66] (Figure 5-1) is used in this study. In this modified model, all conductors are substituted with three-phase lateral overhead lines of ACSR #4 and with twice the length. It is also assumed that buses 2-13 are load buses and 2 houses are connected to each phase at every node; thus, a total of 6

houses are fed by each distribution transformer. Moreover, at the secondary/customer side, the maximum charger power is set to be 1.8 kW for 120V/15A (regular charging rate).

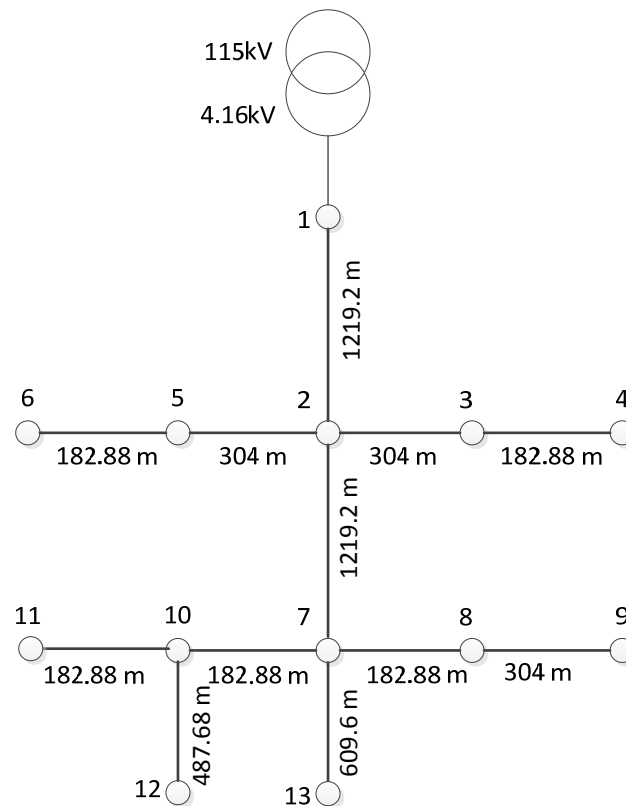


Figure 5-1. The modified IEEE 13-node test radial distribution network

### 5.2.2 Base-load profile of the household

Figure 5-2 shows a typical residential load profile on a weekday during summer, which is employed in the simulations. This curve shows the amount of the demand for every 15-minute interval throughout 24h, and therefore there are a total of 96 points on the graph. In order to partly consider the uncertainty in the base demand for different houses, the curve of Figure 5-2 is randomly shifted in the range of  $[-2h, 2h]$  (as marked) and with 15-



minute step sizes to assign the daily base-load of each household in the simulation. Thus, 17 different load profiles are generated in a random manner.

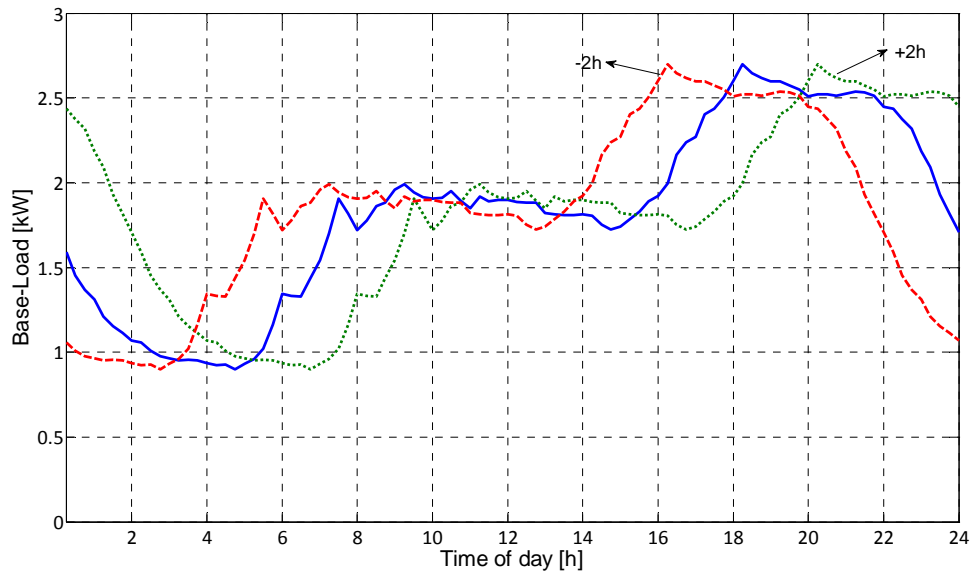


Figure 5-2 Typical residential load for summer

### 5.2.3 PEV charging demand specifications

As it was shown in Figure 4-1 and was also described throughout Chapter 4, flexible (charging) demand and its specifications, including the amount of charge, arriving time, and deadline, are inputs to the customer agents, and are determined according to the transportation requirements of individual customers and their personal preferences.

In order to more realistically demonstrate the performance of the developed algorithm in the actual distribution system, random variations in the features of vehicular load (and thus customers' objectives influencing CAs actions) are emulated by employment of a real-world driving dataset of 66 vehicles (a subset of the driving data introduced in Section 3.2 [57], with at least 15 days of recording during weekdays of summer). To do so,

for each participating vehicle, and for weekdays of summer in the dataset, the arriving time, next-day departure time, and daily energy consumptions/mileage are extracted.

Note that the arriving time and the charging need are approximately dependent on each other as an earlier arrival is most likely equivalent to less charging need (less daily mileage). Therefore, in the simulations for each simulated day to specify the vehicular load of a household the actual arrival time and its associated transportation energy are used together. (See Section 5.3.1 for the details of designation of vehicular loads to a house/customer in the test network.)

Transportation energy consumption or charging need of a vehicle depends on its dynamic specifications as well as its driving pattern. The available driving dataset contains instantaneous speed and location of daily trips of participating vehicles; so by using dynamic specifications of the three vehicles introduced in Chapter 3 and Table 3-3, their instantaneous energy consumption can be calculated according to (3.1)-(3.5). The average value of the total energy consumptions of these three vehicles at arriving time at home is used as the charging need for the next day in the simulation.

