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Plug-In Electric Vehicle Charging Impacts on Power Systems

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ABSTRACT

Individual ICE (Internal Combustion Engine) driven vehicles are essential components of life in nations across the world. However, volatility in petroleum prices, security concerns associated with imported oil and anthropogenic climate change contribute to increasing interest in alternative vehicle technologies that are more efficient than 'traditional' car concepts.

For a number of advantages they offer, PEVs (Plug-In Electric Vehicles) are taking center stage in the current developments to resolve impacts of ICEs in the transportation industry. If this paradigm shifts from conventional oil fueled to grid supplied transportation is to take place, there will be a significant challenges and opportunities waiting for both automobile industries, oil industries and power supply industries. The goal of this thesis is therefore to develop probabilistic models that can quantify charging patterns of PEVs to allow utilities to evaluate their increasing charging impacts on the power systems.

The heart of this diploma work can be split into two parts. The first is the probabilistic models themselves. Given any power systems of study, the outputs from these models can be used with base load profiles to investigate impacts on that system. Two major probabilistic models are developed. The first model quantifies charging patters of PEVs at fast charging station, which are the future equivalents of present petrol filing stations. Four sub-models are developed that play with tuning different input parameters to help us have a broader understanding of fast charging patterns. A number of interesting outputs including load profiles, distribution of SOC (State of charge), and distribution of required number poles, distribution of number of charging per day and similar other distribution are generated f from the fast charging models. The second important models are the model that quantifies residential charging patterns of PEVs. Similar to fast charging models, a number of outputs including load profiles, SOC distribution, parking and charging time interval are among the important.

The second important part is impact analysis of PEV fast charging on a given power system. Three fast charging stations are deployed in Västerås primary distribution network to study impacts PEV fast charging on system bus voltage. Similarly PEV residential charging models are deploying PEVs in Västerås secondary distribution network to study impacts of residential charging on transformer loading, hotspot temperature variation and accelerated aging factor profiles.

Key words: PEV, BEV, PHEV, Plug-In, charging power, charging voltage, charging current, charging interval, probabilistic distribution

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LIST OF SYMBOLS

Symbol	**Explanation**	**Standard unit**
$(\vec{\sigma}^{(c)})^2$	Variance battery capacity in class c	[KWh]
$(\sigma^{(c)})^2$	Variance number of vehicles in each class	[-]
$\left(\sigma_{AT}{}^{(p)}\right)^2$	Variance arrival time of a day in a week	[hour]
$\left(\sigma_{DT}{}^{(p)}\right)^2$	Variance departure time of a day in a week	[hour]
$A_T{}^{(v,c,d)}$	Arrival time of vehicle v of class c on day d	[hour]
$BC^{(c)}{}_{max}$	Maximum battery capacity of class c	[KWh]
$BC^{(c)}{}_{min}$	Minimum battery capacity of class c	[KWh]
$C_T{}^{(v,c,d)}$	Charging interval of vehicle v of class c on day d	[hour]
$D_T{}^{(v,c,d)}$	Departure time of vehicle v of class c on day d	[hour]
$E_{Grid}{}^{(v,,c,d)}$	Grid energy required by vehicle v of class c on day d	[KWh]
$N^{(c)}{}_{PEV}$	Number of PEV in class c	[-]
$\vec{\mu}^{(c)}$	Mean battery capacity of class c	[KWh]
$\mu_{AT}{}^{(p)}$	Mean arrival time of a day in a week	[hour]
$\boldsymbol{\mu_{DT}{}^{(p)}}$	Mean departure time of a day in a week	[hour]
$\mathrm{L_{k,h}}$	Transformer loading at hour h	[KW]
$\mathrm{L_{k,H}}$	Rated transformer loading	[KW]
$BC^{(v,c)}$	Battery capacity of vehicle v in class c	[KWh]

$E_{Grid\_per\_km}$	Required grid energy per km	[KWh/km]
F_{AA}	Accelerated Aging Factor	[pu]
G_o	Transformer oil	[gal]
$I^{(v,c,d)}$	Charging current of vehicle v of class c on day d	[A]
I^*	Maximum charging circuit capacity	[A]
N_T	Total number of vehicles	[-]
$P^{(c)}$	Vehicle class distribution in class c	[-]
$P^{(v,c,d)}$	Charging power of vehicle v of class d on day d	[KW]
P_{PEV}	Penetration level	[-]
$P_{T,0}$	No load transformer loss	[w]
$P_{T,R}$	Rated transformer loss	[w]
$S^{(v,c,d)}$	Distance travelled by vehicle v of class c on day d	[km]
$SOC^{(v,c,d)}$	SOC level of vehicle v of class c on day d	[KWh]
$V^{(v,c)}$	Charging voltage of vehicle v of class c	[V]
n_t	Transformer cooling constant	[-]
p_i	percentage of PEV in each vehicle class	[%]
w_T	Transformer weight	[lb]
$\theta_{A,h}$	Ambient temperature at hour h	[oC]
θ_H	Hotspot temperature	[oC]
$\mu^{(c)}$	Mean number of vehicles in each class	[-]
τ_{To}	Transformer oil thermal time constant	[s]
τ_{Tw}	Transformer winding thermal time constant	[s]
$\Delta\mathrm{\theta_{H,R}}$	Rated hotspot temperature rise over oil	[oC]
$\Delta F_{k,P_{PEV}}$	Change in expected life of transformer	[Year]
$\Delta\theta_{H,h}$	Hotspot temperature rise over oil at hour h	[oC]
$\Delta\theta_{TO,h}$	Top oil temperature over ambient at hour h	[oC]
$\Delta\theta_{To,R}$	Rated top oil temperature rise over ambient	[oC]
Δt	Length of time step	[hour]
$\mathrm{A}(\mathrm{L_{k,h}})$	Transformer loading factor at hour h	[-]
AD	Average	[KW]
B	Constant	[-]
D	Demand	[KW]
d	Day index	[-]
D(i, w)	Demand at feeder i, in week w	[KW]
D(i, w, d)	Demand at feeder I, in week w, on day d	[KW]
D(i, w, d, h)	Demand at feeder i in week w, day d, hour h	[KW]
E	Energy	[KWh]
E(i)	Energy consumption at feeder i	[KWh]
h	Hour index	[-]
i	Feeder index	[-]
LF	Load Factor	[-]
LF(d)	Load Factor of a day in a week	[-]

LF(h)	Load Factor of an hour in a day	[-]
LF(w)	Load Factor of Week w of a year	[-]
LF_type(h)	Load Factor of a given load type in an hour	[-]
MD	Maximum Demand	[KW]
MD(i)	Maximum Demand at load feeder i	[KW]
N	Standard normal value [0 1]	[-]
w	Week index	[-]

LIST OF ACRONYMS

Abbreviation	Explanation
AAF	Accelerated Aging Factor
AC	Alternating Current
AER	All Electric Range
Ah	Ampere-Hour
BEVs	Battery Electric Vehicles (BEV-singular)
C	Charging rate
CD	Charge Depleting
CS	Charge Sustaining
DC	Direct Current
EDVs	Electric Drive Vehicles (EDV-singular)
EREV	Extended-Range Electric Vehicles
EVSE	Electric Vehicle Supply Equipments
FCVs	Fuel Cell Vehicles (FCV-singular)
HEVs	Hybrid Electric Vehicle (HEV-singular)
HEVs	Hybrid Electric Vehicles (HEV-singular)
ICE	Internal Combustion Engine
IEEE	Institute of Electrical and Electronics Engineering
Kg	Kilogram
KW	Kilo watt
KWh	Kilo Watt Hour
LDV	Light Duty Vehicle
LMP	Locational Marginal Pricing
LOL	Loss Of Life
PEVs	Plug-In Electric Vehicles (PEV-singular)
PHEVs	Plug-In Hybrid Electric Vehicles (PHEV-singular)
POP	Preferred Operating Point
PVEVs	Photovoltaic Electric Vehicles (PVEV-singular)
RTS	Reliability Test System
SOC	State Of Charge
THD	Total Harmonic Distortion
TN	Terra-Neutral
TT	Terra-Terra
V2G	Vehicle to Grid

1 CHAPTER ONE: INTRODUCTION

1.1 Background

We are in the era of technology where individual ICE (Internal Combustions Engine) driven mobility is an essential component of life in nations across the world. The car is used for both leisure and business purposes, for transportation of people and goods. It is, at the same time, a status symbol and emotional object. However, volatility in petroleum prices, security concerns associated with imported oil and anthropogenic climate change contribute to increasing interest in alternative vehicle technologies. According to the percent of world oil consumption used for transportation, 27.3 billion barrels of oil was consumed in 2006 worldwide [1.1]. Out of this 16.8 billion was used for transportation, which is about 61% of the total world oil consumption. At present, the U.S. is importing crude oil at the rate of 8.133 Mb/day[1] and approximately 5.46 Mb/day of crude oil are produced domestically, according to U.S Energy Information Administration, Crude oil Supply and Disposition as of December 2009 data in [1.2]. As can be seen in Figure 1.1below, the consumption of oil world wide is rising exponentially while its discovery is falling radically.

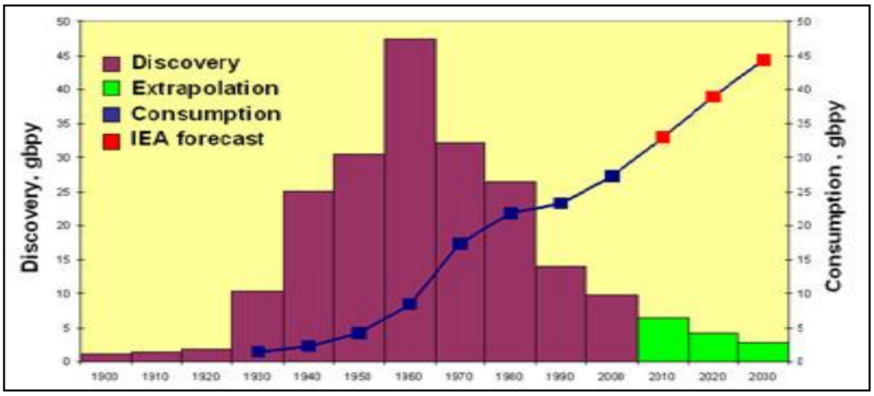


Figure 1.1: Consumption Vs Discovery of oil [1.3]

Two-thirds (62.75%) of the oil used in the US is refined into gasoline and diesel fuel to power U.S. passenger vehicles and trucks, as of February 26, 2010 data in [1.4]. As can be seen in Figure 1.2 below, nearly all energy needed in the transportation industry is covered by petroleum oil, which is indeed the source of environmental and economical impacts in a large scale.

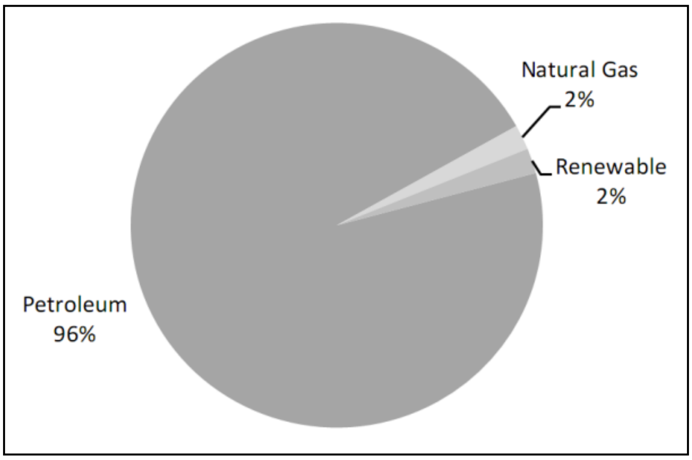


Figure 1.2: Energy mix used in transportation [1.5]

With a growing world-wide demand for crude oil, there has been a significant rate of change in its market price now standing (December 09, 2010) at $75.98 per barrel [1.6].

[1] Millions of barrels per day

One can easily see the historical price change of oil for the last 36 years as illustrated in Figure 1.3.

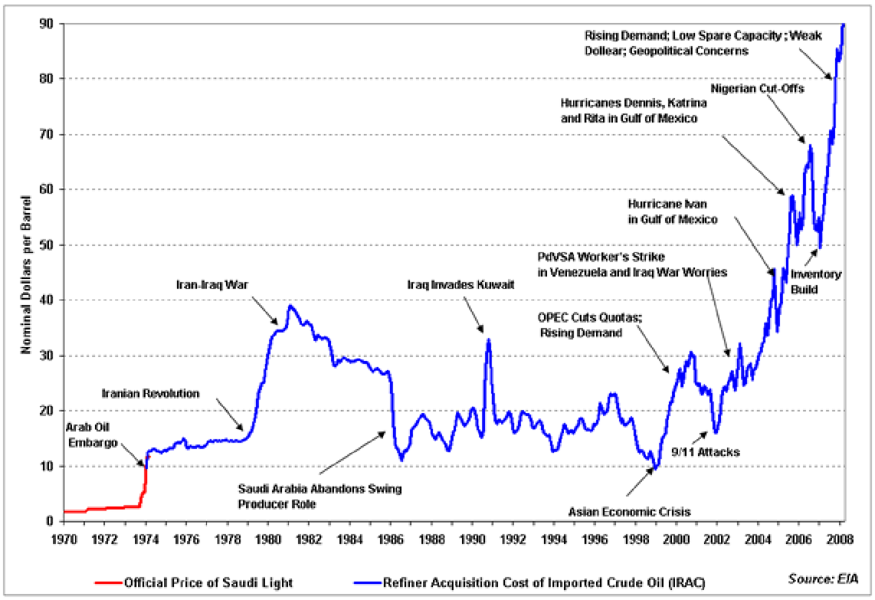
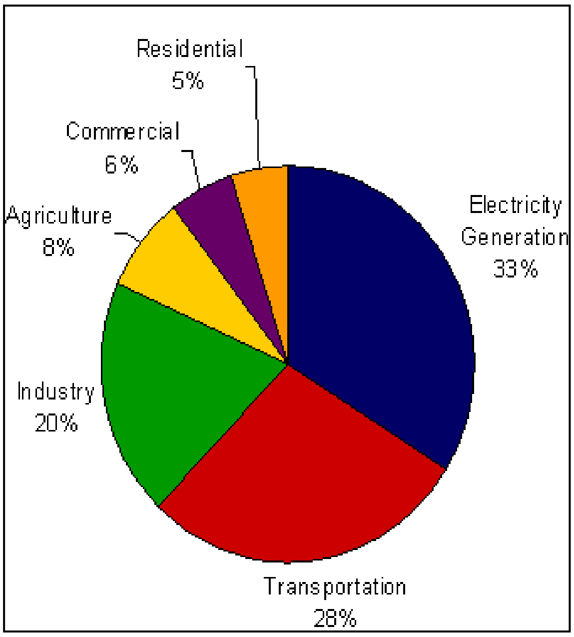


Figure 1.3: World Nominal Oil Price Chronology: 1970-2007 [1.7]

Apart from this, the burning of petroleum fuel emits CO2, the most serious greenhouse gas, into the atmosphere at levels now believed to be causing a global warming effect with very serious changes in global weather patterns, as can be seen in Figure 1.4 and Figure 1.5 below. Both figures show the high proportion of green house gas emission from the transportation sector.



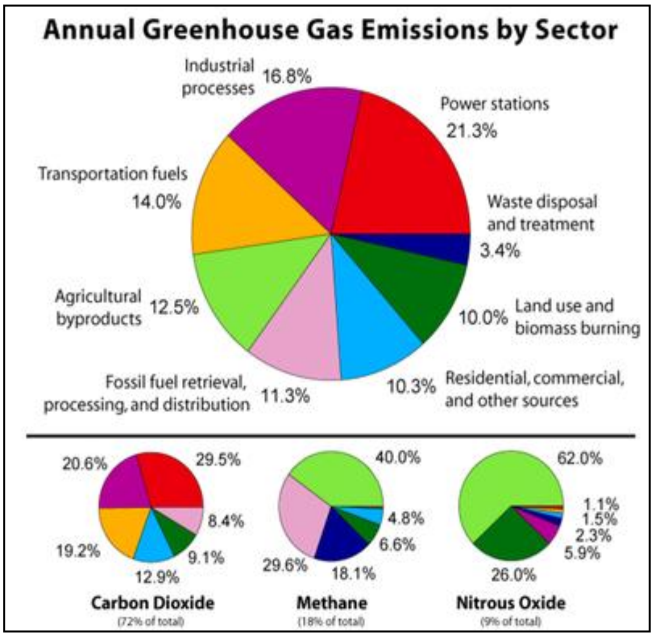


Figure 1.4: U.S. annual Greenhouse Gas Emissions, 2006 [1.8] Figure 1.5: Global annual Greenhouse Gas Emissions, 2000 [1.9]

The four major factors mentioned in the preceding paragraphs demands immediate solutions to shift the energy mix in the transportation industry so that its impact both on national security, economy and environment could be minimized.

Due to the awareness of the negative environmental impacts of conventional ICE driven vehicles, the market today is demanding for alternatives that are more efficient than ‘traditional’ car concepts. A number of solutions have been proposed including increasing fuel economy, the use of ethanol, and the use of conventional HEVs (Hybrid Electric Vehicles) [1.10]. A closer look into performance and efficiency reveals the potentials of PEVs [2] to solve the problems at hand, having its own set of opportunities and challenges. The penetration of PEVs in the transportation industry can displace a considerable amount of oil used in the transportation industry by incorporating considerable electric energy from the grid in the sector, which will be a major step forward to resolve the major problems stated above.

Diesel and Otto motor, both invented by the end of the 19th century, have over the last 100 years been improved in both performance and efficiency. A highly efficient ICE reaches a ratio of about 35% between energy content of the fuel and actual kinetic energy, which is called tank-to-wheel efficiency. However, the ICE operates most of the time with less than 10% efficiency, while the rest of the energy is lost in heat [1.11]. Taking into account the losses for the production of gasoline or diesel from crude oil and its transport, the well-to-wheel efficiency of an ICE averages to 20% [1.11].

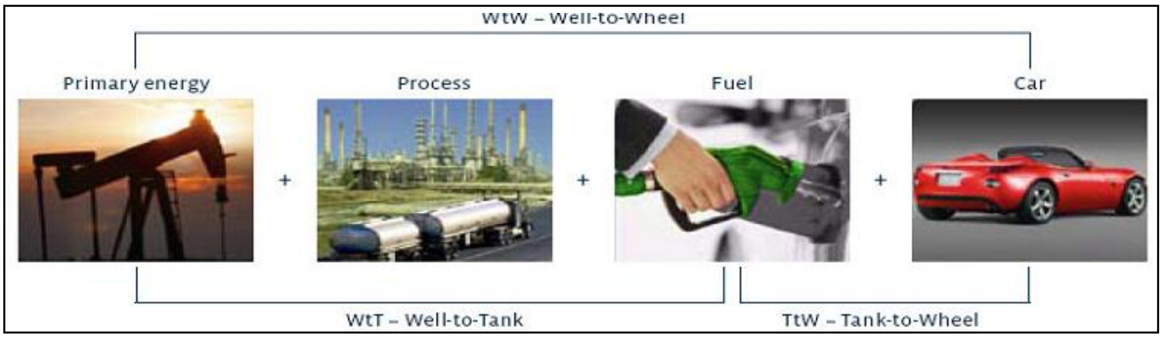


Figure 1.6: Global energy chain Well-to-wheel [1.11]

Alternative drive trains and energy carriers such as fuel cells, bio fuel and natural gas engines have been investigated and installed in many cars, but have not proved to be the ultimate solutions as they only bring slight improvements and come together with a whole list of disadvantages [1.11].

In contrast to this stand BEVs (Battery Electric Vehicles). Invented in the 19th century, they provide a tank-to-wheel efficiency of greater than 86%[3]; enable a drive train without transmission, and produce, compared to an ICE, almost no noise emissions at all. Of course, electricity is not a primary energy carrier but must be produced first. This can, for example, be done by alternative energy sources such as wind or water. But even if the electricity stems from coal or gas power plants, an overall well-to-wheel efficiency of 40% is reached, as can be seen in Figure 1.7 [1.11].

[2] PEVs are electric vehicles which connect (plug-in) to the grid for some or all of its energy demand

[3] Here tank-to-wheel efficiency is defined as the ratio of energy in the battery to kinetic energy at the wheel of the vehicle and this efficiency is calculated base on Figure 1.7

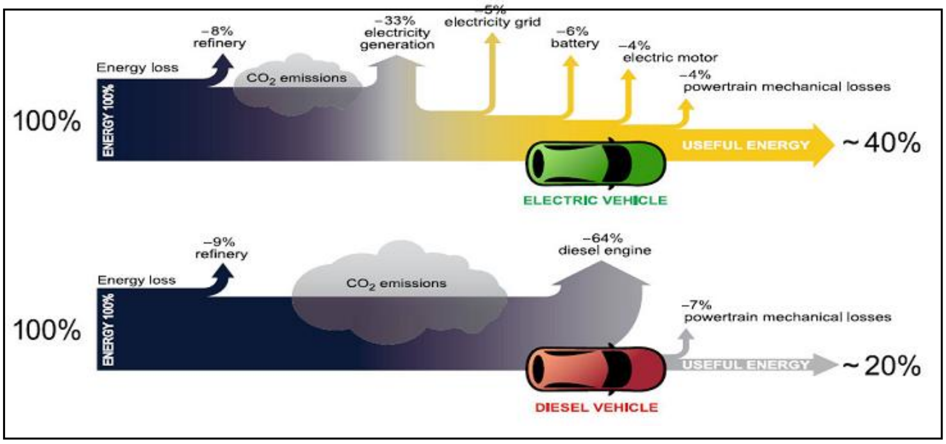


Figure 1.7: Well-to-wheel efficiency of Electric vehicle vs. Diesel vehicle [1.11]

As a result, the introduction of electric driven vehicles in the transportation industries will nearly eliminate 'an addiction' to oil and hence reduce greenhouse gas emission from transportation, open new opportunities for auto and power industries and bring a lower running cost for the consumers as the per mile energy from the grid is much cheaper compared with the same energy cost from oil. This will be discussed more in chapter two.

For all their advantages stated, PEVs are taking a center stage in the current developments to resolve the negative impacts of conventional vehicles from transportation industry. Visions from research institutes even discuss an almost complete substitution of the conventional fleet by 2050 [1.11]. If this paradigm shifts from conventional oil fueled transportation vehicle to grid supplied transportation is to take place, there will be a significant challenges and opportunities waiting for both automobile industries, oil industries and power supply industries.

If this mass deployment of PEVs becomes a reality, the current power system will become the petrol station of the future. Here is where the problem lies. If the current mix of energy in the transportation industry is shifted to the energy from the grid, the impacts of PEVs on the existing power system will be inevitable. This necessitates an extensive investigation to have knowledge of possible impacts they may have on the power systems.

There are a rapidly growing number of studies on PEV performance and impacts. These studies can typically be classified as vehicle performance studies that look at the cost of ownership and emissions impacts of vehicles; supply adequacy studies that aim to assess the potential to meet the growing demand with existing generation assets; Vehicle to Grid (V2G) studies, that look at the value of vehicles for the provision of bi-directional grid support services; and distribution system studies, which are limited in number, and which study the impact of increasing PEVs on the medium and low voltage infrastructure. There are a number of studies that can give fairly comprehensive results particularly for the first three categories. However, if utilities need to invest in the distribution infrastructure to support circuits feeding increasing numbers of PEVs, they will need good decision tools to help in the evaluation of investment. With this in mind, the goal of this diploma work is to develop a probabilistic model that allows distribution utilities to evaluate the impact of increasing PEVs on the power systems.

1.2 Purpose and scope

As stated above, the purpose of this diploma work is to develop a probabilistic model to quantify power system level impacts of PEV. The impacts PEV charging on the power systems can be realized in terms of added load. Formulating the added load profiles from PEV charging on a given power system, based on probabilistic parameters, is the heart of this diploma work. The resulting load profiles from PEV charging can be used along with system base load profiles to investigate impacts on the power system. These two load profiles, base load profiles and added load profiles resulting from PEV charging are the corner stone of impact analysis on the system.

One of the main problems encountered in the initial phase of this diploma work is lack of data on the system base load profile. Annual peak demand and annual energy consumptions at load feeders are the only available data of selected system of study. However to quantify impact analysis, load profiles divided in time on a given interval of time is required. As a result, a model based on IEEE Reliability Test System (RTS-96) is developed to generate load profiles for the selected system of study using available data. This important tool is applied in the selected system of study to generate load profiles for 8760 hours of a year.

Once the base load profiles are at hand, the next challenge was to develop a probabilistic model that can quantify the pattern of load profiles from PEV charging. As a result, two important PEV charging models are developed. These are fast charging models and residential PEV charging models. Fast charging models consider charging of PEVs at fast charging stations[4] whereas residential charging models consider charging PEVs at home.

In residential PEV charging model, two sub models are developed. The first model considers charging PEVs at a fixed charging power level trough out the simulation. This will be compared with the second residential charging model where vehicles are charged at different charging power level which is a function of parking interval[5], daily grid energy requirement by each vehicle and charging voltage level. The daily required grid energy is in turn a function of daily distance travelled by vehicles. The driving motors behind each model are statistic based random parameters which are probabilistically distributed. This includes distribution of daily distance travelled, daily grid energy requirements, and vehicle populations, state of charge (SOC) levels, and arrival and departure times of vehicles, distribution of battery capacities in each vehicle class and similar other parameters dictate the outputs from each models.

There are a number outputs from residential charging models. Among these are per minute and hourly average hourly load profiles. These load profiles, along with base loads, are used to quantify impacts on distribution transformer loading and transformer hotspot temperature variation, which is the basis to determine transformer Accelerated Aging Factor (AAF). AAF can be used to determine transformer Loss Of Life (LOL). The other important output is probabilistic SOC distribution curve. SOC distribution curve can be used as a basis to formulate the optimum size of battery capacities to be used in PEVs. In addition to this, this curve can also be used to determine required charging infrastructures outside home or hybrid energy to be used. More detailed results and analysis will be made in Chapter six.

The next most important model is fast charging models. There are two major differences between this model and residential charging model stated above. The first is the charging power level where PEVs are charged at high power level in an order 100 times higher than that in residential charging model. The second most important difference is the time when the charging takes place. Fast charging model takes into account vehicle arrival time distribution at the fast charging stations which is considered to be the same as vehicle arrival time distribution at petrol filling station today. On the other hand, residential charging model considers statistical daily arrival and departure time distribution from and to work respectively to charge vehicles.

[4] Fast charging stations are future equivalents of the present petrol filling stations

[5] Parking interval of a vehicle is the time interval between arrival time of vehicle on day d and departure time of the same vehicle on day d+1 from and to work respectively

Similar to residential charging models the outputs from fast charging models are also dictated by number of probabilistic parameters including distribution of daily distance travelled, distribution of vehicle arrival time at fast charging stations, ranges of battery capacities, distribution of SOC levels, distribution of vehicles in different classes and others. To appreciate the beauty of the probabilistic model, a deterministic fast charging model is also developed and results are compared at length.

Per minute and hourly average load profiles are among the outputs from PEV fast charging models. These outputs from the model along with the base load profiles are used to investigate the impacts of fast charging on the system bus voltages and results are illustrated and discussed. In addition to this the distribution of voltage dips in the system is also analyzed which can be used as the basis to optimize the size of energy storage devices needed at the fast charging stations to keep the system in the allowable operating limits. The other interesting result from this model is the distribution of required number of charging poles at the fast charging stations from which an economical decision on the optimum number of charging poles can be made. Apart from this, similar to residential charging models, the distribution SOC levels of PEVs coming to the fast charging stations are also covered. In addition to this, probabilistic distribution of number charging required per day per vehicle is also discussed.

What is not included in this diploma work is model integration to accommodate clustering of PEV charging. Each model works independently of the other in its own domain. It is clear that a vehicle can charge both at home and fast charging station at different times on a given day based on daily distance it travelled and driving patterns. As a result, to have a good picture of the impacts of PEV charging on the given power system, it is important to consider this clustering of PEV charging both at home and outside home at different times in a day. This requires the integration the two or more models. However the models developed in this thesis do not consider clustered PEV charging. Residential charging and charging at the fast charging stations are considered independently.

1.3 Structure

This report is structured as follow. Chapter one (this chapter), is an introduction. In this chapter, the purpose and scope of the diploma work are described. In chapter two, the main challenges and opportunities, resulting from penetration of PEVs in the power systems are discussed in details from different perspectives. In Chapter three the domain in which the problems at hand are defined will be discussed and each important component in the domain of study will be described at length. In chapter four, the required parameters to solve the defined problems in chapter three will be elaborated. Chapter five will utilize the parameters defines in Chapter four to develop probabilistic models that can solve the problems. Chapter six is the most important chapter where the model developed in chapter five will be tested with a number of scenarios. Results from the defined scenarios will be presented and detailed analysis will be made in this chapter. In chapter seven important conclusions will be made. In addition to this, this chapter will point out some of important future works which are not covered in this diploma work. Chapter eight provides a list of references used in the whole report and finally in Chapter nine, some important supplementing information used in the project is enclosed.

2 CHAPTER TWO: OPPORTUNITIES AND CHALLENGES

PEVs are taking center stage in the current developments to resolve the negative impacts of conventional vehicles from transportation industry. Visions from research institutes even discuss an almost complete substitution of the conventional fleet by 2050 [2.1]. If this paradigm shift from conventional oil fueled transportation vehicle to grid supplied transportation is to take place, there will be a significant challenges and opportunities waiting for both automobile industries, oil industries and power supply industries. In this chapter some of these challenges and opportunities seen from different perspectives will be discussed.

2.1 Global perspective

The combination of high oil costs, concerns about oil security and availability, and air quality issues related to vehicle emissions are driving interest in the planned mass penetration of electric mobility in the near future. The following subsections will describe the potentials in PEVs in oil displacement, and hence emission shift which will finally lead to reduced cost of operation.

2.1.1 Oil displacement

The use of PEVs would represent a significant potential shift in the use of electricity and the operation of electric power systems to replace a significant portion of the petroleum-fuelled drive energy. For many U.S. drivers, a PHEV-40[6] could reduce average gasoline consumption by 50% or more [2.4]. According the report in [2.5], in 2005, the United States consumed gasoline at a rate that required 9.1 million barrels of crude oil per day. Considering that the LDV (Light Duty Vehicle) fleet consumes 97% of the entire gasoline supply, the conversion of 73% of the LDV fleet to PHEVs could reduce gasoline consumption by a crude oil equivalence of 6.5 million barrels per day. This reduction in the U.S. gasoline consumption is the equivalent of 52% of foreign petroleum imports. In short, this indicates the potential in PEVs in displacing significant proportion of oil.

2.1.2 Emission shift

This significant shift in energy from petroleum to energy from the grid means, as stated in section 2.1.1, shifting emissions from millions of individual vehicles to a few hundred power plants. The conversion of LDVs to PEVs has significant implications for overall emissions as electricity displaces gasoline. According to [2.5], the impact of penetration of PHEV in emission reduction was analyzed and the result shows that for U.S as a whole, the total greenhouse gases are expected to be reduced by a maximum of 27% from the projected penetration of PHEVs (73%). The key driver for this result is the overall improvement in efficiency along the electricity generation path compared to the entire conversion chain from crude oil to gasoline to the combustion process in the vehicle.

2.1.3 Cost of energy

Thirdly, the economic incentive for drivers to use electricity as fuel is the comparatively low cost of fuel. According to the data in [2.4], the electric equivalent of the “drive energy” in a gallon of gasoline delivering 25-30 miles in a typical midsized car is about 9-10 kWh, assuming a vehicle efficiency of 2.9 mile/kWh[7]. The cost of this electricity using the U.S. average residential rate for 2005 (9.4 cents/kWh) is under $1, and could be even less when using off-peak power. This cost is directly comparable to the end-user cost of gasoline, which nationally averaged $2.60 for 12-month period ending in

[6] The notation "PHEV-XX" is commonly used to specify the PHEVs All Electric Range (AER). For instance a PHEV-40 corresponds to a PHEV with a 40 miles electric range. Typical PHEVs AER are in the range 20-60 miles.

[7] Kilo Watt Hour, unit of energy

August 2006. Furthermore, several researchers have noted that by adding V2G capability, where the vehicle can discharge as well as charge, PEV owners may also receive substantial revenue by using the stored energy in their vehicles to provide high-value electric system services such as regulation, spinning reserve, and peaking capacity.

2.2 Consumer perspective

From a consumer point of view the incremental cost of driving PEVs using electric utility energy can be surprisingly attractive. For example, according results in [2.2], gasoline has an energy content of 0.125 Btu/gallon, or 36.5 kwh per gallon. Assuming a $3 per gallon price, the cost of this energy is about 8.22 cents per kWh. This appears to be considerable when compared with average residential electric energy prices. However, one needs to consider energy conversion efficiencies. As we can recall from section 1.1above, moving energy from a battery pack and electric motor, and then into the wheels has an average efficiency of perhaps 86% and ICEs have achieved a ratio of 35% between energy content of the fuel and actual kinetic energy, which is called tank-to-wheel efficiency. However, ICE operates most of the time with less than 10% efficiency, while the rest of the energy is lost in heat. Hence, the incremental operating cost of the PEVs would be expected to be less than 1/5 that of a traditional gasoline engine [2.2]. Furthermore, since the PEV batteries could be charged at home during night (off-peak), substantially lower-priced electric energy could be used.

However the main challenge for the mass penetration to the consumer is the high initial cost associated with it. As a result, to gain the most from these vehicles, there must be an incentive from a third party to subsidize at the initial phase of their penetration.

2.3 Utility perspective

Utilities and grid operators become interested in providing the infrastructure for electro mobility and pushing the entire development. This happens mainly for three reasons: additional electricity sales, grid stabilization and image improvement. At the moment the utilities are the major driving forces behind the development of the electro mobility industry, and invest a considerable amount of money in pilot projects, joint ventures and promotion campaigns [2.1].

If mass scale PEVs are to be introduced, electric utilities will be the *''gas stations of the future''*. This will have a potential challenges and opportunities from utility perspective. PEVs represent a potentially new semi-dispatchable load for electric utility. At a minimum they represent new, primarily off-peak users of substantial amounts of electric energy.

In addition to just being energy users, in aggregate PEVs could also provide large amounts of potentially controllable stored energy, refer section (2.3.1). With such a network, the stored energy in PEVs and their energy storage capacity could become a highly controllable, system-level resource. Potential applications include the ability to greatly reduce spinning generation reserves, the ability to increase transmission system capacity by providing a responsive post-contingent control, and the ability to mitigate LMP (Locational Marginal Pricing) market volatility [2.2].

On the other hand, a mass introduction of PEVs in the transportation industry can create a number of challenges in the current power systems. Unless the charging patterns of PEVs are controlled, this can have a significant impact on the power system components such as distribution transformer, system voltage, distribution cable and harmonic generation. The following sub section will have a closer look at some of the challenges and opportunities from utility perspective.

2.3.1 Vehicle to Grid (V2G)

Vehicles that plug in to the power grid for some or all of their energy needs have the potential to make valuable contributions to the production, transmission, and distribution of electric power. PEVs have a battery pack (energy storage device) and a charger. The charger takes in alternating current (AC) power from the grid and converts it to direct current (DC) to charge the battery pack. This charger can be bidirectional that can be able to deliver power back to the grid from the vehicle's battery as well as charge the battery.

Vehicles with bi-directional chargers can cycle power to and from the grid under remote control, even while charging. Vehicles with unidirectional chargers (i.e. they cannot feed power back to the grid), can still provide services to the grid by allowing the remote control of the battery charging rate or as a controlled load. These concepts of vehicles providing services to the grid are collectively referred to as "vehicle to grid" (V2G). V2G is a term used to describe this use of bi-directional charge/discharge capabilities of PEVs to provide ancillary services and peak shaving for the power grid. V2G does not necessarily mean that power has to flow from the vehicle to the grid; vehicles with unidirectional chargers that are controlled to provide a service to the grid are also providing a V2G service [2.3].

As a result, PEVs will be a new resource to assist with grid operations. Specifically, the energy storage capacity of PEVs can be a storage resource for the grid that can be controlled remotely by the utilities, aggregator or a grid operator to perform ancillary services for the grid. Further, since PEVs' load can be remotely dispatched to provide V2G, the current grid model of dispatching generation to match load can be transformed to load that can be dispatched to match generation.

Electrical grid operation requires, assuming in real time, that the total generation matches the total load. If there is a mismatch between generation and load, the frequency of the grid will deviate from the standard of 60 Hertz. Grid operators use a variety of tools to keep the grid operating smoothly. These tools are commonly referred to as "ancillary services". Some examples of ancillary services are spinning reserves, non-spinning reserves, and regulation [2.3].

According to [2.3], a number of studies have identified regulation as the most valuable ancillary service that PEVs could provide. Regulation is a service that gives the grid operator the ability to directly control the output of a power plant up and down in real time (at 4 second update rates typically). Regulation is used to fine-tune the match between generation, load, and interchange with other control areas and to contribute to overall grid frequency control. Regulation is divided as regulation up and regulation down. Regulation up represents increasing a power plant's output from a nominal level and regulation down represents decreasing a power plant's output from a nominal level. Power plants that provide regulation services will have a nominal scheduled power output level, often referred to as the POP (Preferred Operating Point), and a regulation up limit, and a regulation down limit as can be seen in Figure 2.1.

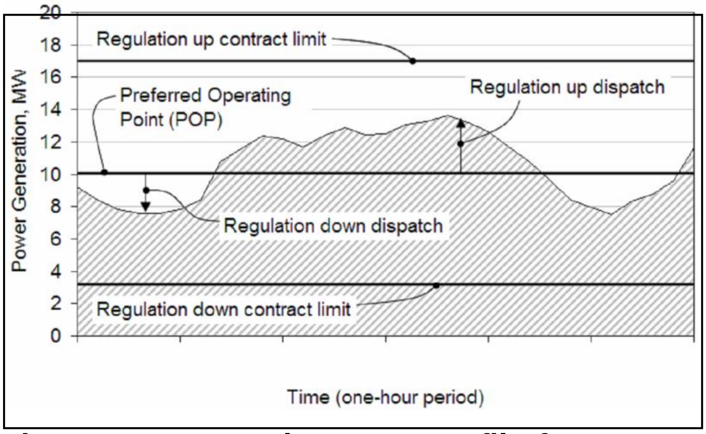


Figure 2.1: Example power profile for a power generator providing regulation up and regulation down. The shaded area represents the energy generated over the one-hour period [2.3]

The power fluctuations due to dispatch of regulation in the power profile shown in Figure 2.1, could equally well come from PEVs whose charger power levels are controlled by a utility, aggregator, or the grid operator. The only difference is the value of the POP. For a power plant, the POP is a positive value (i.e. a nominal generation level). For a PEVs, the POP could be positive (for bidirectional charger), zero, or it could be negative (for unidirectional charger). That is, the regulation service does not directly depend on the value of the POP; it is the capability to deviate up or down from a particular POP value. Hence the POP can just as easily be negative (a load) as positive (generation).

Figure 2.2 illustrates a PEV providing regulation with a POP value of zero. This vehicle has a bi-directional battery charger and is providing power to the grid for regulation up and taking power from the grid for regulation down.

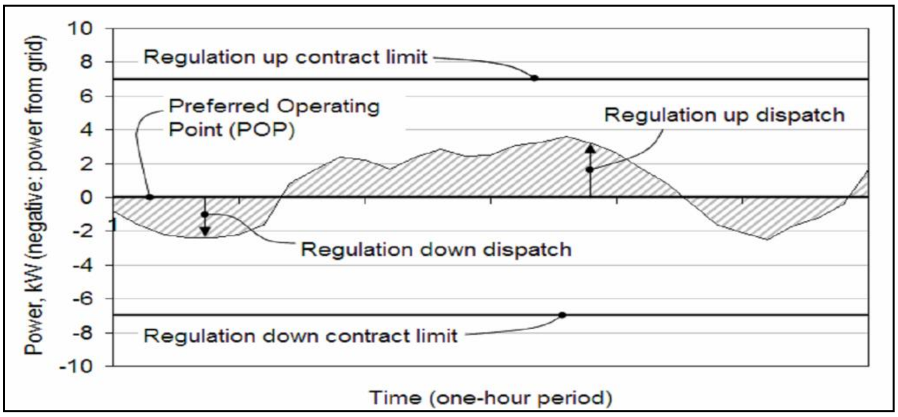


Figure 2.2: Example power profiles for PEVs with a bi-directional charger providing regulation up and down ancillary service with a zero POP. The shaded area above zero represents energy delivered to the grid from the vehicle (regulation up) and the shaded area below zero represents the energy consumed by the vehicle (regulation down) [2.3]

Figure 2.3 illustrates a PEV with a unidirectional charger providing regulation with a -7 kW POP value. The vehicle is drawing power from the grid at a nominal “POP” rate of -7 kW and providing 7 kW of regulation up and 7 kW of regulation down. At the regulation up limit, the vehicle is placing no load on the grid and at the regulation down limit, the vehicle is placing a 14 kW load on the grid.