Figure 5-3 displays the probability distribution of the arriving time for different hours of day. For example, at 18h the value is 0.1369, which means that for 13.69% of all recorded days, for all the participants, the arrival time at home was between 17h and 18h. Figure 5-4 demonstrates the average transportation energy (with removal of the outliers) for arrival in each hour of the day (hours with enough samples). As can be seen, the average of the consumed energy prior to arrival increases modestly in later hours of the day.

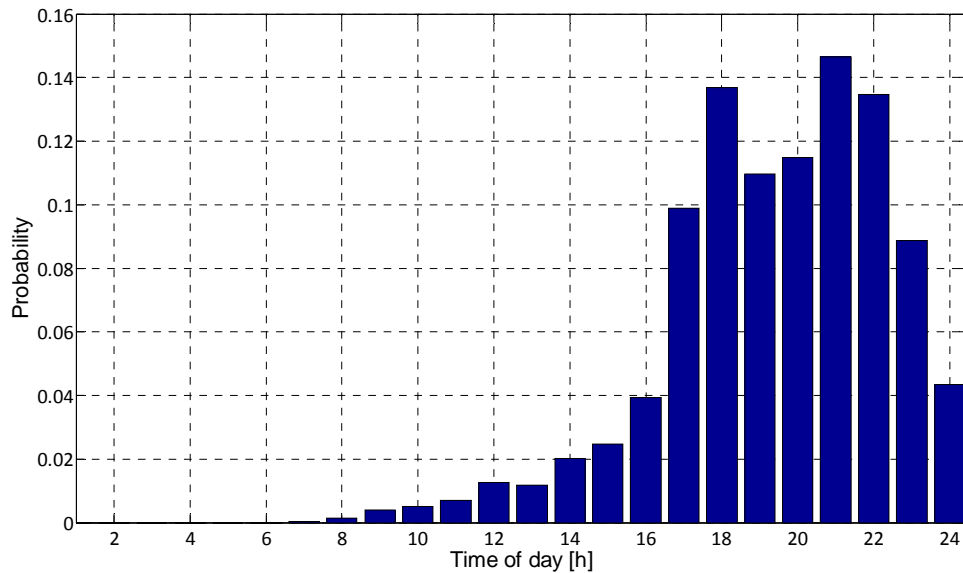


Figure 5-3 Probability distribution of arrival time for hours of day

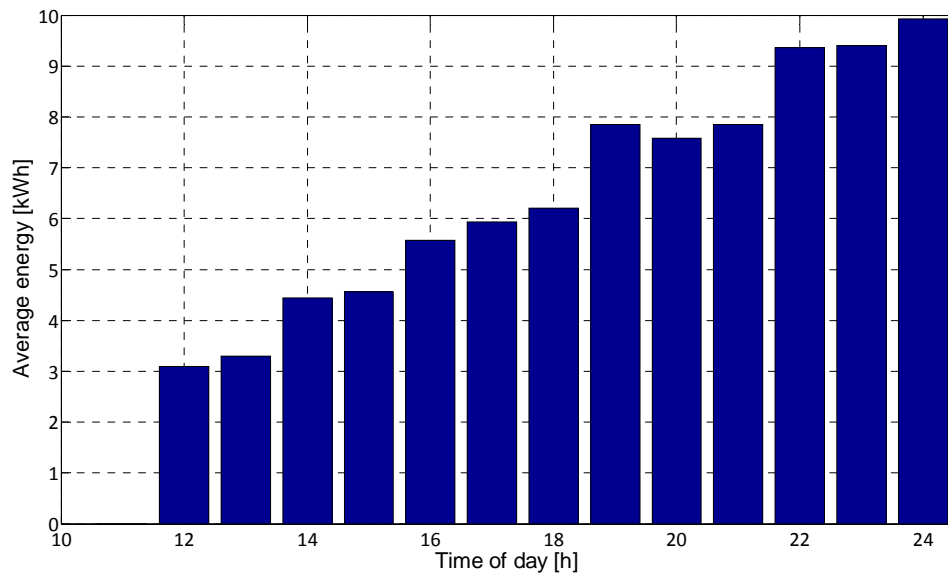


Figure 5-4 Average consumed daily energy for every arrival hour of day

Although the deadline for charging is also dependant to the customer's transportation necessities, as it was explained in Section 4.2.3 and also shown in the block diagram of Figure 4-1 customer's personal preference is also a significant factor in this case. There-

fore, in the simulations the maximum deadline of charging is set deterministically at 8h, unless according to the dataset the participating vehicle' departure time happens earlier, in which case the actual departure time is used to specify the deadline. Figure 5-5 illustrates the probability distribution of departure times associated with the employed data indicating that the majority of departures took place between 7h and 9h.

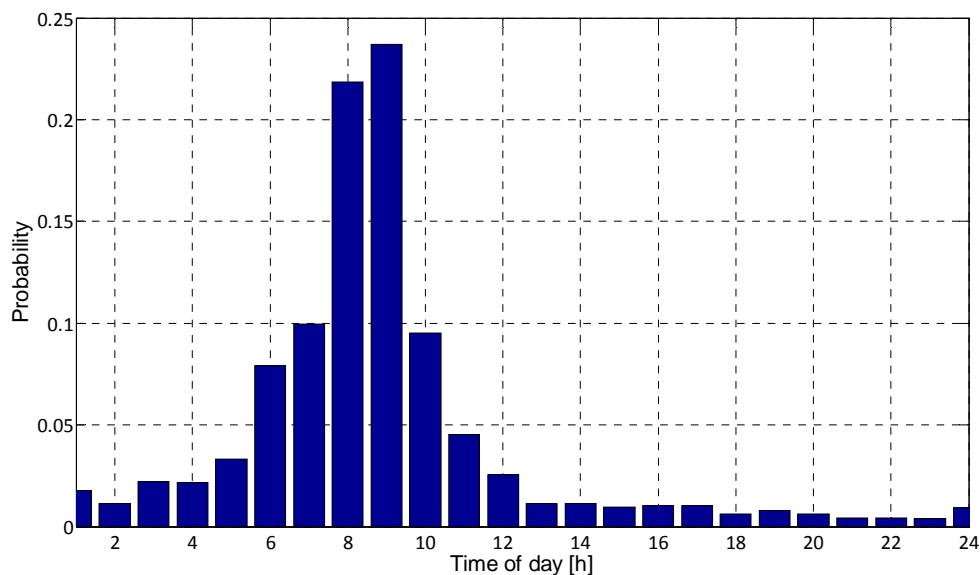


Figure 5-5 Probability distribution of departure time

## 5.3 Analyzing strategy

The data and assumptions introduced in Section 5.2 form the fundamentals of the developed test case study. Figure 5-6 demonstrates the flowchart of the process undertaken to simulate the proposed algorithm and generate results verifying its effectiveness. In order to compare the results, uncontrolled charging is also implemented. The whole procedure

is coded in MATLAB; in fact, in this simulation distributed agents' functionality and their real-time communications are implemented virtually.