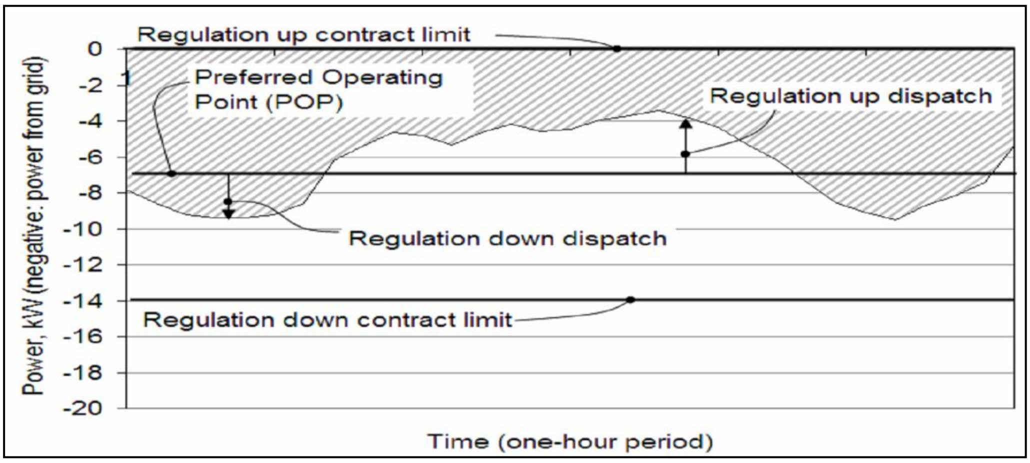


Figure 2.3: Example power profiles for a PEVs with unidirectional chargers providing regulation up and down ancillary service with a POP value of -7kW (ie. 7 kW of load). The shaded area represents the energy delivered to the vehicle by the grid over the one-hour period [2.3]

2.3.2 Power supply adequacy

Electrification of the transportation sector could increase generation capacity and transmission and distribution requirements, especially if vehicles are charged during periods of high demand. If charging patterns of PEVs are controlled by utility or if customer is price sensitive and charge during the off-peak time, both the incremental cost of energy and new investment on the power system infrastructure can be greatly minimized [2.4].

A study by National Renewable Energy Laboratory of U.S Department of Energy investigated Costs and Emissions Associated with PHEV Charging [2.4]. This study was performed on the utility of '***Xcel Energy'*** Colorado service territory which serves about 55% of the state's population. To see the impacts PHEV charging on this system, an overall penetration of 500,000 vehicles was assumed, equal to roughly 30% of LDV in the Xcel Energy service territory. The results for four charging scenarios; i.e. Uncontrolled Charging, Delayed Charging, Off-Peak Charging and Continuous Charging are shown in Figure 2.4 and Figure 2.5 below.

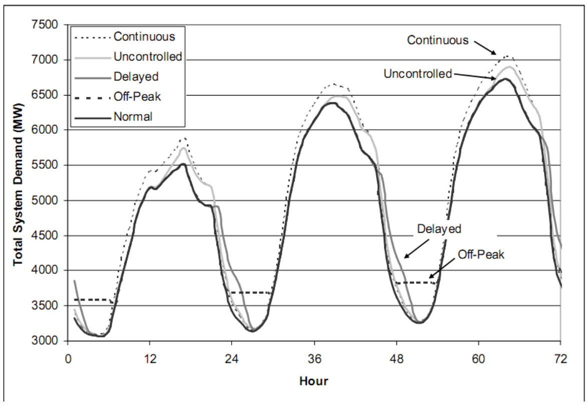


Figure 2.4: Summertime Load Patterns with PHEV Charging [2.4]

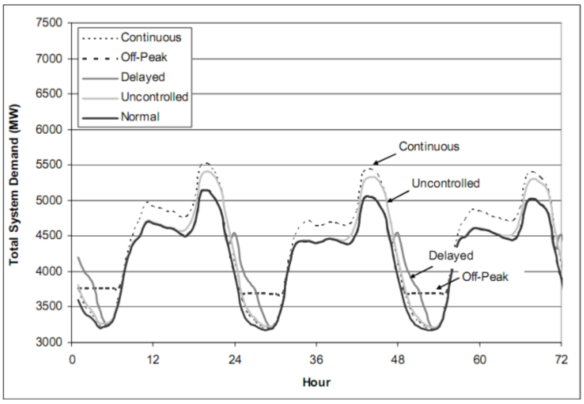


Figure 2.5: Wintertime Load Patterns with PHEV Charging [2.4]

The results in Figure 2.4 and Figure 2.5 above demonstrate that on an annual basis, uncontrolled charging and continuous charging cases require a large fraction of PHEV charging to occur during periods of moderate to high loads. The time-delayed and off-peak charging cases show an improvement in the distribution of additional charging. The majority of the increased load occurs in the lower demand region. A noticeable benefit of off-peak charging is the increased minimum load. Table 2.1, taken from [2.4], summarizes the load impacts resulting from the 500,000 PHEV scenarios.

Table 2.1: Impacts of Various Charging Cases on System Capacity and Energy Requirements

Charging Scenario	Increase in Total Load (%)	Increase in Peak Demand (%)
Uncontrolled	2.7	2.5
Delayed	2.7	0
Off-peak	2.7	0
Continuous	4.8	4.6

According the result from Pacific Northwest National Laboratory study on impacts assessment of PHEVs on electric utilities and regional US power grids [2.5], significant portions of the U.S. gasoline-operated vehicle fleet could be fueled with the available electric capacity. For the nation as a whole, about 84% of the energy needed for operating cars, pickup trucks, and SUVs (or a maximum of 73% of the energy of the LDV fleet) could be supported using generating, transmission, and distribution capacity currently available provided that the charging profiles of the vehicles are controlled.

2.3.3 Distribution system impacts

Distribution systems are typically designed for specific load carrying capability based on typical load consumption patterns of customers. When PEVs are deployed, the patterns of electric power demand change. It is possible that the electric power system may be adequate to handle the new patterns and levels of demand or it is possible that periods of overloads on this system may increase. Both distribution circuits and transformers are vulnerable to these overloads with the transformer being more susceptible to overloads.

Transformers fail most frequently due to line surges/short circuits, the deterioration of insulation, lightning strikes, inadequate maintenance, high oil moisture content, and loose connections [2.6]. Additional load, such as that required to charge PEVs, increases the average operating temperature of the transformer due to increased current in the transformer windings, which contributes to insulation breakdown. Insulation failure increases the quantities of dissolved gases in the insulating oil. Formation of gasses in the insulating oil reduces the dialectic strength of the oil and can create or aggravate short circuits between coil windings; high levels of combustible gasses can lead to explosions [2.6].

Additional demand from PEV charging may have positive or negative effects on transformer aging. Firstly increased charging demand will increase transformer temperatures, which may decrease transformer life expectancy. Secondly, the flatter load profile resulting from off-peak PEV charging could reduce the daily expansion and contraction of the transformer, which could reduce wear-and-tear on the transformer bushings, which are the primary entry points for oxygen, water, and contaminates, which intern decrease the probability of transformer failure.

2.3.4 Harmonic generation

Harmonic distortion from the power electronics in PEV chargers may also have some negative effects on the distribution infrastructure. PEVs charge by drawing low voltage AC power and converting it to DC. This process involves rectifying the AC signal and running the rectified signal through a DC/DC converter. Both of these processes inject harmonic distortion in the distribution system. Harmonic distortion causes power loss in transformers due to increased average temperature generated from increased eddy currents in the transformer core and decreased skin depth on the transformer windings and harmonic distortion also creates higher hotspot temperatures compared to loads without harmonic distortion [2.6].

Large numbers of harmonic loads on a single distribution circuit will result in some harmonic cancellation between the loads which may reduce overall harmonic distortion [2.6]. If PEV penetration was sufficiently high such that the majority of off-peak load was from PEVs, harmonic loading on distribution equipment could be very high during night-time charging hours. However, lower night time temperatures will help cool the transformer, which may keep the transformer from overheating even if the internal losses are higher. According to [2.6] a 10% Total Harmonic Distortion (THD) could correspond to a 6% loss in transformer life, relative to a load with no harmonic distortion.

3 CHAPTER THREE: PROBLEM DESCRIPTION

3.1 Background

Electric Drive Vehicles (EDVs) have gained attention, especially in the context of growing concerns about global warming and energy security aspects associated with road transport. The main characteristic of EDVs is that the torque is supplied to the wheels by an electric motor that is powered either solely by a battery or in combination with an internal combustion engine. This covers HEVs, BEVs and PHEVs, but also Photovoltaic Electric Vehicles (PVEVs) and Fuel Cell Vehicles (FCVs).

PEVs, which include PHEV and BEV, represent a promising future direction for personal transportation sector in terms of decreasing the reliance on fossil fuels while simultaneously decreasing emissions and cost of energy for driving as discussed in section 2.1 above. Energy used for driving is fully or partially shifted to electricity leading to lower emission rates, especially in a low carbon intensive generation mixture as in Sweden. Despite the benefits of PEVs for vehicle owners, care will need to be taken when integrating PEVs into existing electrical grids.

Distribution systems are typically designed for specific load carrying capability based on typical load consumption patterns. When PEVs are deployed in this system, the patterns of electric power demand will change due to added load on the grid system from PEVs. The extent to which the deployments of PEVs affect the distribution system depends on their charging characteristics which include both charging power level and charging time.

Given that the charging patterns of PEVs are controlled either by the utility or the customer side, it is possible that the electric power system may be adequate to handle the new patterns and levels of demand. On the other hand, if the charging patterns of PEV cannot be controlled by either side, it is possible that periods of overloads on this system may increase. As a result, both distribution system’s circuits and transformers are vulnerable to these overloads with the transformer being more susceptible to overloads [3.2].

Given standard loading profiles and proper maintenance, manufactures report an expected transformer lifetime of 40-50 years. Under more realistic conditions the actual average lifetime of a transformer is 17 years [3.2]. Transformers fail most frequently due to line surges/short circuits, the deterioration of insulation, lightning strikes, inadequate maintenance, high oil moisture content, and loose connections. Additional load, such as that required to charge PEVs, increases the average operating temperature of the transformer due to increased current in the transformer windings, which contributes to insulation breakdown. Insulation failure increases the quantities of dissolved gases in the insulating oil. Formation of gasses in the insulating oil reduces the dialectic strength of the oil and can create or aggravate short circuits between coil windings; high levels of combustible gasses can lead to explosions [3.2].

In general, additional demand from PEV charging may have positive or negative effects on transformer aging. Firstly increased charging demand will increase transformer temperature, which may decrease transformer life expectancy. Secondly, the flatter load profile resulting from off-peak residential PEV charging could reduce the daily expansion and contraction of the transformer, which could reduce wear-and-tear on the transformer bushings, which are the primary entry points for oxygen, water, and contaminates, which intern decrease the probability of transformer failure [3.2].

Impacts of PEV charging on the distribution system can be realized in terms of the added load. This added load is a function the additional energy demand due to PEV deployment. As discussed in chapter two, most of existing power systems has the potential to deliver this added energy. The question will be when (charging time interval) and how fast (charging power level) this energy is required from the grid. If the energy required by PEVs can be delivered in a longer time span and during light load condition, this can be achieved with almost no or little impacts on the target system. On the other hand, if this same energy is required in a short time interval and or during a peak load period, that will lead to a serious consequences both on the system voltage and power system components like distribution transformers and cables.

It is the keen interest of this diploma work to develop a probabilistic model of these charging patterns that can help to quantify the impacts on the power systems. This will intern lead to appropriate actions to be taken to bring the system back to the desired operating conditions. To hit this target, a proper understanding of the problem at hand is mandatory. The main objective of this chapter will be to describe the domain in which the problem is defined. Figure 3.1 below illustrates the boundary in which all the problems for this diploma work are defined. In the following subsections, we will take a closer look at the descriptions of some of components in the domain which will help to have a better picture of the problem at hand.

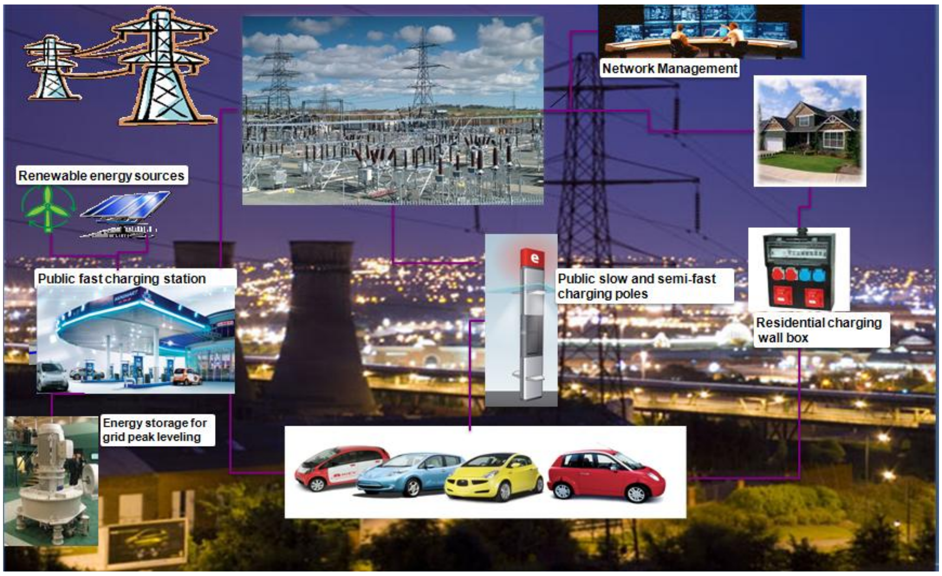


Figure 3.1: Boundary of the problem

As can be seen in Figure 3.1, the domain in which the problem is defined can easily be visualized. It consists of a distribution system which is supplied by sub transmission system. Within the distribution system is a residential area equipped with a residential slow chargers where vehicles can be charged at home. In addition to this, a road side semi-fast chargers are also illustrated where vehicles can be charged (this is not considered in this study). Most importantly, this system includes a fast charging station where PEVs are charged at high power level (less than 10minute charging time). This short lasted delivery of energy at the fast charging station has a serious consequence on the system voltage and distribution system components. To limit this impact, fast charging stations need to be equipped with energy storage device like ultracapacitors and supper flywheel. This fast charging station is the future PEV charging station equivalent of the current petroleum fueling station.

In short, this is a short description of the region where the problem at hand is defined. Our objectives will be developing probabilistic models to analyze the impacts PEV charging in this system. This is why it is so important to define components in within the boundary where the problems at hand are defined.

Section (3.2) starts by defining the power system in general and the distribution system in particular where PEVs are to be deployed. Section 3.3 will define PEV with some of their important parameters. Section (3.4) describes the EU grid in terms of available charging power and grid standards. Section 3.5, which is the last and important section, will define charging parameters and charging infrastructures.

3.2 Distribution system

The major components of an electric power system are shown in Figure 3.2 below. One of these components is distribution system which is the nearest point where electric energy is consumed.

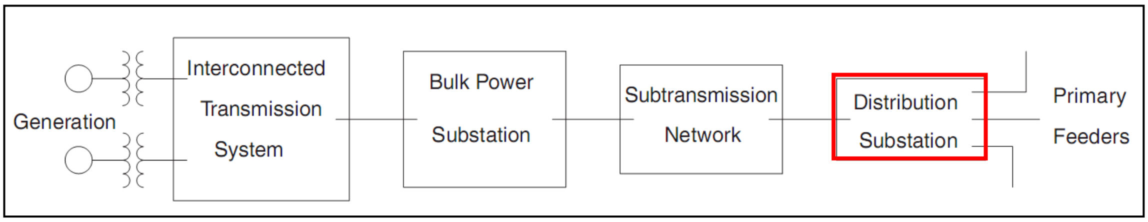


Figure 3.2: Major power system components [3.4]

The distribution system typically starts with the distribution substation that is fed by one or more sub transmission lines as shown in Figure 3.3. In some cases the distribution sub-station is fed directly from a high-voltage transmission line, in which case there is likely no sub transmission system. Each distribution substation will serve one or more primary feeders. With a rare exception, the feeders are radial, which means that there is only one path for power to flow from the distribution substation to the user.

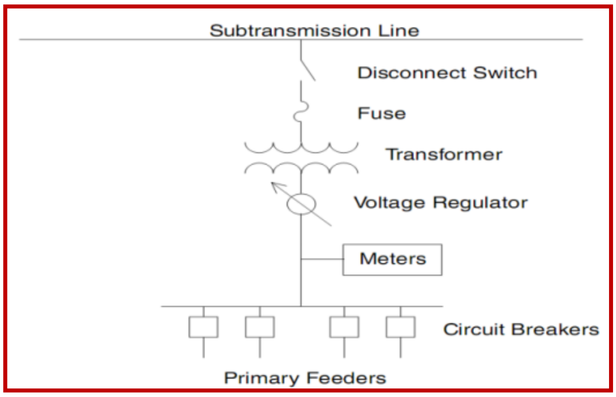


Figure 3.3: Simple distribution substation [3.4]

There are number of components in distribution sub stations. Among this is the distribution transformer which is there to step the voltage down to a level required by the loads at the feeder end as can be seen in Figure 3.3.

3.2.1 Nature of load and Individual Customer Load

The modeling and analysis of a power system depend upon the load on the system. The problem is that the load on a power system is constantly changing. The closer we are to the customer, the more pronounced will be the ever changing load. In order to come to grips with load, it is necessary to have a look at the load of an individual customer [3.4].

The load that an individual customer or a group of customers presents to the distribution system is constantly changing. Figure 3.4 illustrates how the instantaneous kW [8]demand of a customer changes during two 15-minute intervals.

[8] Kilo watt, unit to measure power

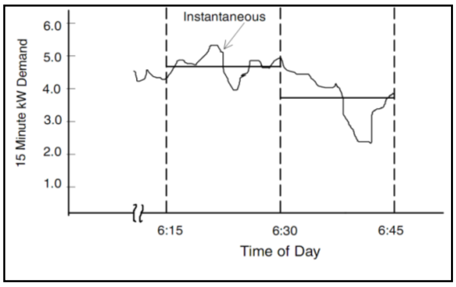


Figure 3.4: Customer demand curve [3.4]

In order to define the load, the demand curve is broken into equal time intervals. In Figure 3.4 the selected time interval is 15 minutes. In each interval the average value of the demand is determined. In Figure 3.4 the straight lines represent the average load in a time interval. The shorter the time interval, the more accurate will be the value of the load. The average value of the load in this interval is defined as the *15-minute kW demand [3.4]*. If we have list of values of these demands over a given interval of time, as shown in Figure 3.5 below, they represent a demand curve or load profile.

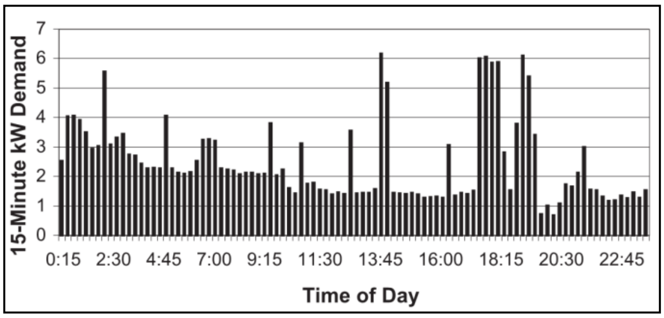


Figure 3.5: Demand curve of a Customer for 24 hours of a day [3.4]

3.2.2 Basic Definitions

3.2.2.1 Demand (D)

Demand is defined as the average value of load over a given interval of time. The 24-hour 15-minute kW demand curve for a customer is shown in Figure 3.5. This curve is developed from a series of values that gives the 15-minute kW demand for a period of 24 hours.

3.2.2.2 Maximum Demand (MD)

The demand curve shown in Figure 3.5 represents a typical residential customer. Each bar depicts the 15-minute kW demand. Note that during the 24-hour period there is a variation in the demand. The largest of these demands is the 15-minute maximum kW demand.