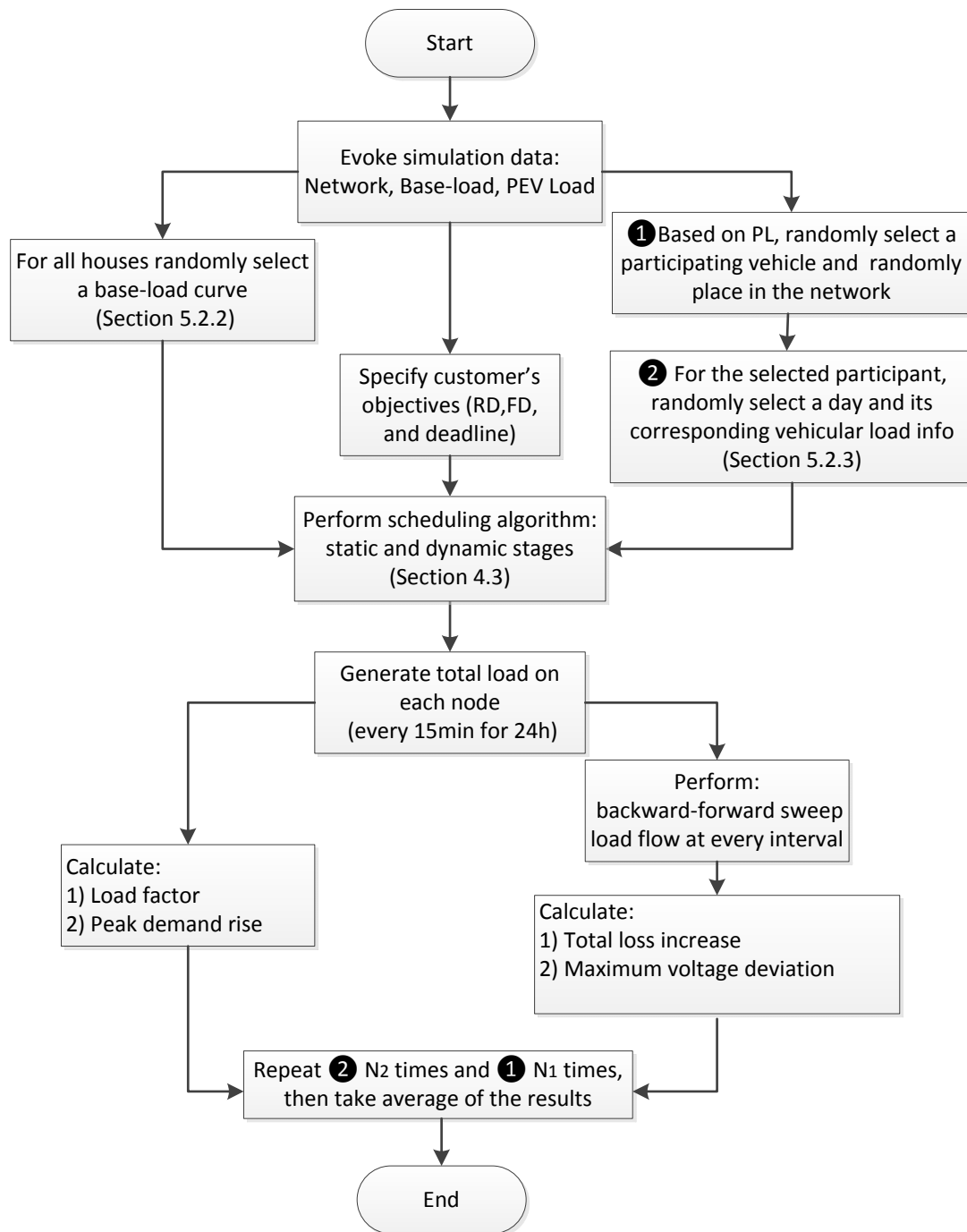


Figure 5-6 Flowchart of test case simulation procedure

In Chapter 4 the kernel of the algorithm (static and dynamic stages) along with a case-study was elaborated; indeed, that example was aimed to demonstrate the functionality of the method and the influence of its different parameters for one of the distributed CAs. However, in this section the performance of the control technique is investigated from the utility's point of view; thus, results showing the status of the distribution network are reported.

To further explain the flowchart of Figure 5-6, the following subsections divide the process into two main parts: (i) simulation of the control scenario to shape the aggregated load on every node of the network of Figure 5-1, which is essentially every block up to the scheduling algorithm block, and (ii) assessment of the performance of the distribution system.

### 5.3.1 Simulation of the controlled scenario

Data evocation is the first step, which comprises test-system topology and specifications, historical demand, and vehicular load data. The number of PEVs in the test network is determined according to the penetration level ( $PL$ ) of PEVs and can vary between 0 and 100%. Here, an increment of 10% for  $PL$  is chosen, so there will be a total of 10 different  $PL$  values in the final result. Then, for the chosen  $PL$ , a corresponding number of participating vehicles are randomly selected from the pool of 66 vehicular samples (introduced in Section (5.2.3)) and are placed in random locations in the network (each assigned to one random house). For each selected vehicle there is a pool of weekdays of summer and for each day the three vehicular load identifiers of arrival time, deadline, and amount of daily transportation energy consumption. In this step, a random day and its associated

identifiers are selected for each chosen PEV. Moreover, the base-load curves of all houses are chosen randomly from the pool of 17 possible curves introduced in Section 5.2.2. It should be noted that this stochastic variation in the base-load is considered to account for the fact that the actual aggregated demand on each node can be somewhat different from the forecasted one. For the forecasted aggregated demand curve on each node, which is used by the UA to determine the  $CP$  curve (with  $SM_{\max}=10\%$ ) and also by the CAs in their static stage scheduling, the original typical residential load (Figure 5-2) times the number of customers ( $N=6$  in this case) is employed (Figure 4-2).

The utility does not have the authority to directly select  $RDs$  and  $FDs$  for distributed customers; in fact, these parameters are specified in a distributed manner by individual customers reflecting their objectives and preferences. It can be expected that customers will gradually develop an optimal trend in the choice of parameters for their better satisfaction, which, eventually, in most cases, contributes to the utility's objectives as well; however, in the simulations, the  $RD$  of the customers is selected randomly between zero and one to ensure that the obtained results are independent of the choice of  $RDs$ .

The strategy for the selection of  $FDs$  is quite different: as it was alluded to in Chapter 1 there are a number of main issues hindering penetration of PEVs in the market; among them the necessity to recharge their relatively light-duty battery capacities and not having enough opportunity for charging away from home or other convenient charging stations are significant. Therefore, in the simulations, when a higher penetration level is assumed, it is taken to imply that the PEV owners are more likely (as a whole) to have access to off-home charging stations and this has contributed to their higher acceptance of electrified transportation. Hence for higher  $PL$  values, it can be assumed  $FDs$ , which are ex-

pressed by customers and mainly depend on the opportunity of charging away from home, also increase correlatively. However, the convenience of home charging cannot be completely neglected; as a result, in the simulations, the  $FDs$  are randomly selected between zero and  $PL/2$ ; for example in 100%  $PL$ ,  $FDs$  can have a random value (uniformly distributed) between zero and 50%. Note that, even with 100%  $PL$  there is a chance that a customer wishes or has to charge only at home ( $FD=0$ ); thus only the maximum possible  $FD$  is increasing with  $PL$  and  $FDs$  are still selected randomly to obtain independent results from customers' choices.

Another essential factor in the specification of  $FDs$  and  $RDs$  is the actual cost of charging. This depends on the actual regular tariff (for below the  $CP$  curve), incremental tariff figures (for above the  $CP$  curve), off-home charging tariff, and most importantly their values in comparison to one another. An investigation of the effect of relative prices on the customers' decisions is outside of the scope of this study.

### 5.3.2 Investigation of the simulated performance results

The total demand on each node of the system is generated for every time interval (15 minutes in this case) after executing the distributed static and dynamic stages. In Section 4.2.2, it was stated that preserving the peak demand is considered as the main objective of the utility in this study to postpone upgrading of network assets by better utilization of their available capacity. This is the only consideration the utility uses in designating the  $CP$  curve. In fact, it is assumed that the utility's main agenda in this case is treating all customers at all nodes in the same way; in other words, in determining the  $CP$ , the UA does not pursue other overall network-performance improvements such as reduction of



losses or voltage deviation at the expense of restricting some customers' demand on certain nodes in order to achieve an optimal load profile. Moreover, such actions by the UA might also be considered as its direct interference in control of the flexible loads, which is in contradiction to the decentralized control concept in real-world.

Consequently, in order to gauge the effectiveness of the proposed control technique the parameters that indicate the state of the aggregated demand on every target node are considered. They are (i) the load factor, and (ii) the peak demand rise.

Furthermore, striving to preserve the peak demand indirectly aims to fill valleys of the load curves as far as possible and ultimately makes them smoother; it is expected that having a smoother demand on every node of the system enhances the performance of the overall network as well.

To investigate the network performance a load flow analysis is performed on the test system of Figure 5-1 using the backward-forward sweep method [67], [68] suitable for distribution networks: a flat voltage is assumed for node 1 (the slack bus). Loads of each household including the base load and the PEV load are modeled as constant real power during each interval. Adding reactive power only makes the assessment more complex and does not contribute drastically to the drawn conclusions [25], [26]. The increases in the total losses (kWh) as well as the maximum voltage deviations are considered parameters in this part.

In the final step, for each  $PL$  value, the simulations are conducted  $N_2$  (30 in this case) times, each comprising the same randomly drawn participants placed at the same random locations for  $N_2$  randomly selected days. This is repeated  $N_1$  (100 in this case) times for the same  $PL$  level but with  $N_1$  different combinations of participants at different loca-

tions. This will result in  $N_1 \times N_2$  simulations. The average of these random day selections and vehicle placements for every  $PL$  varying from zero to 100% with 10% step are then reported.

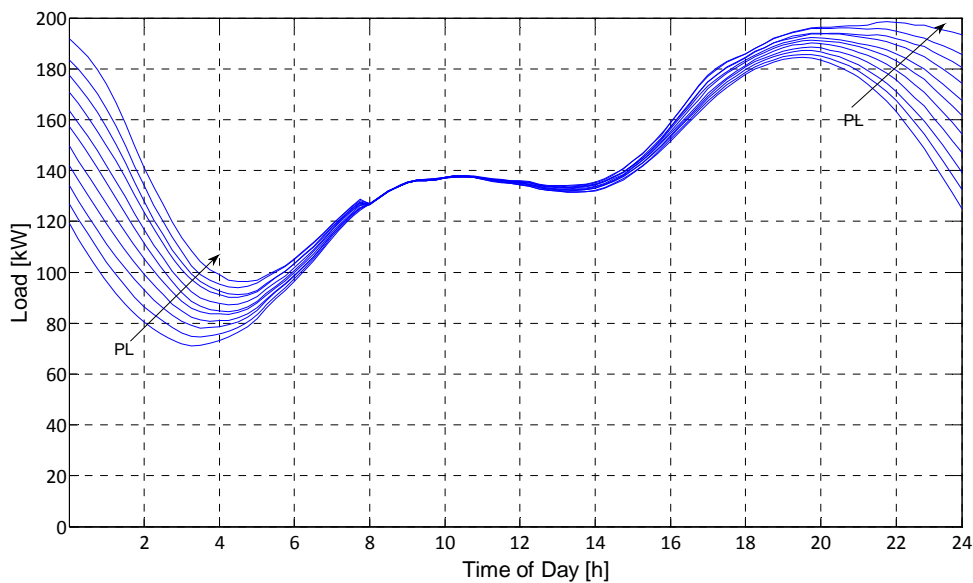
Ultimately in order to compare the results with uncontrolled charging within the test residential network, the same selected random base-load and PEV features (i.e. sample days) are used and it is assumed that, in the uncontrolled condition, charging starts at the onset of arrival with full strength ( $P_{\max}$ ) until the required energy is obtained or the deadline is reached.