3.2.2.3 Average Demand (AD)

During the 24-hour period, energy will be consumed. For example, the energy consumed in kWh during each 15-minute time interval is computed by:

$$\boldsymbol{E = (15\ min\ kW\ D) * \frac{1}{4} hou} \qquad \textbf{3-1}$$

The total energy consumed during the day is the summation of all of the 15-minute interval energy consumptions. The 15-minute average kW demand of a day is computed by:

$$\boldsymbol{AD = \left(\frac{Total\ energy}{Hours}\right)} \qquad \textbf{3-2}$$

Where, $Total\ energy$ is the total KWh energy consumed by the load in a given day and $Hours$ is intervals in 24 hours of a day. This formula can be applied to calculate an average demand in a given interval of time provided that we have the total energy consumed in that interval of time.

3.2.2.4 Load Factor (LF)

LF is a term that is often used when describing a load. It is defined as the ratio of the average demand to the maximum demand.

$$\boldsymbol{LF} = \left(\frac{\boldsymbol{Average\ Dermand}}{\boldsymbol{Maximum\ Demand}}\right) \qquad \textbf{3-3}$$

If we know $\boldsymbol{LF}$ and Maximum Demand in a given time interval, we can determine the average demand in that time interval. In many ways load factor gives an indication of how well the utility's facilities are being utilized. From the utility's standpoint, the optimal load factor would be 1.00 since the system has to be designed to handle the maximum demand.

All these important terminologies defined above will extensively be used in section (5.1) to generate the base load profile of the given distribution system which is one of the corner stone to start system analysis combined with the load profiled from PEVs.

3.2.3 Distribution transformer loading

A distribution transformer provides service to one or more customers. Each customer has a demand curve similar to that shown in Figure 3.5. However, the peaks, valleys and maximum demands will be different for each customer. The load curves for each customers served by the distribution transformer show that each customer has its unique loading characteristic. If the load curves of each load, connected to the transformer, are added within each respective time interval, the result is the *diversified distribution transformer loading curve*. Figure 3.6 below shows an aggregated 24-hour demand curve on a transformer.

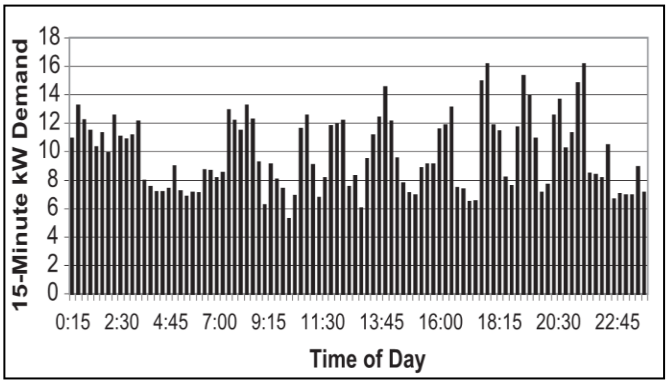


Figure 3.6: Transformer *diversified* demand curve [3.4]

It is important to know transformer loading curve. If PEVs are to be deployed on this transformer, the load profile due to PEV charging will be added on this base lading which can then be used for the system analysis.

3.3 Electric Derive Vehicles

3.3.1 Definition

EDVs, which include PHEVs and BEVs, are important components of the problem at hand. As described earlier, the main characteristic of EDVs is that the torque is supplied to the wheels by an electric motor that is powered either solely by a battery or in combination with an internal combustion engine. In this section PHEVs and BEVs along with ICE and HEVs will be defined that can help to have a better image of vehicles in the study domain.

- Internal Combustion Engine (ICE) Vehicles

ICE vehicle refers to the vehicle which is mainly propelled by the energy from the fuel tank. The internal combustion engine is an engine in which the combustion of a fuel (generally, fossil fuel) occurs with an oxidizer (usually air) in a combustion chamber. The main advantage of using ICE in vehicles is that it can provide high power-to-weight ratios together with excellent fuel energy density [3.6].

- Hybrid Electric Vehicle (HEV)

HEV refers to vehicles which combine conventional ICE propulsion system with an electric propulsion system. The presence of the electric powertrain is intended to achieve either better fuel economy than a conventional vehicle, or better performance [3.6].

- Plug-In Hybrid Electric Vehicles (PHEV)

PHEV refers to vehicles that can use, independently or not, fuel and electricity, both of them rechargeable from external sources. PHEVs can be seen as an intermediate technology between BEVs and HEVs. It can indeed be considered as either a BEV supplemented with an ICE to increase the driving range or as a conventional HEV where the All Electric Range (AER) is extended as a result of larger battery packs that can be recharged from the grid [3.6]. PHEVs can be designed with the same types of technological architecture as current hybrid vehicles, namely series-hybrid, parallel-hybrid, or combined series-parallel hybrid (split). *Series-Hybrid* is to be associated with electric cars since only the electric motor provides power to drive the wheels. Sources of electrical energy are either the battery pack (or ultra capacitors) or a generator powered by a thermal engine. An example of PHEV series is the famous Chevrolet Volt developed by General Motors. Such vehicles are also called Extended-Range Electric Vehicles (EREV) [3.7]. In *Parallel-Hybrid,* both the electric motor and thermal engine can provide power in parallel to the same transmission. *Power split or series/parallel hybrid* combines the advantages of both parallel and series hybrid concepts. This is for instance the architecture implemented in the Toyota Prius model. This relatively complex architecture allows running the vehicle in an optimal way by using the electric motors only, or both the ICE and the electric motors together, depending on the driving conditions. Figure 3.7 shows important similarities and differences between HEV and PHEV.

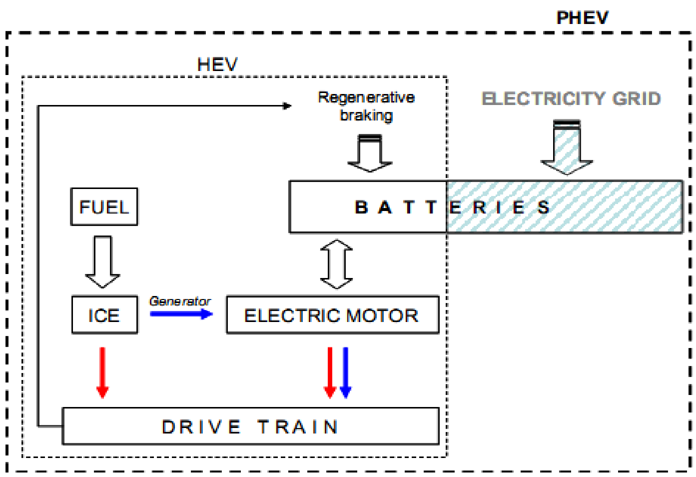


Figure 3.7: Simplified representation of HEV/PHEV configuration (blue: series; red: parallel) [3.7]

- Battery Electric Vehicles (BEV)

BEV refers to vehicles propelled solely by electric motors. The source of power stems from the chemical energy stored in battery packs which can be recharged on the electricity grid. Similar to HEVs and PHEVs, BEVs have the ability to recapture some of the energy utilized through regenerative breaking by converting the propulsion motor into a generator when breaking. Since the BEVs have no other significant energy source, the battery must be selected to meet the BEV range and power requirements. The future of such vehicles strongly depends on the battery developments (performance and cost) [3.7].

3.3.2 Control strategy

A key aspect of vehicle operation is the control strategy or algorithm used for the PEV powertrain. When driven, the PEV SOC, i.e. the fraction of total energy capacity remaining in the battery, varies within a certain range of values, given by the difference between maximum and minimum allowable SOC of the battery. There are two modes of control strategy, Charge Sustaining (CS) mode and Charge Depleting (CD) mode.

- CS mode

In this mode of operation, the SOC over a driving profile may increase and decrease but will, on the average, remain at its initial level, as can be seen in Figure 3.8. The battery pack in HEV is sized only to provide accelerating power, to overcome vehicle inertia, for the electric drive to work synergistically with the ICE in providing propelling torque. The control algorithm for a CS HEV maintains the battery SOC at a relatively high level, generally around an SOC ≈ 80% in order to allow for maximum use of regenerative braking recapturing some portion of the vehicles kinetic energy. Then the IC engine is used primarily to provide sustaining torque to maintain essentially constant speed operation. Thus, if the battery started out at an SOC = 100%, the algorithm would provide driving torque in such a fashion as to deplete the battery charge until the desired SOC ≈ 80% level is reached, and then run charge sustaining about this level. During driving periods that involve constant speed cruising and regenerative braking, battery energy used for acceleration is replaced [3.7], [3.13].

- CD mode

In this mode of operation, the vehicle is powered only or almost only by the energy stored in the battery, and the battery's SOC gradually decreases up to a minimum level, which depends on the battery size. The vehicle thus mostly behaves as an electric car in this mode of operation, which particularly suits to urban driving. A simplifying concept for the control of a CD PEV is that this it can be considered similar to a CS HEV algorithm except that a much lower SOC, perhaps an SOC ≈ 25%, is used before charge-sustaining control is implemented in PHEV. This lower value of SOC is maintained to extend the life of the battery [3.7], [3.13]. Depending on the driving conditions, the two modes can be combined over the distance travelled in such a way as to reap the full advantage of the PHEV and extend the driving range. The different modes of operation used in BEV, PHEV and HEV are illustrated in Figure 3.8.

The control strategies in PHEV and BEV are similar as they follow charge depleting strategy. Their difference stems when lower SOC limit is reached. At this point, PHEV switch to CS mode to extend distance where as BEV has to stop or recharged to travel further.

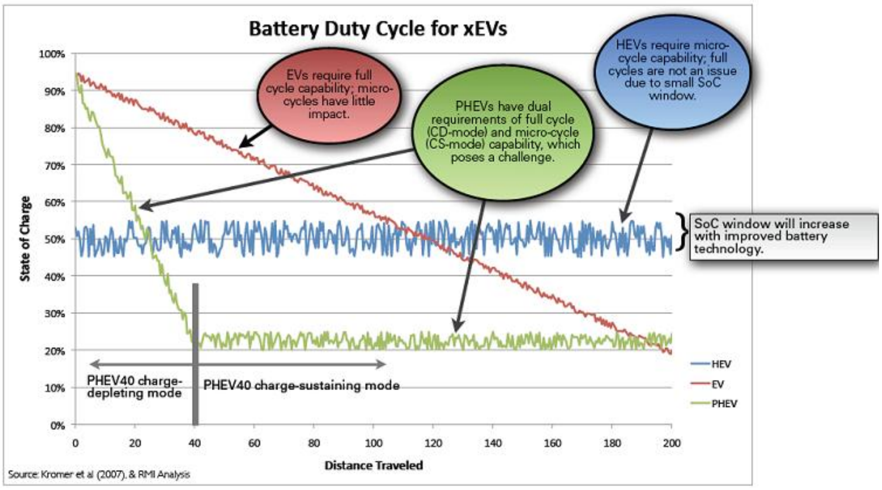


Figure 3.8: Example of discharge cycles for BEVs, HEVs and PHEVs [3.7]

3.4 Available charging power

Europe has several types of grid systems. The main two systems are TN (Terra-Neutral), which is dominant in the German speaking countries and TT (Terra-Terra) in the countries, where homes are typically supplied by gas (for cooking and heating – e.g. Italy, Spain, France, Benelux) [3.5]. Those grid systems are characterized by a different quantity of phases typically delivered to a household and different levels of current typically delivered per phase. In TN Countries, user over-proportionally own a garage or private parking spot (50%-70%), compared to TT countries, where this percentage can shrink down to about 20% [3.5].

In TN-countries, 2 or 3-phase is available in most of the households. A typical value for current assured is 25 - 40A where voltage level is 230V (phase to neutral) and 400V line voltage. This is sufficient for heating, cooking, washing and even charging PEVs with a power of up to 3x32A=22kW [3.5]. In TT countries, 1-phase only is available in most household. Typical range for current is 16-20A. In the best case (if no other appliances are used in the meantime), a maximum charging power of up to 3.7kW is available for charging PEVs [3.5].

According to Protoscar's conclusion [3.5], TN countries can support up to 3x16A at 400V line voltage (11 kW), or 1x32A at 230V phase voltage (7.4 kW) residential chargers. Higher power is technically feasible but related to very high cost for network connection. On the other hand, TT countries cannot support more than 3.7kW chargers. For PEV charging in those countries, the only alternative above 3.7kW home charge is public fast charging. Finally it is concluded that, up to 3.7kW on board chargers (with possibility to further limit the current) will be the only EU-standard for EV residential charger.

3.5 Charging infrastructures and charging power levels

There are different types of charging infrastructures, in this case called Electric Vehicle Supply Equipments (EVSE), which are used as a gateway to connect PEVs with supply utility. As can be seen in Figure 3.1, there are different types of EVSEs that are installed at residential, road side and fast charging stations having different charging power levels. In general, charging can be classified as AC charging and DC charging. This section will describe different types and ranges of charging power and some EVSEs that can provide this charging power.

3.5.1 AC Charging

This charging consists residential charging, roadside charging poles and fast ac charging poles. The EVSE provides an outlet for PEVs to be Plugged-In to the utility and supplies an AC power to the vehicle and the vehicle's onboard charger intern converts this into DC and charges its battery. In this section, only charging infrastructures and charging power levels, important for the study are considered.

- ***Residential charging (AC, 230V, 10-16A, 2.3-3.7kW)***

Residential slow charging is typically associated with overnight charging. This charging scheme makes use of the PEV on-board charger, which is sized based on input voltage from the grid. These on board chargers charge the battery pack of PEVs with energy from the grid provided by EVSE. A PHEV with a 5kWh battery pack, for example, would have a 2.4kW on-board charger that allows complete recharge on the order of two hours. Similarly, a BEV with a 40kWh battery pack might have a 3.7kW charger, which allows complete recharging on the order of ten to eleven hours, depending on thermal considerations and charge algorithms for the battery chemistry. This type of charging infrastructure is available at domestic socket or wallbox at domestic garage where a charging power level in the range of 2.3-3.7KW at 230V/10-16A [3.8].

Residential charging infrastructure, EVSE, used to charge LAMPO2[9], an electric vehicle from Protoscar, is shown in Figure 3.9 below. This home charging equipment is developed by ALPIQ to charge the vehicle at 3.3KW charging power level [3.9].

Figure 3.9: Residential Charging Infrastructure used to Charge LAMPO2 [3.10]

3.5.2 DC Charging

DC charging EVSE supplies a DC power to PEVs. In this case, EVSE consists of an off-board charger which is used to convert the AC power from utility into DC to facilitate fast charging. There are two types of DC charging as described in [3.8], only one of this considered in this section.

- **DC-Ultra Fast Charging Station (>100kW)**

Figure 3.10 below shows the ultimate goal of future charging stations for PEVs. In this charging station, charging PEVs takes place in less than 10 minute by high DC output power from the off-board chargers in the charging station. This infrastructure is crucial to overcome one of the main hurdles of the BEVs, the so called "range anxiety", i.e. the fear to be without energy and without available charging point.

[9] LAMPO2 is an electric sports car developed by Protoscar demonstrated on 2nd of March 2010 at the Geneva Motorshow [3.10]

Figure 3.10: Level III Fast Charging Station, AKERWADE POWER TECHNOLOGIES [3.12]

Figure 3.11 below illustrate ABB fast charging pole used to supply 80KW power to charge LAMPO2 [3.9]. Combinations of these chargers can be used to form the fast charging station shown in Figure 3.10 above.

Figure 3.11: ABB Fast Charger used to Charge LAMPO2 [3.10]

3.5.3 Energy storage system

The major problem at fast charging station is a jump in load due very high power demand due to PEV charging. As can be seen from Figure 3.10 above, if there are eight charging poles at the fast charging station with 250KW charging power capability and there is a probability that eight PEVs arrive at the charging station at a time in a given hour of a day, this will have a total power demand of 2MW. This sudden jump in power demand can seriously affect the system bus voltage and distribution system equipments. To control this short time high demand, local energy storage systems like ultracapacitors and advanced flywheel can be used. These energy storage devices store energy during low demand period and dump their high power during short timed high charging power demand occasions. Figure 4.4 illustrates different energy carriers that can be used as energy storage at fast charging stations.

4 CHAPTER FOUR: REQUIREMENTS

In the preceding chapter, the problem at hand was defined with the help of components within the boundary of defined study area. This included defining a general distribution system, charging power levels, charging infrastructures, charging parameters and different types of PEVs with their corresponding characteristics.

Our objective is to develop a probabilistic model that can quantify the impacts of PEV charging on a given power systems. To get to that point we need to define the parameters which are important to develop the model which can intern help us to solve the problems defined in Chapter three. Hence, this chapter will have a closer look at those parameters which are important to develop the model.

The first thing to know will be the particular distribution network into where PEVs are to be deployed. In section (4.1), the distribution network in Västerås, which is selected for the study to represent the distribution network defined in section 3.2.1, will be discussed. Following this, available PEV technologies on the market will be presented in section (4.2). In this section important vehicle parameters which are the stepping stones for the simulation to come are illustrated. Section (4.3) will discuss the most important battery parameters. In section (4.4) vehicle charging parameters, which gives light on charging characteristics of PEVs and on their load profiles will be discussed. Section (4.5) will close the chapter by defining parameters which dictate grid energy requirements of PEVs.

4.1 Area of study

4.1.1 Selected Network topology

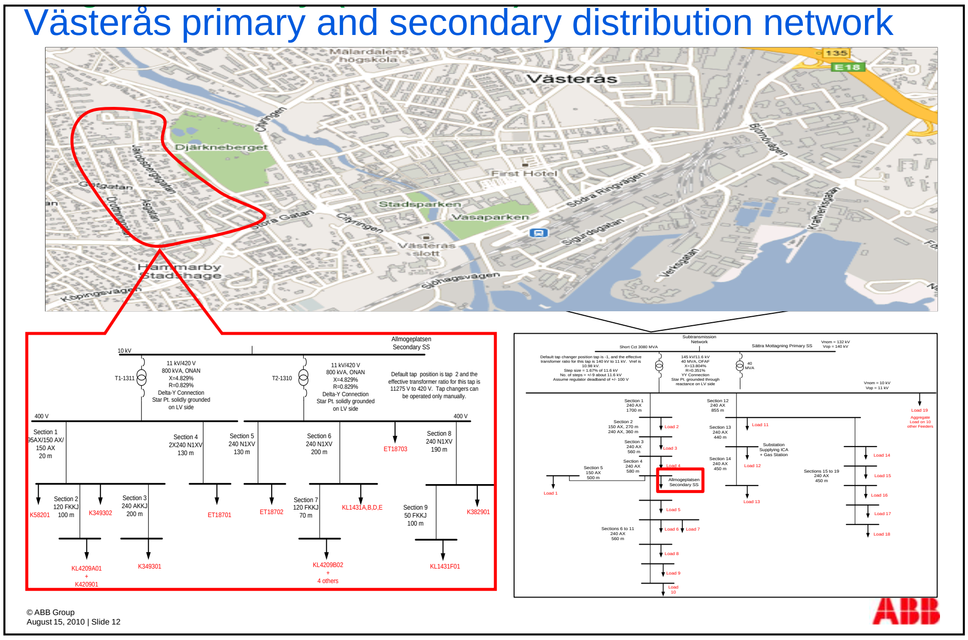


Figure 4.1: Selected area of study

Figure 4.1 above illustrates the topology of selected study network and Figure 4.2 represents 132KV/11KV primary distribution system in Västerås, Sweden within the selected network topology. This is the distribution network where fast charging stations are to be deployed. It consists of a number of secondary substations, which steps down 11kv to 400v for distribution. It is also characterized by light load conditions. The station was built in less than 20 years ago with significant spare capacity of future expansion of load. It was designed for a maximum of 80MVA peak load, while currently it is a loaded with a peak load of 20MVA, which is only 25% of its maximum capacity [4.1].