When investigating the results, one must always be attentive to the fact that, in reality, the vehicular load is not specified based on grid's enhancement criteria but based on individuals' transportation requirements. As it is stated in Section 5.2.3 and can be seen from associated figures, in real world, the vehicular load features vary in a wide range. In the literature this realistic consideration is referred to as heterogeneous PEV demand as opposed to homogeneous vehicular load where it is assumed that the characteristics of the vehicular load for all customers are similar. Most flexible demand management techniques are designed to enhance the forecasted aggregated demand. Therefore, advantages of their control technique are more evident while a deterministic homogeneous flexible load is assumed at the customer side which idealistically fill the valley of the aggregated demand curve. However, the main aim of this chapter has been providing a realistic picture for real-world implementation of the developed algorithm; all random selections of vehicular demand features,  $RD$  and  $FD$ , as well as the random shift of base-load will shift the final result from idealistic towards realistic.

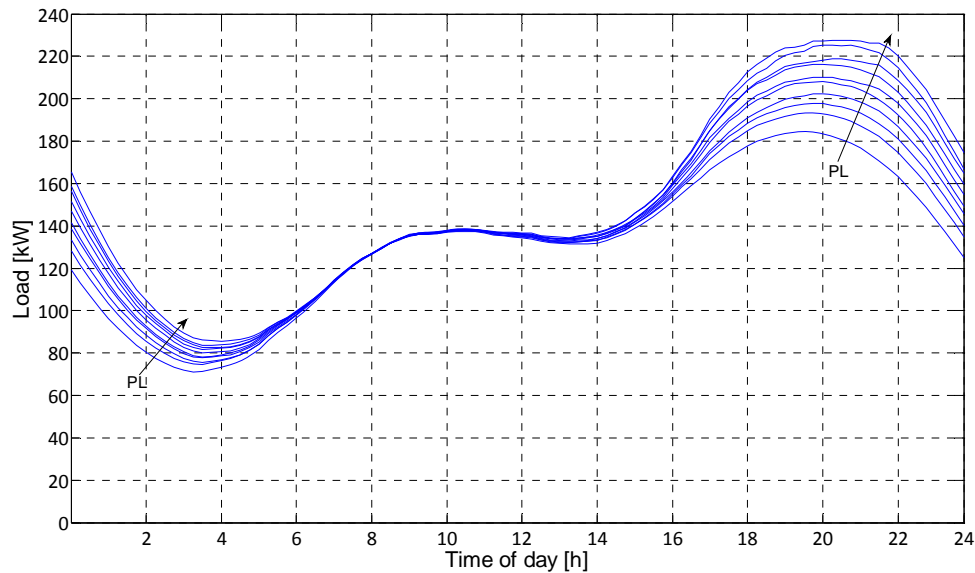
## 5.4 Simulation results

In this section, simulation results for the introduced strategies including the developed distributed control method and its associated uncontrolled charging mode are presented.

Figures 5-7 and 5-8 illustrate daily load curves of the entire test system on the main distribution transformer for the developed distribution control method and uncontrolled charging, respectively. As can be seen, with an increase in the number of PEVs in the system (increasing  $PL$ ) the peak demand in the uncontrolled charging rises up to 230 kW, while in the distributed control case it remains below 200 kW. From these curves it is expected that performance of the network shows proper improvement by employing the developed technique. The results are classified based on objective-related parameters, being the load factor and the peak demand rise, beside load flow related parameters, being the total loss increase and maximum voltage deviation.



**Figure 5-7 Proposed distributed control algorithm: Entire load on the test network's main transformer, while  $PL$  increases from 0 to 100%**

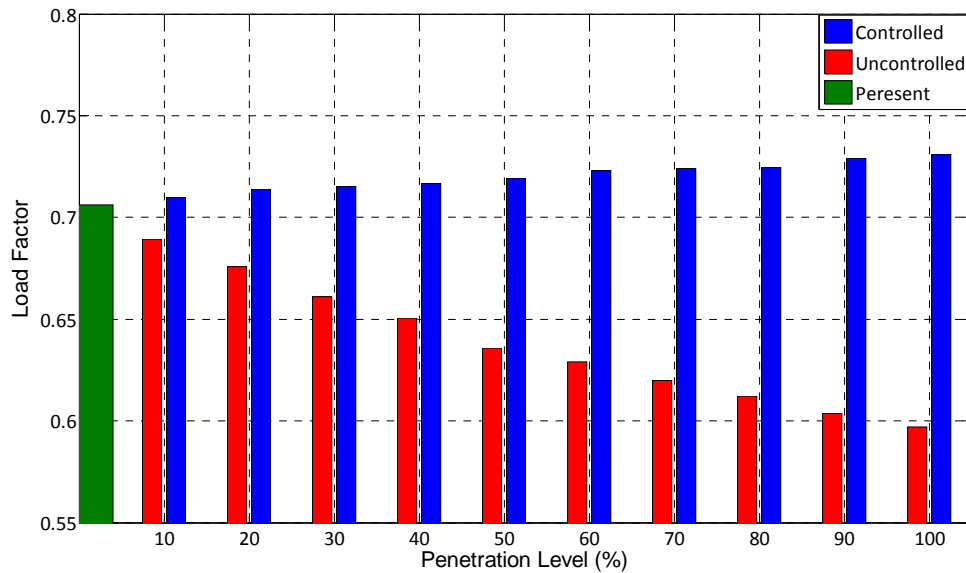


**Figure 5-8 Uncontrolled charging: Entire load on the test network's main transformer, while  $PL$  increases from 0 to 100%**

#### 5.4.1 The utility's objectives results: load factor and peak rise

The average load factor and maximum peak rise for the 12 load-buses of the test network for different penetration levels are shown in Figures 5-9 and 5-10, respectively.

In Figure 5-9, it is shown that the average load factor of buses improves slightly by adding the vehicular loads; as it was explained earlier, vehicular loads in realistic situation do not exactly fill the valleys of the aggregated demand, but they are specified according to customers' transportation need and preferences. However, it can be seen from Figure 5-9 that employing the proposed technique causes the average load factor to have an ascending trend with the penetration level of PEVs and to be much better than the uncontrolled charging mode.



**Figure 5-9 Average load factor for distributed controlled, uncontrolled strategies, and present**

Peak demand rise can be considered as the main criteria for the utility to consider upgrading its assets. The success of the developed algorithm in controlling the additional PEV demand below the present peak demand can be realized through this parameter. Depending on their present capacity, aging considerations, and peak duration, the assets might tolerate some limited percentage of increase in the peak demand. That must be determined locally based on specific conditions for each transformer or feeder. However, from Figure 5-10 it can be easily seen that the peak rise in the developed multi-agent distributed control has significant advantage over the uncontrolled charging mode and will postpone the upgrading for a long time for the shown case.

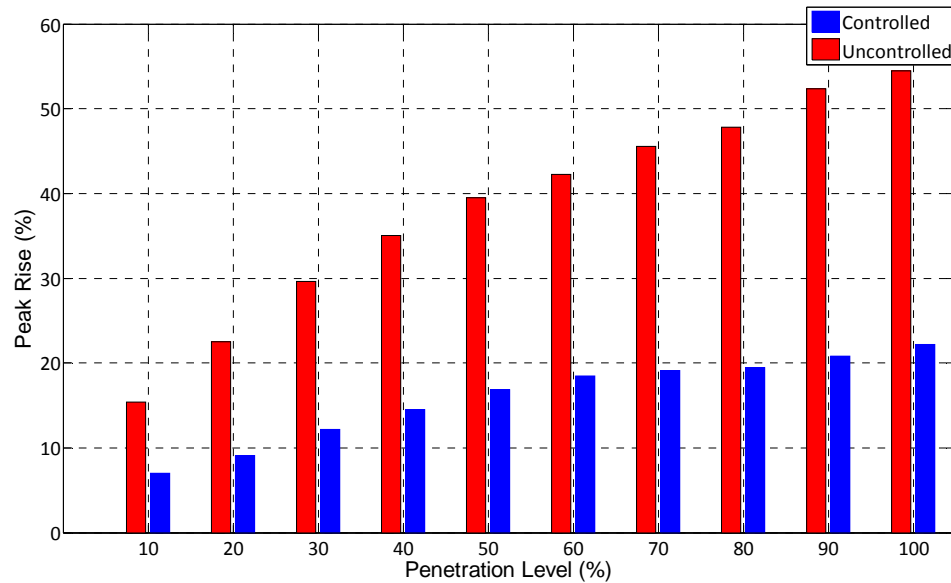


Figure 5-10 Maximum peak rise for distributed controlled an uncontrolled strategies

#### 5.4.2 Load flow results: total loss increase and voltage deviation

The total loss increase and maximum voltage deviations throughout a day, as a function of the penetration level of PEVs in the test network, are shown in Figures 5-11 and 5-12, respectively. As can be seen, both of these quantities improve as a result of employing the proposed technique.

Total losses in an operating day mainly depend on the consumed energy and thus the difference between uncontrolled and controlled modes is not significant; however, high demands in short intervals still cause more losses than when the same amount of energy demand is distributed within a longer period.

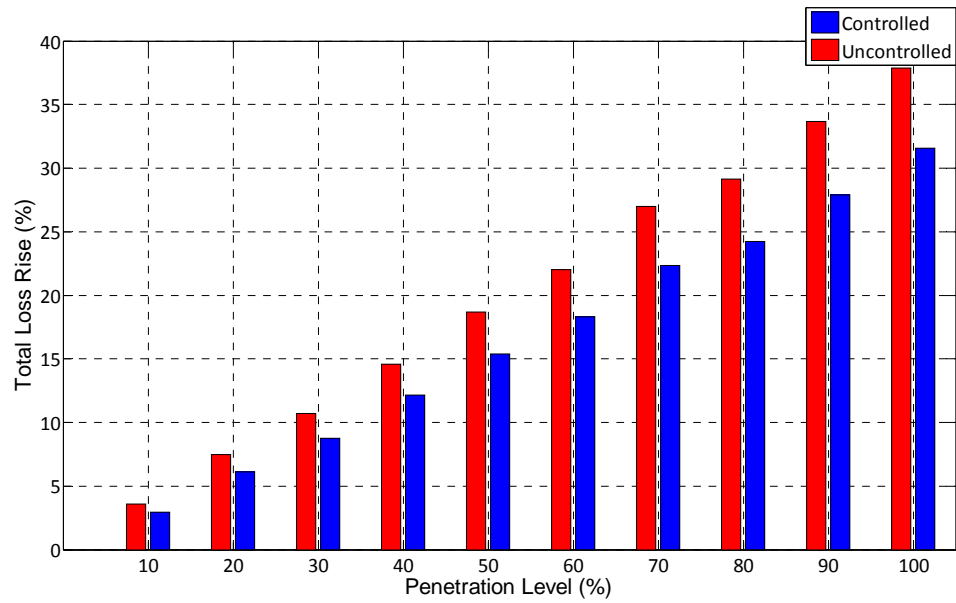


Figure 5-11 Total daily loss rise for distributed controlled an uncontrolled strategies

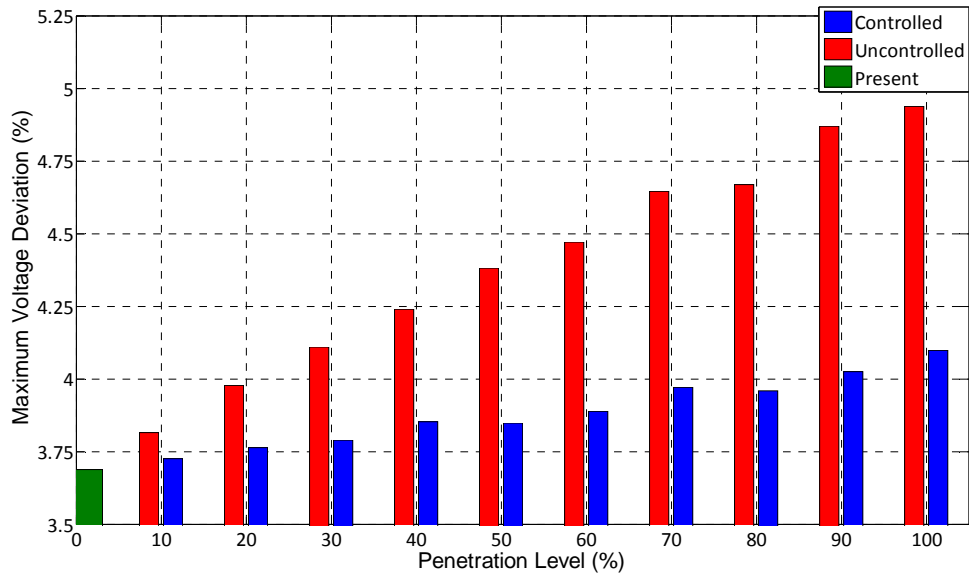


Figure 5-12 Maximum voltage deviation for distributed controlled, uncontrolled strategies, and present

## 5.5 Complementary discussion

The aim of this section is to shed further light on the attributes and constraints of the proposed control algorithm. In addition, complementary discussions about the real-world implementation and future developments of the method are presented.