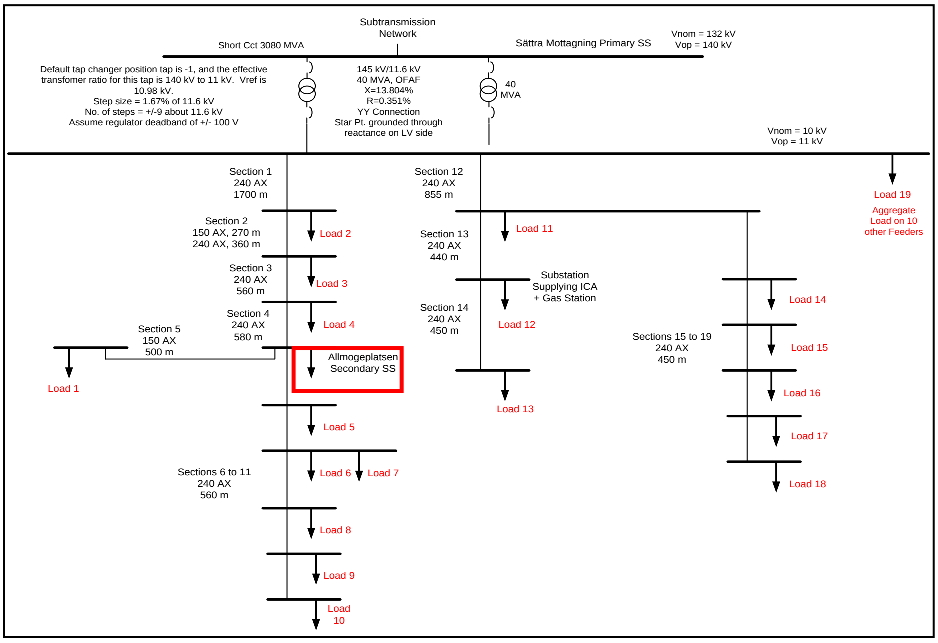


Figure 4.2: Västerås primary distribution network

Within the primary distribution network, there are a number of secondary sub-stations, which are used to further distribute the power down to consumer level. One of these secondary sub-stations, marked in red box, in Figure 4.2 above is expanded and shown in Figure 4.3 below.

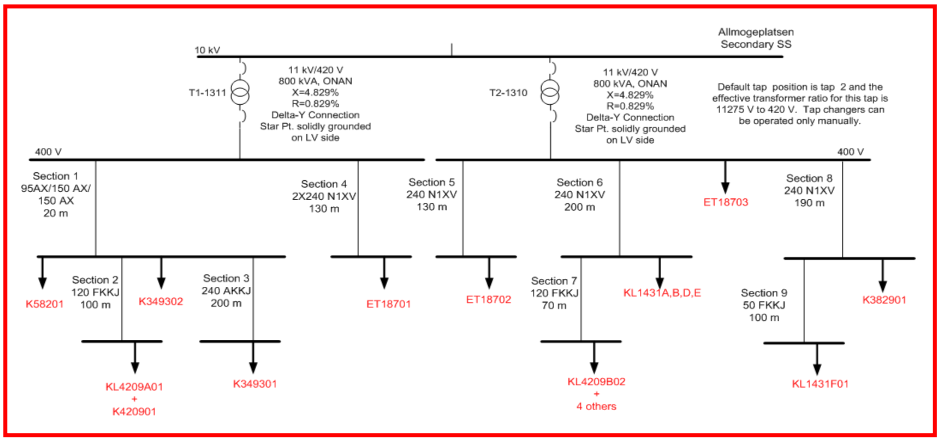


Figure 4.3: Västrås secondary distribution network, Allmogeplatsen secondary SS

This substation is called 'Allmogeplatsen' secondary substation. The distribution network represents a single line diagram of 400/230V three phase systems. It consists of eleven load feeders. Some of the load feeders feed residential loads, some feed commercial and others feed mixed load types (residential and commercial). This is the distribution network where residential PEV charging is to be deployed [4.1].

4.1.2 Network data

All the network data for both primary and secondary distribution network are taken from ABB internal report, PHEV Task force. Those data include substation data, distribution transformer data of both primary and secondary distribution and distribution feeder data [4.1].

4.1.3 Base load data

The impact of PEV charging on a given power system can be realized in terms of the additional load they impose on the system. For the system to be analyzed, two load profiles are mandatory. One load profile is the existing base load profile and the other is the load profile from PEV charging. The load profile can be hourly load profile or per minute load profile. Once these two load profile are made available, they will be added together and applied to the network to make required system analysis. However, there is no enough data of base load profile for the selected system. In the primary distribution network shown in Figure 4.2, the only available base load data are annual peak power demand at each load feeder as shown in Table 4.1 below. This table does not include the base load data for 'Allmogeplatsen' substation.

Table 4.1: Annual peak demand power in the primary distribution network

Feeder Name	Annual peak demand at load feeders			Power Factor
	Active Power (MW)	Reactive Power(MVr)	Apparent Power(MWA)	
Load (1)	0.3039749	0.1472218	0.33775	0.9
Load (2)	0.4676537	0.2264951	0.519615	0.9
Load (3)	0.3507403	0.1698713	0.389711	0.9
Load (4)	0.2338269	0.1132475	0.259808	0.9
Load (5)	0.2572095	0.1245723	0.285788	0.9
Load (6)	0.374123	0.1811961	0.415692	0.9
Load (7)	0.2104442	0.1019228	0.233827	0.9
Load (8)	0.374123	0.1811961	0.415692	0.9
Load (9)	0.5611844	0.2717942	0.623538	0.9
Load (10)	0.00467653	0.00226495	0.005196	0.9
Load (11)	0.5611844	0.2717942	0.623538	0.9
Load (12) - Station and Commercial	0.4208883	0.2038456	0.467654	0.9
Load (13)	0.1870614	0.09059805	0.207846	0.9
Load (14)	0.02338269	0.01132475	0.025981	0.9
Load (15)	0.4208883	0.2038456	0.467654	0.9
Load (16)	0.444271	0.2151703	0.493635	0.9
Load (17)	0.5611844	0.2717942	0.623538	0.9
Load (18)	0.2338269	0.1132475	0.259808	0.9
Load (19) - Aggregate load	7.061573	3.420076	7.846192	0.9

Similarly, the only available data in 'Allmogeplatsen' secondary distribution network shown in Figure 4.3, is 1.081MW annual peak power demand at the substation and annual energy consumptions at each load feeders. The load feeders represent different groups of loads as shown in Table 4.2 below. Some of these loads are purely residential; others commercial and the remaining are mixed loads. The proportion of residential and commercial loads in the mixed load types are illustrated in Table 4.2. All the data in the given tables are taken from ABB internal report [4.1].

Table 4.2: Annual energy consumption in the secondary distribution network

Load name	Load type	Annual energy consumption(KWh)
ET18701	**Mixed (12.5% residential, the rest commercial)**	1108982
ET18702	**Commercial**	1824326
ET18703	Residential	33341
K349301	**Mixed (12.5% residential, the rest commercial)**	441155

K349302	Residential	67141
K382901	Residential	148149
K58201	Residential	63045
KL1431A.B.C.D.E	Residential	312330
KL1431F01	Residential	75201
KL4209A01 + K420901	Residential	255704
KL4209B02 + 4 others	Residential	402580

As we stated before, it is mandatory to have a base load profile for a given interval of time so that it can be added with the load profile from PEV charging which will intern be used for a system impact analysis. However, we don't have a base load profiles of the type stated in section 3.2.2, except that given in Table 2.1 and Table 4.2. As a result, we need to find a way to generate the base load for a desired interval of time based on the data given in the tables. Models, based on IEEE Reliability Test System (RTS 96), are developed to generate base load profiles using these data. This will soon be discussed in Chapter five.

4.2 Electric Vehicles on the market

Electric vehicles are no longer a dream; they are already there on the market. The following table, Table 4.3 illustrates some list of electric vehicles from different manufacturers which are already on the market [4.2]. The table also gives some important data associated with the particular vehicle including battery capacity and grid energy requirement per unit distance which are all important to determine energy requirements of vehicles.

Table 4.3: Main features of the fully electric vehicles (cars and light duty vehicles) already present in the market

	Brand	Model	Capacity (kWh)	Range (km)	Consumption (kWh/100km)	Classification	Dat
Cars	Renault	Twingo Quickshift E	21.45	129	16.60	Medium	http
	Fiat	Panda	19.68	120	16.40	Medium	http
	NICE	Mega City	10.50	80	13.05	Small	http
	FIAT	500	22.00	113	19.53	Medium	http
	Mitsubishi	i-MIEV	16.00	160	12.50	Medium	http
	MINI	MINI-E	35.00	180	19.44	Big	http
	TESLA	Roadster/Model S	55.00	300	18.33	Big	http
	CODA	CODA-EV	33.80	180	18.78	Big	http
	Lighting	GTS	35.00	175	20.00	Big	http
	MILES	ZX40S/ZX40ST	10.00	105	9.56	Small	http
	Phoenix	SUV/SUT	35.00	209	16.73	Medium	http
Light Du	AIKè	ATX	8.40	70	12.00	LDV	http
	Piaggio	Porter	25.74	110	23.40	LDV	http
	LDV	Maxus Electric		160		LDV	http

Table 9.4 and Table 9.5, enclosed in chapter 10, provides additional information on different classes of PEVs including both PHEV and BEV from different manufacturers with their detailed vehicle characteristics including battery capacity, the type of battery used, AER and similar other characteristics.

4.3 Battery characteristics

4.3.1 Energy and power density

Success and defeat of electric cars directly depend on battery. Battery performance and cost are essential factors for the development of electric vehicles and has been the main bottleneck in the history of electric mobility. One of battery characteristics which have been a bottleneck for the development of PEVs is the energy density. The energy density of conventional batteries such as Lead-acid or Nickel-metal-hydride is by far lower as the energy density of fuel. PEVs therefore reached unacceptable overall weight. Only lithium-ion technology enabled the recent development of batteries in acceptable dimensions [4.3]. Figure 4.4 shows energy density and power density of different energy carriers.

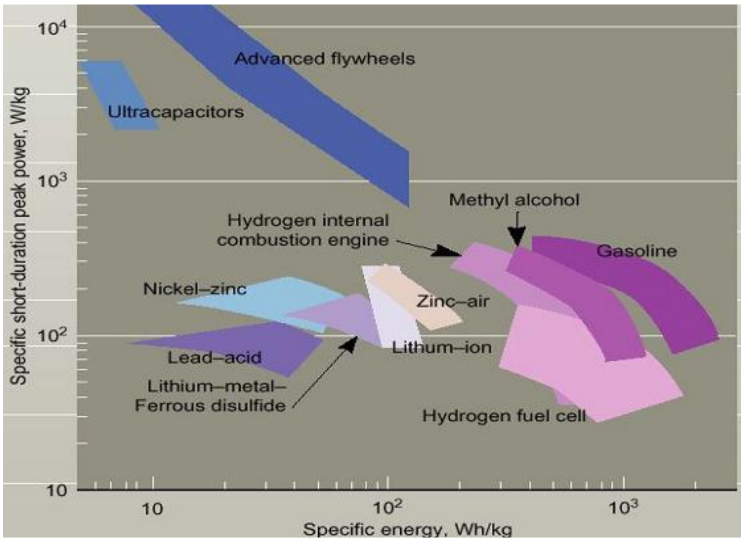


Figure 4.4: Energy density and power density of different energy carriers [4.3]

The most important specification for PEV application is the specific energy density, meaning how much energy can be stored per kg (Kilogram) of the storage medium. Only a high specific energy density allows for a large range while keeping the overall weight acceptable. Looking at Figure 4.4, we notice that conventional fuel has a specific energy density that is about 10 times higher than the one of a Li-ion battery[10] [4.3].

4.3.2 Battery capacities

The energy storage capacity or battery capacity, measured in KWh, is of high importance since it will directly determine the distance the vehicle can drive on the CD mode, as well as the mass of the battery pack. For PHEVs, the energy storage requirement considered in the literature typically varies from ~6kWh to 30 kWh depending on the CD range. This can be compared to 1-2 kWh for conventional HEVs and 30-50 kWh for BEVs [4.4].

The energy storage capacity represents the 'available' or 'total' energy capacity depending on whether the SOC level is taken into account or not (e.g. a 10 kWh of total energy capacity operating with a 65% charge swing[11] would have only 6.5 kWh of available energy).

[10] The actual heating value of gasoline, and therewith the total stored energy, is actually 47MJ or 13kWh per kg
[11] The useable range of battery capacity

4.3.3 Allowable SOC limits

PEV batteries, particularly Li-ion batteries can be extremely dangerous if mistreated. They may explode if overheated or if charged to an excessively high voltage. Furthermore, they may be irreversibly damaged if discharged below a certain voltage. To reduce these risks, Li-ion batteries generally contain a small circuit that shuts down the battery when discharged below a certain threshold or charged above a certain limit [4.4]. Regarding PEV applications, this imposes the absolute need of an advanced BMS[12] and explains why the car's battery usually operates between 10% and 80% SOC [4.4].

4.4 Vehicle charging parameters

4.4.1 Charging and Discharging

The charging rate is stated in the unit 'C' and displays the charging current relative to the battery's capacity. Hence, a charging rate of 1C means a charging current of 48.5A in one hour for a battery with 48.5Ah[13] capacity. In order not diminish capacity and durability of the battery, the charging rate[14] should ideally be kept between 0.6 and 1C[15] [4.3]. Table 4.4 illustrates different charging rates associated with charging modes [4.3].

Table 4.4: Terminology for charging modes

Terminology	Charging rate
Slow charging	0.1 C
Quick charging	0.3 C
Fast charging	1.0 C
Ultra-fast charging	>>1.0 C

4.4.2 Charging control

- ***Constant-current - Constant-voltage control***: Figure 4.5 shows conventional approach for charging Lithium batteries which are vulnerable to damage if the upper voltage limit is exceeded. The charge voltage rises rapidly to the cell upper voltage limit and is subsequently maintained at that level. As the charge approaches completion, the current decreases to a trickle charge. Cut off occurs when a predetermined minimum current point, which indicates a full charge, has been reached. This explains why charging to 100% takes disproportionately longer than charging to 80%.

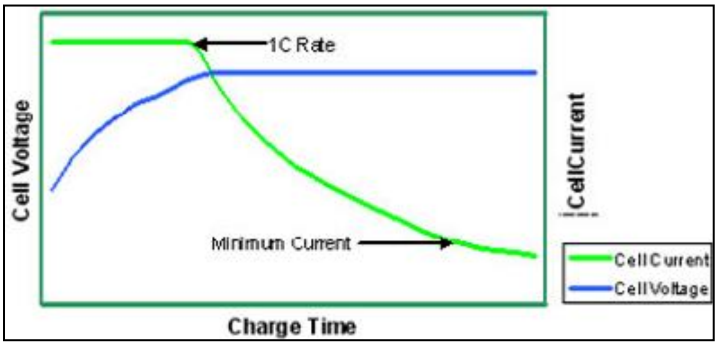


Figure 4.5: Li-ion charging characteristics [4.3]

[12] Battery management system (BMS) mainly controls charging and discharging of the battery in order to prevent damage, overloading and overheating
[13] The capacity of a given battery is often expressed as Ah (Ampere-hour)
[14] For a given battery capacity given in Ah, the charging or discharging rate C can be calculated by dividing the charging or discharging current in ampere to the battery capacity in Ah
[15] Recent research promises the possibility of safe charging at rates that are about 30 times higher [4.3]

- ***Intelligent Charging System***: Intelligent charging systems integrate the control systems within the charger with the electronics within the battery called BMS[16], to allow much finer control over the charging process. The benefits are faster and safer charging and battery longer cycle life.

4.4.3 Charging an electric vehicle

This section is meant to illustrate the requirements for charging of PEVs. Based on the Mitsubishi i-MiEV data taken from Table 4.3, this specific vehicle has total cell voltage of 330V and battery capacity in 16KWh. From these battery parameters, the storage capacity in Ah is calculated to be 48.5Ah[17] , from which charging or discharging rate can be calculated for a given current.

As stated before, when charging electric vehicles, the closer the battery gets to 100% the more the charging power must be reduced in order to prevent overcharging and overheating. Therefore, for this illustration a case in which the battery is only charged from 0% SOC to 80% SOC at a constant charging current is considered to determine values in Table 4.5 [4.3].

Table 4.5: Required time to charge a battery to 80% SOC for different grid voltage and currents

	Phases at interface to car	(P-N) Voltage at interface to car [V]	Current going into car [A]	Current relative to capacity [C][18]	Power [kW][19]	Required time [h][20]
Slow charging	1 phase AC	230	6	0.1	1.4	9.3
	1 phase AC	230	10	0.2	2.3	5.6
Quick charging	1 phase AC	230	15	0.3	3.5	3.7
	3 phase AC	230	16.0	0.3	11.0	70mts
	3 phase	230	32.0	0.7	22.1	35mts
AC Fast Charging	3 phase	230	63.0	1.3	43.5	18mts
DC Fast Charging	DC	330	151.5	3.1	50.0	15mts
DC Ultra fast	DC	330	303.0	6.3	100.0	8mts
	DC	330	606.1	12.5	200.0	4mts
	DC	330	1212.1	25.0	400.0	2mts

Table 4.5 gives an overlook of a few realistic cases of charging infrastructure. In a modern house, this car could be charged within 3 hours and 42 minutes at a standard plug. Fast charging at 400V and 55.4A (3-phase, 230V, 32A) would still take 35min. In the considered cases, the charging rate does not exceed 2.6C, which is still acceptable to not damage the battery. Recent research promises the possibility of safe charging at rates that are about 30 times higher [4.3]. DC-ultra-fast charging, enabling a charge in

[16] Battery management system (BMS) mainly controls charging and discharging of the battery in order to prevent damage, overloading and overheating
[17] The storage capacity of a given battery is often expressed as Ah (Ampere-hour). If battery capacity in KWh and total cell voltage in V are given, the storage capacity in 'kAh' is calculated by dividing kWh by the total cell voltage
[18] Calculated by dividing current going into car to battery capacity in Ah, 48.5Ah in this case
[19] Power is calculated by multiplying charging voltage and current at the car interface
[20] Calculated by dividing useable battery capacity, in this case 80% of 16KWh by the available charging power

two minutes would require a power of 400kW. If this is done in the range of the cell voltage (330V), a current of 1212A would be required.

4.5 Grid energy requirement

PEV charging parameters, including charge power, charge energy, and charge times, can be established by evaluating typical daily vehicle trips and daily vehicle distance traveled. Actual PEV driver behavior and an evaluation of charge power requirements bring additional light to charging infrastructure requirements for PEVs.

As stated earlier, one of our objectives is to determine the load profile due to PEV charging. In other word, we want to determine the load profile of PEV charging seen from the grid side. This load pattern is a function of required energy from the grid, charging power level and the required charging interval which determines how fast the charging time will be.

The daily energy requirement of vehicles from the grid is a function of the statistical daily distance it travels. As a result, to determine the energy requirements of vehicle in a given study area on a given interval of time, it is crucial to know the statistical distribution of vehicle distance travelled in the desired region and interval of study.

Once the statistical distribution of distance traveled by PEVs in the study interval is determined, the next important step will be to know grid energy requirements of each vehicle per unit distance travelled. This data, which is dependent on the driving pattern, vehicle mass, driving speed and other vehicle parameter, varies from vehicle to vehicle. According to some literature, this value is estimated in the ranges of 20--35kWh/100km [4.2]. Comparing this value with the data provided by some manufacturers given in Table 4.3, this looks a bit over estimated. This is probably due to a possible mistake of the authors that convert the energy from liter of gasoline equivalent/100km to kWh/100km assigning the half part to the electric consumption [4.3]. According to [4.4], this grid energy requirement in per unit distance increases linearly with the vehicle mass, around 6-7 Wh[21]/km for every 100 kg.

With the knowledge of daily distance travelled and grid energy requirements in per unit distance traveled by PEVs, total daily grid energy required by each vehicle can be determined. How fast this energy is obtained from the grid depends on the available charging power level of chargers and the charging capability of BMS.

[21] Measure of electrical energy in watt-hour (Wh)

5 CHAPTER FIVE: THE MODELS

This chapter is one of the most important chapters where everything described in the preceding chapters are put together to develop probabilistic models that can quantify impacts of PEV charging on a given power system. It is organized into three main themes including base load profile model, PEV charging model and distribution system impact model. In the first subsection, section 5.1, models to generate base load profiles for the selected system based on IEEE Reliability Test System (RTS-96) will be developed. Following this, in section 5.2, probabilistic models to quantify the load profiles from PEV charging will be developed. In this section, residential charging model and fast charging models are considered. The last section, section 5.3, will discuss a model to quantify the impacts of the load profiles resulting from residential charging models.

5.1 Base load profile model

As stated in section 4.1.3, it is important to have base load profile of the target system to be studied. Once we have the existing base load profile of the system, a load profile due to PEV charging will be added on the base load to be used for system analysis. The existing base load profile of the target system of study tells us the strength of the system. The classification of the system as strong or weak grid depends on the existing base load. However, only limited base load data are given for the system of study as is shown in Table 4.1 and Table 4.2. As can be seen from these tables, only annual peak load data is given in Table 4.1 and annual energy consumption is given in Table 4.2. However what is important for system analysis is a load profile divided in time. This is why it is important to develop a model to generate the base load profile of the system at hand. It is therefore the goal of this section to formulate a mathematical model to generate base load profile based the available data.