1) One of the advantages of the power network over other technological complex networks is that it has a consistent topology of edges between vertices and for most of the time forecasting the behavior and the trend of the load is possible with an acceptable degree of confidence. Applying an agent-based control for such a stable network will ensure that any change in the performance and criteria of each part of the network can be seen and handled locally within a proper time by suitable actions, while the rest of the network remains unaffected following their routine trends. This certainly reduces the cost of centralized control (i.e. communication and computation) and makes the response time to probable disturbances much faster.

Furthermore, higher utilization of network assets as well as more secured and flexible control in the smart grid environment, when the privacy concerns and communication cost comes to picture with a stronger stance, are other benefits of relying on a distributed control with agents.

However, it must be noted that in a wide area with few customers where an unintelligent distribution network is designed with a capacity more than customers' consumptions and distribution system loss and its utilization factor is not a utility's concern, the capital cost of having such intelligent control system will not be economically justifiable. Therefore, such intelligent and comprehensive control schemes mainly concern weak distribu-



tion networks with dense population where network assets function close to their capacity and are vulnerable to additional unsupervised vehicular charging load.

2) Simplicity of the proposed algorithm makes it intelligible for most customers, who constitute the main part of a decentralized control scheme and without their collaboration any solution is not doable: therefore, simplifying the interaction with the algorithm and ease of its required inputs are important attributes of a successful technique.

3) Gradual development from the present unintelligent network to a highly intelligent system with distributed agents will involve a transient period. In that period, a less idealistic version of the algorithm needs to be used, which for example does not require real-time communications. In fact, separating the two stages of the control scheme has been done with the same purpose. The static stage is accomplished only based on the historical data and independently for the distributed PEVs and if the risk of trusting the average behavior of others is included in the scheduling process, this stage can approximately handle the load management to an acceptable level. Enabling real-time communication will make the dynamic stage possible for the sake of better utilization of assets by modification of the distributed PEVs' charging plans.

4) It is important to be always aware of the fact that in this proposed multi-agent system every agent is supposed to pursue its own benefit in a non-cooperative manner; however, the utility agent with dominant social intelligence and authority plays the role of an intermediate object between the CAs by assigning *CP* and real-time communication while still perusing its own target of better utilization. The overall result of this control scheme will be indirect collaboration of the CAs to some extent: they charge less when others consume more, to achieve an overall less cost.

The same strategy can be expanded for a game-based control scheme with a major difference that the CAs have wider social intelligence and can bid their own needs with other agents, taking their own risks. The result might be better or worse than the former control method depending on which agent plays wiser. The UA still supervises the overall circumstances and regulates appropriate rules and limitations.

5) Pricing scenario will certainly influence the whole scheduling process, and thus the developed algorithm is valid only with its corresponding pricing scenario. For example if the utility decides to use variable incremental curves for different hours, the amount of reward and penalty in different hours will be certainly different; and so the agents might alter their strategies as violation of the  $CP$  curve will have different costs depending on the time. A solution to address this change can be assigning different target SOC<sub>s</sub> with associated  $RD$ ,  $FD$ , and deadline.

6) In the proposed scenario every customer for its selected  $RD$  and  $FD$  achieves the minimum possible cost. However, there might exist a better charging profile (i.e. less costly) according to the actual aggregated demand, but a CA decides only based on its defined tasks as well as the forecasted demand at every interval, so cannot foresee the following intervals' actual demand (i.e. other customers' future decisions). This makes the final results more realistic rather than idealistic.

7) Privacy concerns have been pointed out as one of the major issues associated with all control strategies of flexible demands at customer side. The developed distributed algorithm in this regard has a highly secure plan as only under-load and maximum over-load are communicated in each interval and the actual arrival and departure time are not accessible to the UA.

8) The proposed algorithm has a high degree of scalability as adding a new customer only affects each individual's share from the common asset's capacity; this can be simply reflected in critical point calculation.

9) For determination of the flexibility degree availability of off-home charging stations plays a critical role. Accessibility of an individual to these stations as well as comparative price of home charging and off-home charging are the most significant factors for each PEV owner to decide on his/her flexibility degree. Having an estimation about daily trips (i.e. daily mileage and thus daily energy consumption), traffic conditions and discharging performance of the battery storage in various seasons and day-type of the week (week-end, weekday) provide a reasonable picture for a driver to make a sound decision.

10) The role of the risk degree (*RD*) in the developed algorithm is critical to make the scheduling close to reality. The deadline is the intended time to leave, which is subjected to change. Suppose in a condition with a high degree of risk that the main part of the charging is drawn much later than the arriving time which in an urgent need for vehicle will lead to failure of customer satisfaction. As a result, there must be a parameter to reflect the customer's will on this crucial matter.

11) There might be other criteria for specific power system for example due to transient lack of generation or fault, which might force the utility to modify its objective for a short period; this can be reflected in the calculation of *CP* and accordingly regulations should be considered to compensate customers' dissatisfaction resulting from an abrupt change in *CP*.

## 5.6 Conclusions

A sample residential distribution network was investigated under control of the developed decentralized charging scheduling algorithm with PEV penetrations in various levels. A set of real-world driving data was employed to specify the vehicular load. In order to simulate a closely realistic situation, a stochastic approach for distribution of participating PEVs, recorded days, and base loads was adopted.

The idealistic common assumption is that by optimal management of the charging demand it is possible to postpone the upgrading of the network assets up to the point their capacity is fully utilized (by completely filling the valleys of the aggregated demand curve). The main deduction from the simulated results however, is that in reality this assumption is not exactly true; in fact under realistic conditions distributed customers' charging demand will have different features in terms of time and amount, which might not take place exactly at valleys of the load curve; therefore, upgrading will be required prior to full utilization of the assets. However, employment of the developed control strategy will indeed significantly delay the necessity for upgrading and will also enhance the network operation in comparison to an uncontrolled charging scheme.

It should be also noted that the results presented in this chapter are valid for the given case-study and its corresponding attributes in terms of topology, base load, vehicular demand, and so on. Therefore, if, for example, fast charging is made feasible for customers in a residential distribution network, the assets (i.e. transformers) will be saturated in much smaller penetration levels.

# Chapter 6

## Conclusions, Contributions, and Future Work

### 6.1 Conclusions and contributions

In this thesis the charging demand of upcoming PEVs on a power systems was classified spatially as stationary (i.e. home charging) and mobile (i.e. off-home charging) vehicular demand; then planning issues regarding each class of vehicular load were addressed.

#### *1) Mobile vehicular demand at off-home charging stations:*

In the first phase of this research a location-based procedure for predicting the charging load at off-home charging stations was proposed and implemented. A fuzzy logic-based charging decision-making engine was designed to emulate the realistic behavior of the driver at the instant of arriving at an off-home charging location. The method was then exemplified by means of a driving dataset for two major shopping centers. The forecasted

loads by the developed algorithm are the initial and essential information for investigation of the required scale for upgrading the network, the rate and/or number of charging facilities, and related economic studies on the profit versus expenses of adding new infrastructure.

The main contributions of the first phase of the research included (i) developing a location-based fuzzy decision making unit for prediction of off-home charging behavior of drivers; and (ii) designing a procedure for vehicular load forecasting at potential public charging stations by means of real-world driving data from the area(s) of interest.

*2) Stationary vehicular demand at residential distribution network:*

In the second phase of the research the stationary class of the vehicular load was assessed. The main focus was on a realistic scheduling of the charging demand at residential distribution networks and a multi-agent decentralized control strategy was proposed and investigated.

The developed procedure localizes the realization of the charging profile for each PEV while it simplifies and individualizes the scheduling process for customers. The aggregated impact of the distributed, supervised charging patterns obtained through the proposed algorithm will result in enhanced utilization of the assets and a moderate growth of the peak demand. It will therefore, postpone the necessity for their upgrading. The consequence of such load management at the customer side will also moderately improve the performance of the power systems in comparison to an unsupervised mode of charging.

The main contributions of the second phase of the research included (i) development of a novel decentralized control strategy to manage flexible demand at the customer's

side to satisfy customers' transportation requirement while fulfilling the utility's objectives at the same time; (ii) design of a two-stage scheduling algorithm comprising static and dynamic stages, (iii) assigning critical points of the demand (*CP*) by the utility along with a specific pricing scenario in order to charge customers in a fair manner; (iv) engaging customers' defined risk degrees (*RD*), to account for the uncertainty in the forecasted demand, and flexibility degrees (*FD*), to account for the opportunity of off-home charging. These two are new parameters designed to capture the customers' desires and to reflect them in the scheduling algorithm. The proposed algorithm features simplicity in terms of computations and implementation, and protection of customers' privacy to the extent possible.

The overall conclusion from the two phases of the research is that although the main share of the charging load of each PEV occurs most likely during home parking, prediction of off-home charging behavior of the PEV owners is still a challenging and essential question in the planning procedure. Several factors contribute to this fact. Firstly, an adequate number of charging stations in eligible locations must be accessible to the PEV owners in order to encourage the society to switch at a faster rate to the more-electric transportation. Secondly, every candidate location requires an individual study of driving and parking patterns for the majority of the vehicles in the area of interest to realize the scale of fortifications as well as the rate of capital return required. Thirdly, alleviating the charging demand at home (i.e. higher flexibility degrees) by providing ample off-home charging opportunity in many cases can lower the probability of coincidental home-charging at lower levels of the distribution network.

To sum up, the implication of the results is that, although addition of the vehicular load in the system is inevitable, it is possible to obtain better satisfaction of both the customers and the utility through efficient management of the location and time of this demand.

*3) Publications arising from the thesis:*

At the time of writing this document, the following publications had resulted from the work carried out:

- 1) N. Ghiasnezhad, and S. Filizadeh, "Location-based forecasting of vehicular charging load on the distribution system," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 632-641, March 2014;
- 2) N. Ghiasnezhad, and S. Filizadeh, "Characterization of prospective charging locations of plug-in vehicles using real-world driving data," in *Proc. IEEE Power & Energy Society General Meeting*, Vancouver, Canada, July 2013.

## 6.2 Future work

From the viewpoint of classification of the vehicular charging demand on the power network as mobile and stationary, the following areas are found to be essential and useful to be investigated in the future.

- 1) For the mobile vehicular load, optimal placing of fast chargers in the transportation network can effectively accelerate the trend of adoption of a more green transportation. Unlike regular chargers, PEVs receive a substantial amount of charge in a short period from a fast charger; thus, in comparison to the regular



charging case, parking duration will not be as important. In fact, the main challenge in the case of fast charging stations is to answer the following questions: (i) where in the area of interest the public charging station should be installed, and (ii) what should be the pricing scenario to make it beneficial to drivers to charge at such stations rather than home (where the power network is more vulnerable). The answers to these questions will be based on the majority's driving habits, and transportation network's attributes (which make the issue complicated in terms of time and intensity of load).

- 2) In the present power systems where the initial stages of a smarter distribution network are still under development, strategies such as the one developed and investigated in this research are proposals for the future developments. In a smart distribution system, which is fully controlled with a multi-agent system, many other approaches can be assessed to achieve an optimal control strategy; however, there needs to be a great deal of consideration and regulation in terms of market, communication, and security as well as physical infrastructure to enable possibilities of some strategies such as monitoring the states of the network in various levels or bidirectional flow of power in case of vehicle-to-grid to gradually get closer an comprehensive supervisory condition. Eventually, in an idealistic free market situation, agents with a high level of intelligence and authority can participate in a complex game in which they interact directly with others and the utility agent(s) to finalize their decision on demanded power in every interval.

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