5.1.1 IEEE Reliability Test System (RTS-96)

The basic data which is used to generate the base load profile is taken from ‘The IEEE Reliability Test System-1996 (RTS-96)’. It is a report prepared by the Reliability Test System Task Force of the Application of Probability Methods Subcommittee. It describes an enhanced test system (RTS-96) for use in bulk power system reliability study, which permits comparative and bench mark studies to be performed on a new and existing reliability evaluation techniques. This test system, RTS-96, is so advanced that it can be used as a representative of any typical power systems for it has almost all the different technologies and configurations that could be encountered in any power systems [5.1].

What is important about this test system is that it contains a load factor, defined in section 3.2.2.4, which is missing from the give base load data of the target system. As we recall from section 3.2.2, the load factor (LF) defines the relationship between the average demand or the demand in a given interval and the peak demand in that interval. If we have the load factor and peak demand in a given interval of time, we can determine the average demand or, in a technical sense of the word, the demand in that interval of time. Refer section 3.2.2 for the basic terminology definitions. IEEE RTS-96 network topology and the load factors for Weekly Peak Load in Percent of annual peak, Daily peak load in Percent of Weekly Peak and Hourly peak load in Percent of daily Peak are given Chapter 10 (Figure 9.1, Table 9.1, Table 9.2, Table 9.3).

5.1.2 Primary substation base load model

The primary distribution network, which is used for the study is shown in Figure 4.2 and base load data in the distribution network are given in Table 4.1. As we can see from the table, the only data we have are annual peak load at each load feeder. As stated above, we know from section 3.2.2.4 that if we have a load factor and a peak in a given interval of time, the average demand or demand in that interval of time is calculated as:

$$\boldsymbol{D = LF * MD} \quad \text{5-1}$$

Where:-D: $Demand$, LF: $Load\ Factor$, MD: $Maximum\ Demand$

From RTS-96, Table 9.1 we have load factors for 52 weeks of a year and from Table 4.1, we have a list of annual peak load for each load feeders in the substation. From these two data, we can calculate the weekly peak demand for each feeder in the substation as a function an annual peak of the load feeder and its load factor in that week. This can be formulated as:-

$$\boldsymbol{D(i,w) = LF(w)} * M\boldsymbol{D(i)} \quad \text{5-2}$$

Where:-

$D(i,w)$: $Demand\ at\ feeder\ i, in\ week\ w\ of\ the\ year$

$LF(w)$: $Load\ Factor\ in\ week\ w\ of\ the\ year, taken\ from\ Table$ 10.1

$MD(i)$: $Annual\ Peak\ Demand\ in\ load\ feeder\ i$

From equation 5-2, we see that we have a peak demand for each particular week in a year. And if we have a peak demand in a particular week, the demand in the days of that particular week can be calculated using the RTS-96 load factor data given in Table 9.2. This can be formulated as in equation 5.3 below.

$$\boldsymbol{D(i,w,d) = LF(w) * LF(d) * MD(i)} \quad \textbf{5-3}$$

Where:

$D(i,w,d)$: $demand\ at\ feeder\ i, in\ week\ w\ of\ the\ year, day\ d\ of\ the\ week$

$LF(w)$: $Load\ Factor\ in\ week\ w\ of\ the\ year, taken\ from\ Table$ 10.1

$LF(d)$: $Load\ Factor\ in\ day\ d\ of\ the\ week, taken\ from\ Table$ 10.2

$MD(i)$: $Annual\ Peak\ Demand\ in\ load\ feeder\ i$

At this point, we have a peak load in a particular day of the year. If we have a peak load in a particular day of the year, an hourly load profile for 24 hours of that particular day can be calculate based on RTS-96 load factor data given in Table 9.3. The whole RTS-96 load profile calculation is summarized in equation 5.4 below.

$$\boldsymbol{D(i,w,d,h) = LF(w) * LF(d) * LF(h) * MD(i)} \quad \textbf{5-4}$$

Where:

$D(i,w,d,h)$: $Demand\ at\ feeder\ i, in\ week\ w\ of\ the\ year, day\ d\ of\ the\ week\ and\ hour\ h\ of\ the\ day$

$LF(w)$: $Load\ Factor\ in\ week\ w\ of\ the\ year, taken\ from\ Table$ 10.1

$LF(d)$: $Load\ Factor\ in\ day\ d\ of\ the\ week, taken\ from\ Table$ 10.2

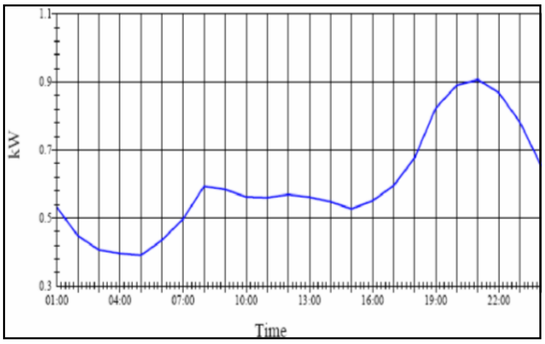
$LF(h)$: $Load\ Factor\ in\ hour\ h\ of\ the\ day, taken\ from\ Table$ 10.3

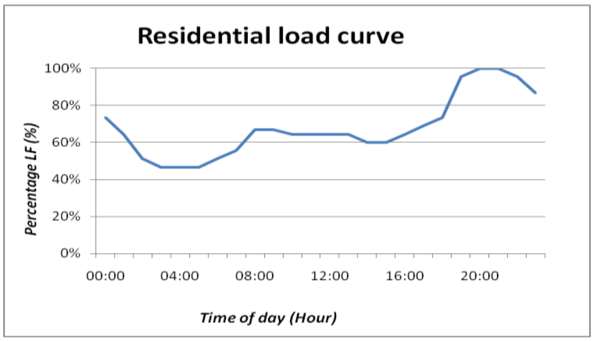
$MD(i)$: $Annual\ Peak\ Demand\ in\ load\ feeder\ i$

From equation 5-4, we can generate an hourly load profile for 8760 hours of a year for each load feeder in the given substation!

5.1.3 Secondary substation base load model

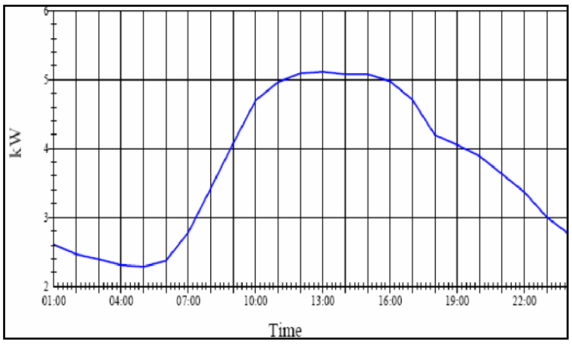
Figure 4.3 illustrates ‘Allmogeplatsen’ secondary distribution network taken from the primary distribution network. An hourly load profile for this distribution network is calculated in a similar fashion with that of primary distribution network, with two exceptions. First, for this distribution network, we have only one annual power peak at the substation and annual energy consumption at each load feeder. (Refer section 4.1.3). Second, we are nearer to the consumer or load center in this secondary distribution network than we were in the primary distribution network. As a result, the type of the load on the feeder matters in the load profile calculation for that feeder. This is to say, we may have different types of loads at the load feeders such as residential, commercial and mixed types which have different daily load profile curve with different peaking time. For this reason, data from residential and commercial daily load profile curve are taken to modify the result generated from RTS-96. These two load curves are taken from Public Service Electric and Gas Company (PSE&G) and shown in Figure 5.1 (a) and Figure 5.2 (a) below [5.2].

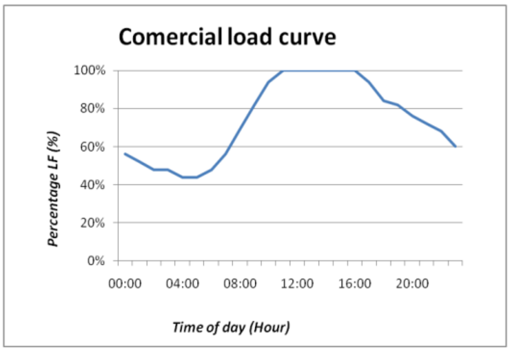




(a) Actual load profile from [5.2] (b) Approximated percentage residential load profile

Figure 5.1: Daily residential load profile





(a) Actual load profile from [5.2] (b) Approximated percentage commercial load profile

Figure 5.2: Daily commercial load profile

PSE&G has developed this Dynamic Load Profiling by reading the load samples from meters each day and producing daily load shapes which reflect actual usage for that customer segment for the same day. To make it suitable for usage to generate hourly load profile for the system, data in Figure 5.1 (a) and Figure 5.2 (a) are sampled at each hours of the day and expressed as percentage of the peak in a particular day as shown in Figure 5.1 (b) and Figure 5.2 (b) above.

At this point we have all we need to generate the load profile at load feeder in the secondary distribution network. This is given in equation 5.5 below.

$$\boldsymbol{D(i,w,d,h) = L(w) * LF(d) * LF\ (h) * \left[\frac{E(i)}{\sum_{k=1}^{n} E(k)}\right] LF\_type(h) * MD} \qquad 5\text{-}5$$

Where:

$D(i, w, d, h)$: $Demand\ at\ feeder\ i, in\ week\ w\ of\ the\ year, day\ d\ of\ the\ week\ and\ hour\ h\ of\ the\ day$

$LF(w)$: $Load\ Factor\ in\ week\ w\ of\ the\ year, taken\ from\ Table$ 10.1

$LF(d)$: $Load\ Factor\ in\ day\ d\ of\ the\ week, taken\ from\ Table$ 10.2

$LF(h)$: $Load\ Factor\ in\ day\ d\ of\ the\ week, taken\ from\ Table$ 10.3

$E(i)$: $Annual\ energy\ consumption\ at\ load\ feeder\ i$

$\sum_{k=1}^{n} E(k)$: $Total\ annual\ energy\ consumpyion\ in\ the\ substation$

$LF\_type(h)$: $Load\ Factor\ in\ hour\ h\ of\ the\ day\ and\ given\ type\ of\ load, taken\ from$ Figure 5.1 and F

MD: $Annual\ Peak\ Demand\ at\ the\ substation$

5.1.4 Simulated base load profiles

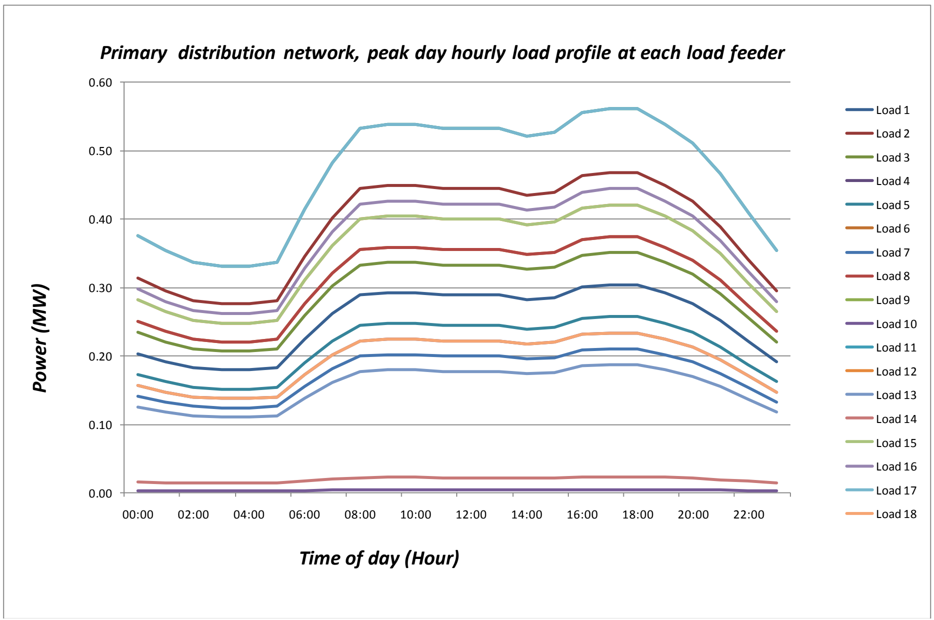


Figure 5.3: Simulated peak day hourly load profile in the primary distribution network

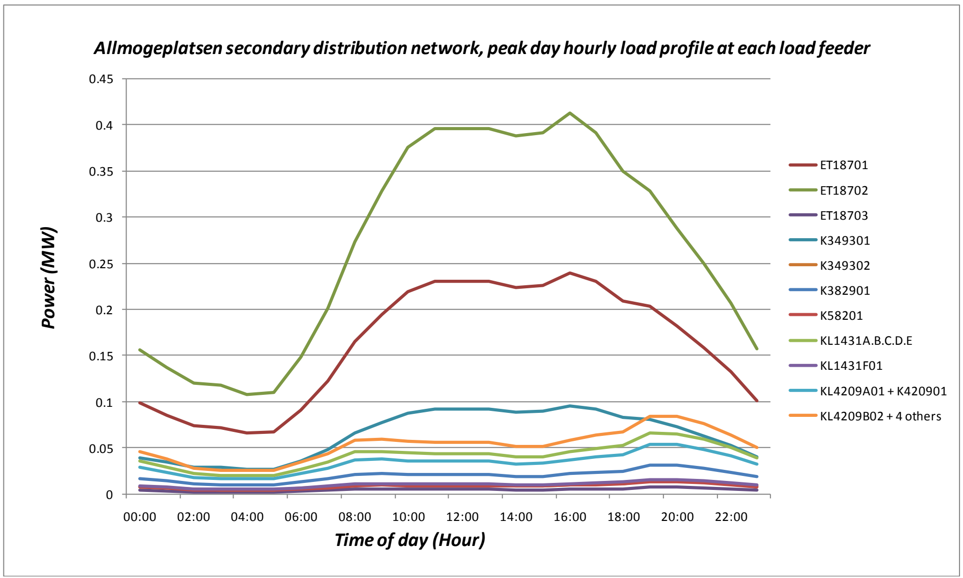


Figure 5.4: Simulate peak day hourly load profile in Allmogeplatsen secondary distribution network

Figure 5.3 and Figure 5.4 shows hourly load profile of peak summer day of a year for primary and secondary distribution network respectively. Similar load curves for the whole distribution network can be generated by the model for 8760 hours of the year. Note that Load 19 is not illustrated in Figure 5.3 for convenience.

To raise the degree of confidence on the accuracy of the generated load profile from the simulation, one test was carried out in 'Allmogeplatsen' distribution network to verify the result. The test was based on the comparison of the measured annual peak power demand and annual energy consumption at the secondary distribution substation and the simulated annual peak demand and annual energy consumption at the same substation. The result was found to be about 0% error in annual peak at the distribution substation and -2.78% error in KWh annual energy consumption at the substation. This error in the base load profile tells us that the model used to generate the base load profile is the best way of generating the base load in case one does not have enough information on the system base load profile for the selected network for study.

5.2 PEV Charging Models

Once we have the base load profile at hand, the next step will be to determine the load profile from PEV charging. It is at this point that formulation of a probabilistic charging model to quantify PEV charging is important. The reason why the model is called 'Probabilistic' is because of the random nature of most of the parameters defining the problem at hand. Some of these random parameters are daily distance travelled by each vehicle, grid energy requirement in per unit distance travelled, vehicle charging time and charging interval, vehicle battery capacity and SOC level which are all statistical in nature. Therefore, it is the keen interest and devotion of the following sections to develop probabilistic, mathematical model based on statistical data that can help us generate the load profile from PEV charging.

In this section, two major PEV charging models will be developed, residential and fast charging models. Section 5.2.1 starts by describing and defining important parameters common to the models. Following this, section 5.2.2 will develop and discuss residential PEV charging model. In this same subsection, two sub case models are considered which depend on the available output power from the charger. The last section, section 5.2.3, will describe and develop PEV charging model at fast charging stations.

5.2.1 Common random input parameters

There are three common random input variables for both residential and fast charging models. These are:

- Vehicle class population
- Battery capacity and
- Daily grid energy requirement

All these input parameters are probabilistic in nature as will soon be evident. This is in fact some of the parameters which made the model to be probabilistic, which primarily depend on the stochastic behavior of consumers.

5.2.1.1 Classes of vehicle population

The model begins by defining four classes of PEVs as shown in Table 3.1 below. These four vehicle classes were purposely selected to provide a diverse vehicle fleet representative of what a real vehicle fleet could look like in the future [5.3].

Table 5.1: Definition of vehicle classes

Vehicle class	Description	% of PEV
1	Compact passenger cars	$P1$
2	Full size passenger cars	$P2$
3	Medium size SUV and pick-up trucks	$P3$
4	Large size SUV and pick-up trucks	$P3$

The parameter p_i defines the percentage of PEV in each vehicle class. The sum of the percentage in each vehicle class represents the total penetration level of PEVs. This is represented as:

$$\sum_{i=1}^{4} \boldsymbol{p_i} = \boldsymbol{p_1} + \boldsymbol{p_2} + \boldsymbol{p_3} + \boldsymbol{p_4} = \boldsymbol{P_{PEV}} \tag{5-6}$$

Where: P_{PEV} $is\ percentage\ penetration\ level\ of\ PEV$

Thus, if there are N_T total passenger vehicles in the defined system area, then the total number of PEVs in $Class - i$ will be given by ($p_i * N_T$).

PEV class population describes the expected number of PEVs in each vehicle class described in Table 5.1. It is a random variable because it is a function of vehicle class distribution, $P^{(c)}$, shown in Table 5.2 below. This table shows the future distribution vehicles on the road in each class [5.3].

Table 5.2: IC vehicle class distribution

	Class 1	Class 2	Class 3	Class 4
Distribution of vehicles, $\boldsymbol{P^{(c)}}$	0.2	0.3	0.3	0.2

Given the total number of vehicles in the system is N_T and the percentage penetration level of PEVs is P_{PEV}, the total number of PEV in the system will be $N_T * P_{PEV}$. Then the number of PEVs in each vehicle class will be normally distributed with mean $\mu^{(c)}$ and variance $(\sigma^{(c)})^2$ which are calculated as:

$$\boldsymbol{\mu^{(c)}} = \boldsymbol{N_T} * \boldsymbol{P_{PEV}} * \boldsymbol{p^{(c)}} \tag{5-7}$$

$$(\boldsymbol{\sigma^{(c)}})^2 = \boldsymbol{\alpha_p} * \boldsymbol{\mu^{(c)}} \tag{5-8}$$

Where α_p is usually set to be 1% [5.3]

To determine the random values of the number of PEVs in each class, normal distribution is selected because normal distribution occurs naturally and it can realistically represent stochastic behavior of customers [5.3]. The 'Box-Műller 'method is used to compute normally distributed random variables as:

$$\boldsymbol{N} = \sqrt{-\boldsymbol{2} * \boldsymbol{In}(\boldsymbol{U_1})} * \boldsymbol{cos}(\boldsymbol{2\pi} * \boldsymbol{U_2}) \tag{5-9}$$

Where, N is a standard normal value (a normal random variable with a mean of zero and a variance of one), U_1 and U_2 are independent and identically distributed pseudo random numbers distributed uniformly over the range [0, 1]. Then the number of PEVs in each class,$N^{(c)}{}_{PEV}$, is calculated as:

$$\boldsymbol{N^{(c)}}_{\boldsymbol{PEV}} = \boldsymbol{\mu^{(c)}} + (\boldsymbol{\sigma^{(c)}})^{\boldsymbol{2}} * \boldsymbol{N} \tag{5-10}$$

Where the number of PEV in each vehicle class, $N^{(c)}{}_{PEV}$ is randomly distributed with mean $\mu^{(c)}$ and variance$(\sigma^{(c)})^2$

5.2.1.2 Battery capacity

The only way these four classes of vehicles defined above can be distinguished in the models is by their battery capacities. As a result a range of battery capacities that that can represent vehicles in each class are defined. This is important because the battery capacity is the only factor which can limit daily distance travelled by each vehicle. It is assumed that each vehicle class is represented by a range of battery capacity with minimum and maximum limit. This is to say each vehicle in class 'c' can have any random value of battery capacity in the range between $BC^{(c)}{}_{max}$ *and* $BC^{(c)}{}_{min}$ where $BC^{(c)}{}_{max}$ *and* $BC^{(c)}{}_{min}$ are parameters which define range of battery capacity for vehicles of class c.

Similar to the distribution of vehicles in each class, normal distribution is assumed for the battery capacity of a particular vehicle in a given class in the defined range. Hence the battery capacity of vehicle 'v' in class 'c' is formulated as:

$$\boldsymbol{BC^{(v,c)} = \vec{\mu}^{(c)} + (\vec{\sigma}^{(c)})^2 * N} \quad \text{5-11}$$

$$\boldsymbol{\vec{\mu}^{(c)} = \left[BC_{max}{}^{(c)} + BC_{min}{}^{(c)}\right] \Big/ 2} \quad \text{5-12}$$

$$\boldsymbol{(\vec{\sigma}^{(c)})^2 = \left[BC_{max}{}^{(c)} + BC_{min}{}^{(c)}\right] \Big/ 4} \quad \text{5-13}$$

Where:

$BC^{(v,c)} = Battery\ capacity\ of\ vehicle\ v\ in\ class\ c$

$\vec{\mu}^{(c)} = mean\ battery\ capacity\ of\ class - c$

$(\vec{\sigma}^{(c)})^2 = \ variance\ of\ battery\ capacity\ in\ class - c$
$N = standard\ normal\ value, \in [0, 1]$

5.2.1.3 Distribution of daily distance travelled

This is one of important parameters to the model. Daily grid energy required by each vehicle is a function of daily distance travelled and SOC level remaining in the battery. SOC by itself is a function of daily distance travelled and battery capacity. As a result, knowing the statistical distribution of daily distance travelled by each vehicle in the area of study is the key to determine the required energy from the grid.

Once the daily energy requirement of a particular vehicle is determined, generating the load profile resulting in from this energy demand will be easy. It merely depends on how fast (charging power level) and when (charge start time) to get this energy from the grid.

Daily grid energy required by each vehicle, which is a function of distance travelled, SOC level and required grid energy per unit distance, is calculated as:

$$\boldsymbol{E_{Grid}{}^{(v,,c,d)} = S^{(v,c,d)} * E_{Grid\_per\_km} - SOC^{(v,c,d-1)}} \quad \text{5-14}$$

Where:

$E_{Grid}{}^{(v,,c,d)} = Grid\ energy\ required\ by\ vehcle\ v\ of\ class\ c\ on\ day\ d$

$S^{(v,c,d)} = Distance\ traveled\ by\ vehicle\ v\ of\ class\ c\ on\ day\ d$

$SOC^{(v,c,d-1)} = remaining\ SOC\ level\ of\ vehicle\ v\ of\ class\ c\ from\ day\ (d-1)$

$E_{Grid\_per\_km} = grid\ energy\ required\ per\ km\ distance\ travelled$

As we can see from equation 5-14 above, the daily distance travelled, useable SOC and grid energy required per km determines the daily energy requirement of a particular vehicle from the grid. The useable SOC level of a particular vehicle in a particular day is calculated as:

$$\boldsymbol{SOC^{(v,c,d)} = BC^{(v,c)} - D^{(v,c,d)} * E_{Grid\_per\_km}} \quad 5\text{-}15$$

Where:

$SOC^{(v,c,d)} = useable\ SOC\ of\ vehicle\ v\ of\ class\ c\ on\ day\ d$

$BC^{(v,c)} = useable\ Battery\ capacity\ of\ vehcile\ v\ of\ class\ c$

$S^{(v,c,d)} = Distance\ traveled\ by\ vehicle\ v\ of\ class\ c\ on\ day\ d\ in\ km$

$E_{Grid\_per\_km} = grid\ energy\ required\ per\ km\ distance\ travelled$

As we can see from this equation, the useable SOC can be negative which indicates that the distance traveled on that particular day is beyond the capacity of the battery. In this case, the solution will be either that the vehicle is recharged more than once per day, as is done for fast charging model, or use a hybrid energy source to finish the distance as is considered in residential charging model. If none of these are possible, the car has to stop or the consumer behavior has to change to lower the maximum daily distance travelled or battery capacity has to be increased. The detailed analysis of this will be made in chapter 5.

5.2.2 Residential charging model

The main differences between residential charging model and fast charging model are the charging power levels and arriving time distribution of vehicles for charging. This model considers the charging characteristics when PEVs are charged at home only. Normally daily charging is assumed to starts when a particular vehicle arrives home from work. This daily vehicle arrival time from work is statistical in nature with a mean and variance arrival and departure time.

For the time performance parameters of departure time and arrival time, normal distribution are assumed as a best estimate of random consumer behavior. Different timing distributions are used to model the potential different consumer behavior on weekdays versus weekends. Hence the random arrival and departure times of vehicles on a given day of a week are formulated as:

$$\boldsymbol{A_T{}^{(v,c,d)} = \mu_{AT}{}^{(p)} + \left(\sigma_{AT}{}^{(p)}\right)^2 * N} \quad 5\text{-}16$$

$$\boldsymbol{D_T{}^{(v,c,d)} = \mu_{DT}{}^{(p)} + \left(\sigma_{DT}{}^{(p)}\right)^2 * N} \quad 5\text{-}17$$

Where:

$A_T{}^{(v,c,d)} = arrival\ time\ of\ vehicle\ v\ of\ class\ c\ on\ day\ d$

$D_T{}^{(v,c,d)} = departure\ time\ of\ vehicle\ v\ of\ class\ c\ on\ day\ d$

$p = reperesent\ particular\ day\ type, weekday\ or\ weekend$

$\mu_{AT}{}^{(p)} = mean\ arrival\ time\ for\ the\ day$

$\sigma_{AT}{}^{(p)} = standard\ deviation\ of\ arrival\ time\ for\ the\ day$

$\mu_{DT}{}^{(p)} = mean\ departure\ time\ for\ the\ day$

$\sigma_{AT}{}^{(p)} = standard\ deviation\ of\ arrival\ time$

$\sigma_{DT}{}^{(p)} = standard\ deviation\ of\ departure\ time\ for\ the\ day$

$N = standard\ normal\ distribution$

All the parameters given above are probabilistic and depend on statistics. The arrival time $\boldsymbol{A_T}^{(\boldsymbol{v,c,d})}$ for $vehicle - v\ of\ class\ c\ on\ day\ d$ must occur after the departure time $\boldsymbol{D_T}^{(\boldsymbol{v,c,d})}$ for $vehicle - v\ of\ class\ c\ on\ day\ d$ in the simulation. To achieve this specification, an acceptance-rejection method is used in the model. Let $A_T{}^*$ be a particular generated arrival time and $D_T{}^*$ be a particular generated departure time, both generated based on given statistics. Each generated pair ($A_T{}^*$, $D_T{}^*$) is checked, and if $A_T{}^* < D_T{}^*$, then a new pair is generated. The process is repeated until $A_T{}^* > D_T{}^*$ and the generated pair is accepted and stored for further use.

Two specific case models are considered in residential charging model. The first model, Case I, charges the vehicle during parking interval, the time interval between daily arrival time of vehicle (v) on day (d) and its departure time to work on the next day, day (d+1). The output power required from the onboard battery charger may vary from day to day which is a function of random daily energy requirement and random daily parking interval of vehicles which is a function of arrival and departure times. In this case, if the maximum required charging current exceeds the maximum circuit current, there is a probability that the vehicle may not be fully charged the next day when leaving to work since the model monitors the current drawn by the vehicles not to exceed the maximum circuit capacity.

In the second case, Case II, a model which does not consider the parking interval is developed. In this case, vehicles are charged with a fixed power from the onboard battery charger every day and charging time interval is determined by the output power from the charger and the random daily energy requirement. If this charging interval is greater than the parking interval[22], there is a probability that a driver may be delayed the next day to go to work or leave home with battery capacity which is not fully charged.

5.2.2.1 Case I: Charge during parking interval

In this model, vehicles are charged at home in the interval between daily arrival time from work and departure time to work next day. In other word, vehicles are charged in the parking interval at home during night. The power output from the charger will be determined by charging voltage level, parking interval and daily energy requirement. The step by step procedures, used to develop this model, are described as follow.

- Step one

  The first step is to determine daily charging time or parking interval at home ($C_T{}^{(v,c,d)}$) which is formulated as:

$$\boldsymbol{C_T}^{(\boldsymbol{v,c,d})} = \begin{cases} \left(\boldsymbol{24} - \boldsymbol{A_T}^{(\boldsymbol{v,c,d})}\right) + \boldsymbol{D_T}^{(\boldsymbol{v,c,d+1})}, & \boldsymbol{if\ PEV\ arrived\ on\ day\ (d) and\ left\ onday\ (d+1)} \\ \boldsymbol{D_T}^{(\boldsymbol{v,c,d+1})} - \boldsymbol{A_T}^{(\boldsymbol{v,c,d+1})}, & \boldsymbol{if\ PEV\ arrived\ on\ day\ (d+1)\ and\ left\ and\ left\ on\ day\ (d+1)} \\ \boldsymbol{D_T}^{(\boldsymbol{v,c,d})} - \boldsymbol{A_T}^{(\boldsymbol{v,c,d})}, & \boldsymbol{if\ PEV\ arrived\ on\ day\ (d) and\ left\ on\ day\ (d)} \end{cases} \quad \textbf{5-18}$$

  Where:

  $C_T{}^{(v,c,d)} = parking\ interval\ of\ vehicle\ v\ of\ class\ c\ on\ day\ (d)$

  $A_T{}^{(v,c,d)} = arrival\ time\ of\ vehicle\ v\ of\ class\ c\ on\ day\ (d)$

  $D_T{}^{(v,c,d)} = departure\ time\ of\ vehicle\ v\ of\ class\ c\ on\ day\ (d)$

[22] The time interval between probabilistic daily arrival time on day (d) and departure time on day (d+1)

$A_T{}^{(v,c,d+1)} = arrival\ time\ of\ vehicle\ v\ of\ class\ c\ on\ day\ (d+1)$

$D_T{}^{(v,c,d+1)} = departure\ time\ of\ vehicle\ v\ of\ class\ c\ on\ day\ (d+1)$

Note that all these parameters are probabilistic.

- Step two

  The second step in this procedure will be to set the charging grid voltage level ($V^{(v,c)}$), which is a charging voltage level for $veheicle - v$ of $class - c$. This is the available grid charging voltage which is to be set in the model as 230/400V, for example.

- Step three

  The third step is to determine the charging current ($I^{(v,c,d)}$). This is the amount of current that $veheicle - v$ of $class - c$ draws on one specific charging $day - d$. This current value, along with the available voltage and energy requirement, will determine the required output power from the charger. This is calculated as:

$$\boldsymbol{I^{(v,,c,d)}} = \boldsymbol{min}\left\{\frac{\boldsymbol{E_{Grid}{}^{(v,c,d)} * 1000}}{\boldsymbol{V^{(v,c)} * C_T{}^{(v,c,d)}}}, \boldsymbol{I^*}\right\} \qquad 5\text{-}19$$

  Where:

  $I^{(v,c,d)} = current\ demand\ by\ vehicle\ v\ of\ class\ c\ on\ day\ d$

  $E_{Grid}{}^{(v,c,d)} = required\ grid\ energy\ by\ vehcile\ v\ of\ class\ c\ on\ day\ d$

  $V^{(v,c)} = charging\ voltage\ level\ of\ vehcile\ v\ of\ class\ c$

  $C_T{}^{(v,c,d)} = parking\ interval\ of\ vehicle\ v\ of\ class\ c\ on\ day\ d$

  $I^* = maximum\ current\ capacity\ of\ charging\ circuit$

  Note that the calculate current is in ampere [A], provided that voltage is given in volt [v] and energy is given in [KWh]. This value is limited by the maximum current available, I^* [A], from the charging circuit. This means that for the given charging voltage level $\boldsymbol{V^{(v,c)}}$ and randomly determined daily energy requirement $\boldsymbol{E_{Grid}{}^{(v,c,d)}}$**,** if the charging interval is so small that the required charging current is higher than the maximum rating of the circuit, the charging circuit will limit the output current to its maximum value and the vehicle may depart partially charged the next day.

- Step four

  Finally, the power output from the charger, which will determine the load profile of PEV charging, $\boldsymbol{P^{(v,d,c)}}$ of $veheicle - v$ of $class - c$ on $day - d$ is calculated as a function of voltage and current and is calculated as:

$$\boldsymbol{P^{(v,c,d)}} = \boldsymbol{V^{(v,c)}} * \boldsymbol{I^{(v,d,c)}} \qquad 5\text{-}20$$

  Where:

  $P^{(v,c,d)} = power\ demand\ of\ vehicle\ v\ of\ class\ c\ on\ day\ d$

  $V^{(v,c)} = charging\ voltage\ level\ of\ vehcile\ v\ of\ class\ c$

  $I^{(v,c,d)} = current\ demand\ by\ vehicle\ v\ of\ class\ c\ on\ day\ d$

Once the charging power level from the charger is determined, this is used to determine load profiles on the given charging interval and added to the load profiles of all the vehicles in the system on the specific simulation time slot. Figure 5.5 below shows the flow chart of Case I residential charging model.

As can be seen from the flow chart in Figure 5.5, the program starts by initialization. It starts by taking input from the user including total number of vehicle population in the study area, penetration level of PEVs, distribution of PEVs in each classes of vehicles, charging voltage and maximum available current from the charging circuit, battery capacities of vehicle classes, statistical arrival and departure time of vehicles from and to work respectively, statistical distribution of daily distance traveled by vehicles and the average grid energy required per km. These important parameters are the back bones of the model. They determine all aspects of the output from the charger.

Following initialization, it will start processing these data as can be seen Figure 5.5. First, for the given total vehicle population and distribution of vehicles in each class in the study area, number of PEVs in each vehicle class is determined. Following this, per minute and hourly load profiles are generated for each vehicle for one week, based the input data. Note that this process is repeated a number of times, which is controlled by Monte Carlo loop to refine the result to a certain degree of confidence level. Note also that all important parameters are stored during the whole simulation and made available for processing after the simulation. Flow chart in Figure 5.6 illustrates the detailed steps, marked red in Figure 5.5, to generate load profiles for each vehicle population.

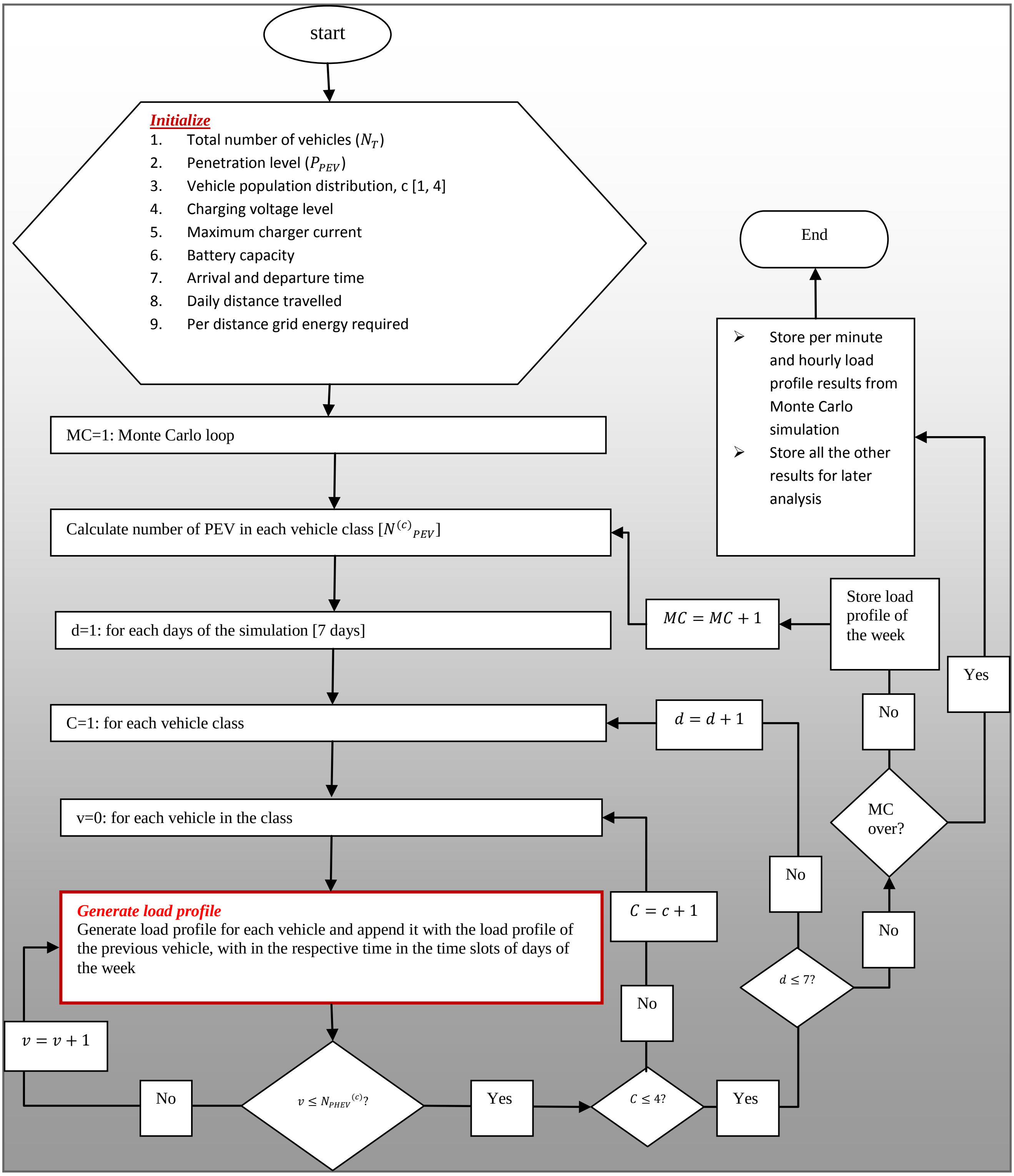


Figure 5.5: Residential slow charging, case I charger model flow chart

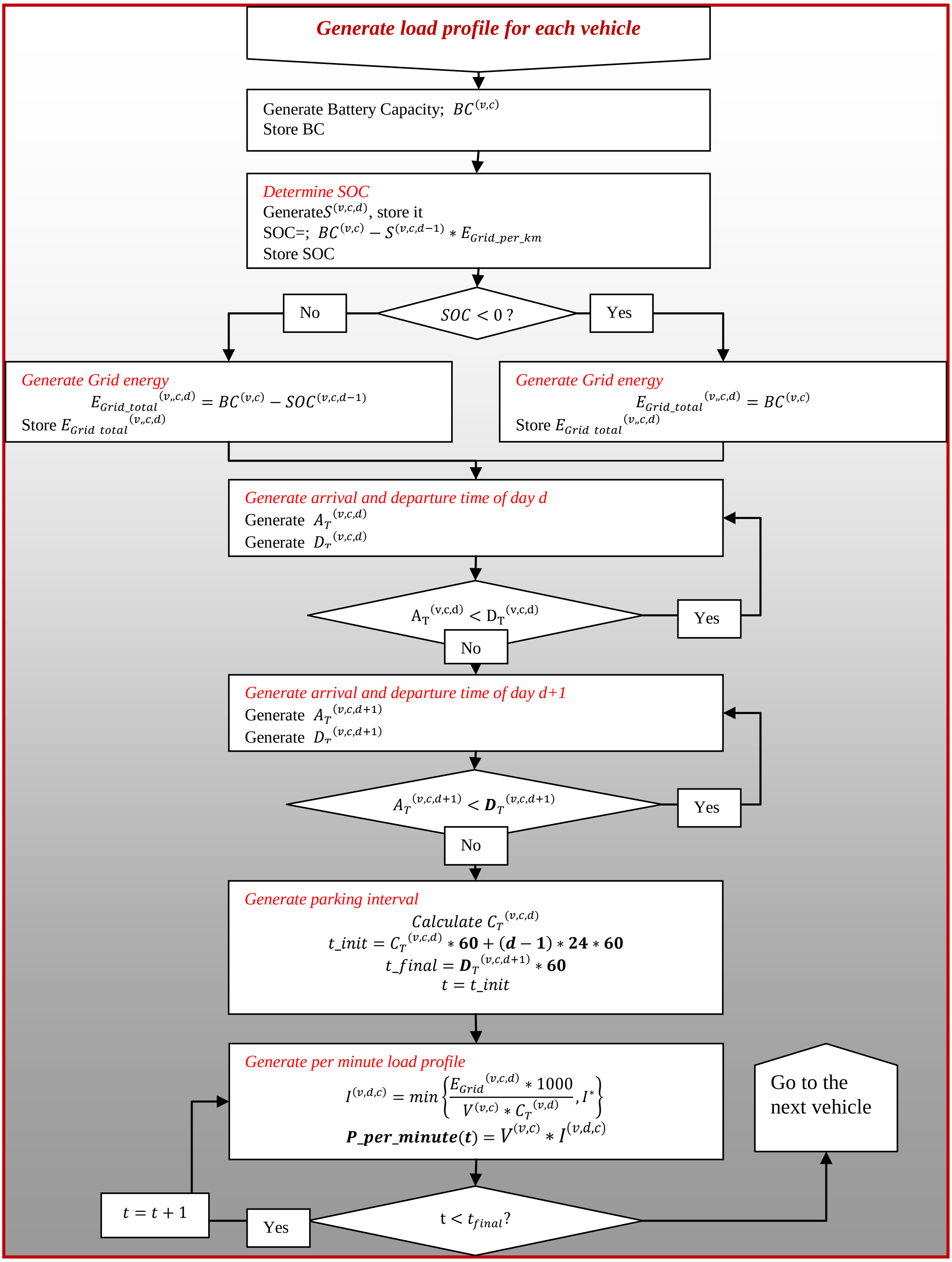


Figure 5.6: Residential slow charging, case I charger model flow chart, detailed load profile generation algorism

As discussed in section 5.2.2, in this case all vehicles are charged with a fixed output power from on board charger every day. As a result, charging power level is set in the initialization phase. Since the power level is fixed, there is no need to worry about the current limit in the model. The assumption is that the circuit in which the charger is connected is capable of carrying the current demand. In this model, the charging time interval is dictated by charging power level and energy required by vehicles. Except for these differences, other inputs are the same as that of Case I residential charging.

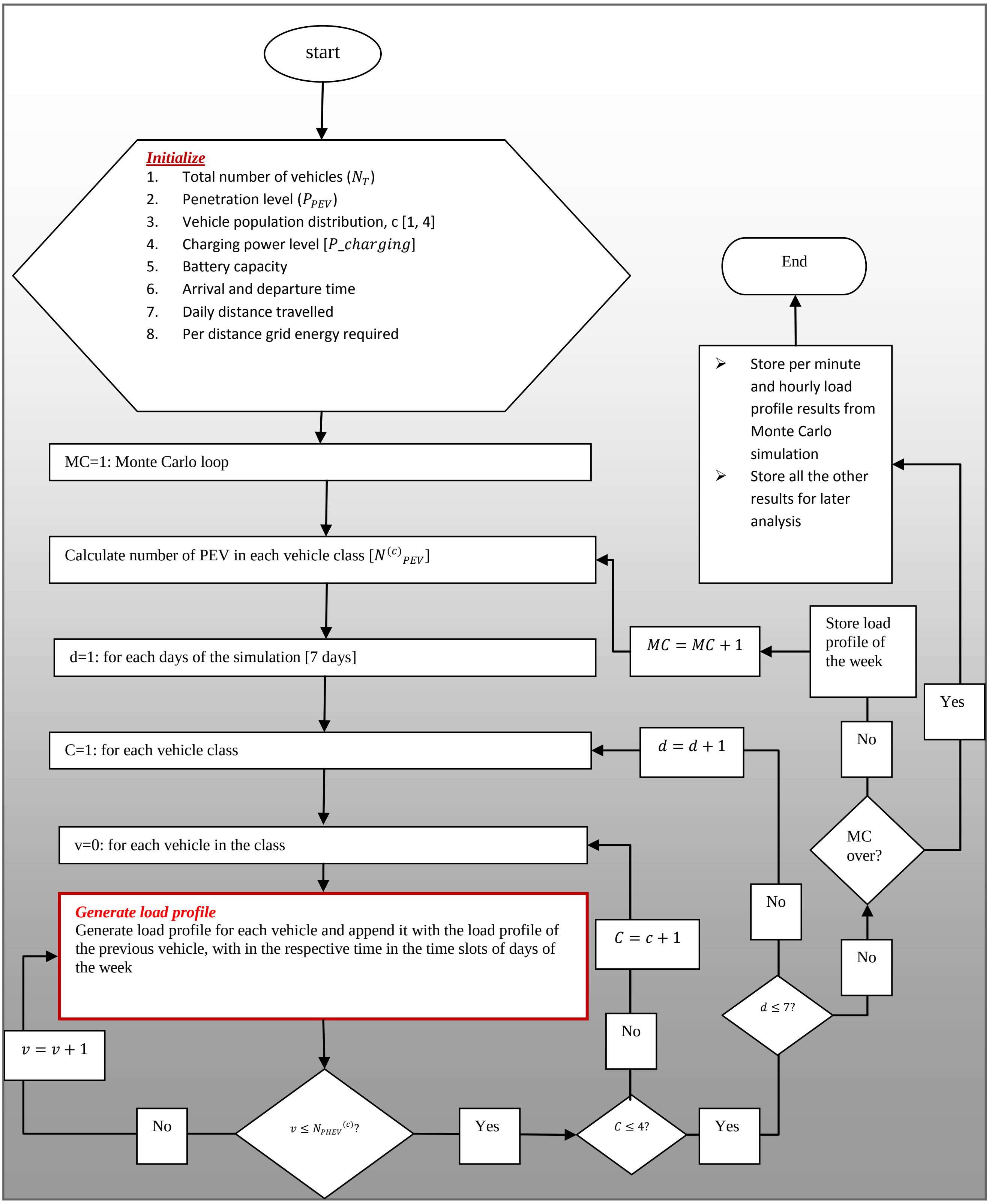


Figure 5.7: Residential slow charging, case II charger model flow chart

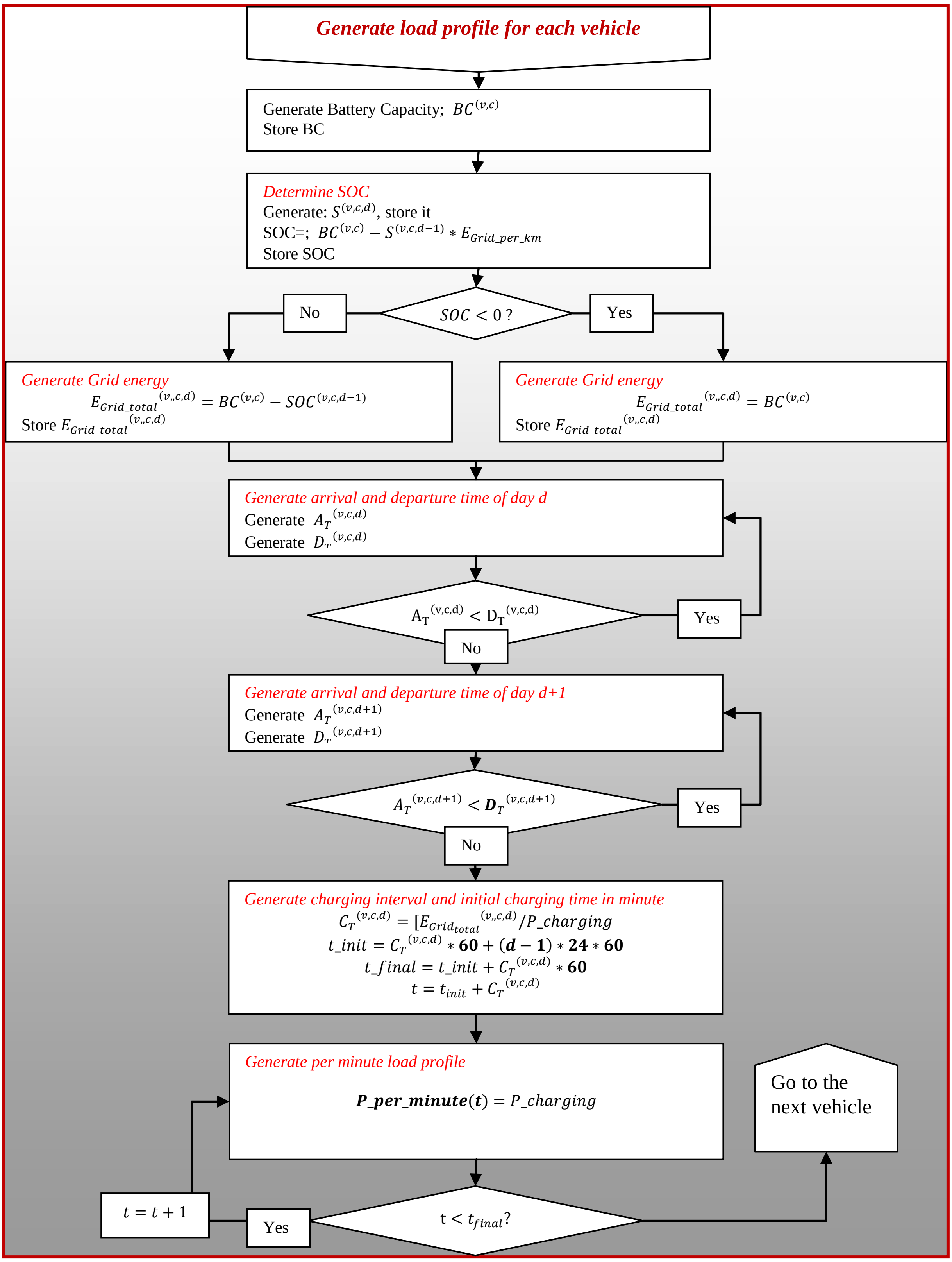


Figure 5.8: Residential slow charging, case II charger model flow chart, detailed load profile generation algorism

Figure 5.8 illustrates a flow chart for the detailed load profile generation for each vehicle, in each vehicles class for whole simulation time interval. This flow chart is similar to that shown in Figure 5.6 for Case I residential charging with some differences. Their differences stem from the fixed charging power level for all day in Case II and daily variable charging power level in Case I.

Their similarity is that they both generate per minute and hourly average load profiles. To generate this result, they start by generating the battery capacity for a particular. Following this, they probabilistically generate the distance that vehicle travel on that specific day to calculate the remaining useable SOC level. If the calculated useable SOC is negative, this means that the vehicle has used up all the energy in the battery and used another alternative energy to finish the statistical distance for that day or it has recharged its battery outside home, may be at public charging station or at the fast charging station to finish this distance. Whatever may happen, the model doesn't consider the stated possibilities since clustering is not considered. In residential charging models, it assumed that vehicles charge only once per day at home. And hence, when useable SOC is negative, since SOC could never be negative, the model interprets this as if the vehicle arrived with zero useable SOC and it requires energy from the grid which is equivalent to its full useable battery capacity. At this point both models know how much grid energy is required to recharge that specific vehicle of specific class on that particular day. Next to this, both models calculates the arrival and departure time of the current day and next day based on 'acceptance-rejection' techniques stated in section 5.2.2. The major differences of these two models start from this point onward.

The model in Case I, shown in Figure 5.6 calculate the parking time interval of that particular vehicle by taking the difference between the arrival time and departure time of the vehicle as defined in equation 5-18 above. In addition to this, it will also calculate the charging power from the given charging voltage and the allowable charging current, which will define the demand of this particular vehicle at each minutes of the charging interval.

On the other hand, Case II calculates the charging time interval by dividing the energy required for the day by the vehicle with charging power level. And then start charging the vehicle until the vehicle is fully charged. At this point it is good to note that the charger will start charging just as the vehicle arrive from work and will continue charging until the battery is fully charged. In fact the model also has the capability for a delayed charging after arrival.

5.2.3 Fast charging model

This is the last and most important charging model. This model is used to charge vehicle at the fast charging station. This means, if we have fast charging station similar to petrol filling station, then this charger model can generate charging load profile at the fast charging station, which can later be used for system study.

In the initialization phase, the model is similar to residential charging Case II (see section 5.2.2.2). However, there are two important differences between these models. These are charge starting time, which determines the shape of the load profile and charging power level. Charging power level is much higher than residential case which is in an order of about 100 times higher. The second most important difference is the charging time distribution. As we recall from section 5.2.2.2, the charging time in residential charging Case II is dictated by the statistical daily arrival and departure time of vehicles from and to work respectively. Charging starts when vehicle arrive home from work where charge stating time is determined probabilistically based statistical data. Hence, charging time interval is determined by the available charging power and grid energy requirement of vehicles on that particular day.

On the other hand, fast charging model of this section considers totally different timing approach. The charging time in this model is dependent on the statistical data obtained from petrol filling stations we have today in the market. Figure 5.9 shows a sample vehicle arrival time distribution at one petrol filing station.

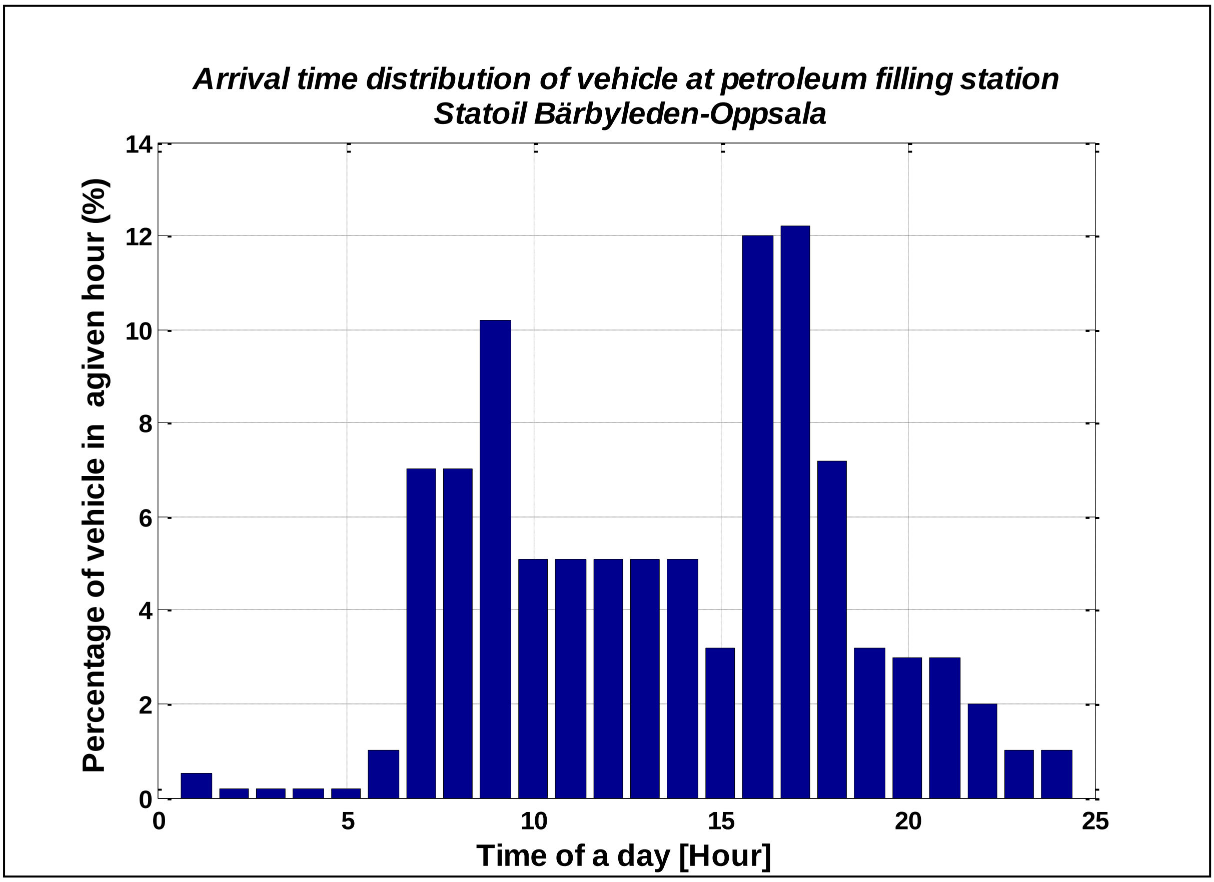


Figure 5.9: Arrival time distribution of vehicle at petroleum filling station, Statoil Bärbyleden-Oppsala, Sweden

This figure shows the percentage arrival time distribution of vehicle at Statoil Bärbyleden-Oppsala, petrol filing station. For example, if a total 500 vehicles arrive in this station on a particular day, 12% of them, i.e. 60 vehicles arrive in 16:00 and 17:00 time interval as can be seen from Figure 5.9. This is an important dimension of this model. Vehicle arrival time distribution at given petrol filling station should be known for this model to work. This data will be used in the model to represent vehicles arrival time distribution at fast charging station which we assume is to replace this petrol filing station. In short, the main differences between the stated two models stems from this charging time distribution.

This model starts by initializing vehicle arrival time distribution and other inputs like total number of vehicle arriving at the charging station in a particular day for that charging station, the penetration level of PEVs, the distribution of these vehicles among different classes, charging power level, ranges of battery capacities of vehicles arriving at the charging station, distribution of vehicles' daily distance travelled and grid energy requirement per unit distance. Figure 5.10 shows the detailed flow chart used.

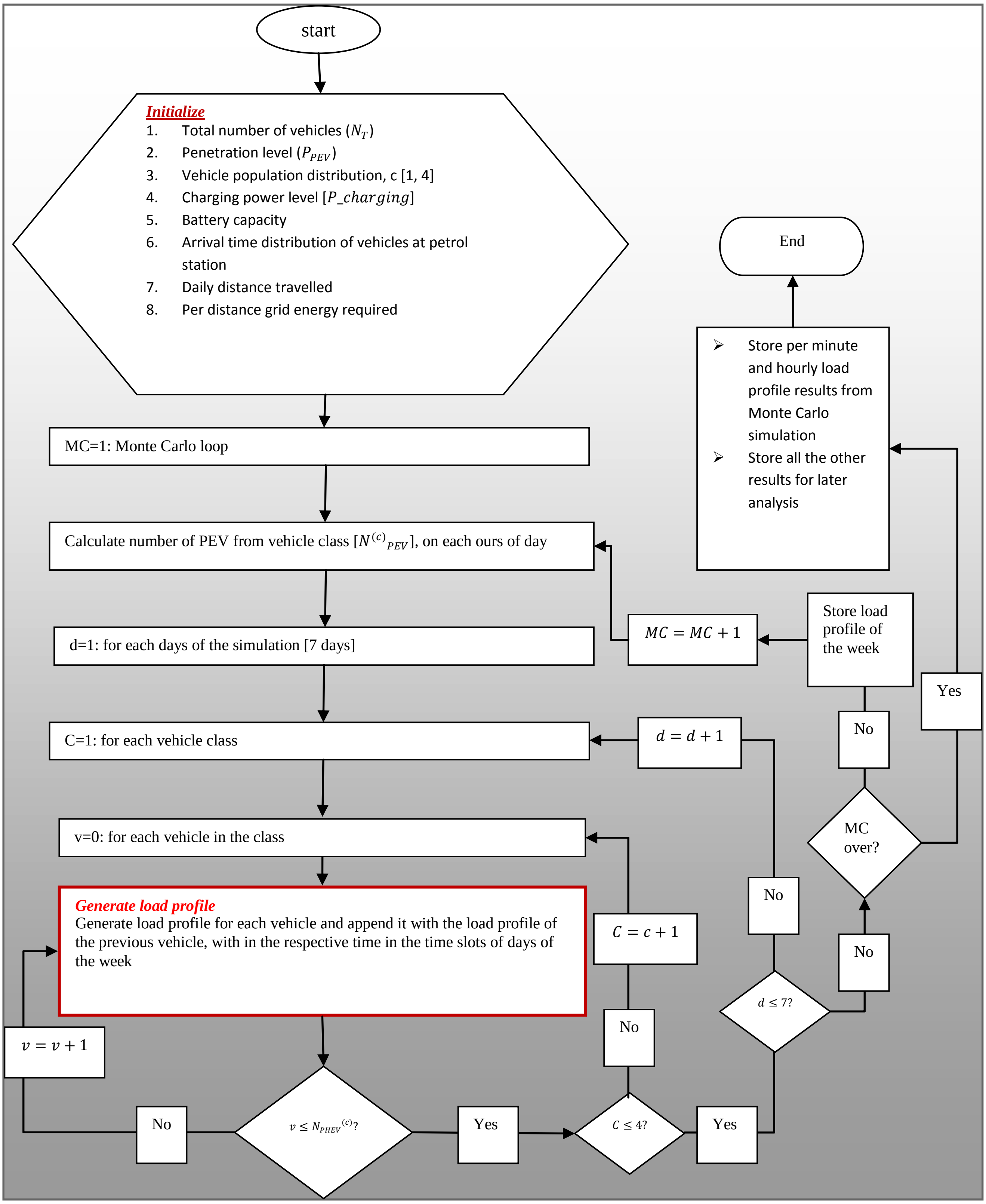


Figure 5.10: Fast charging model flow chart

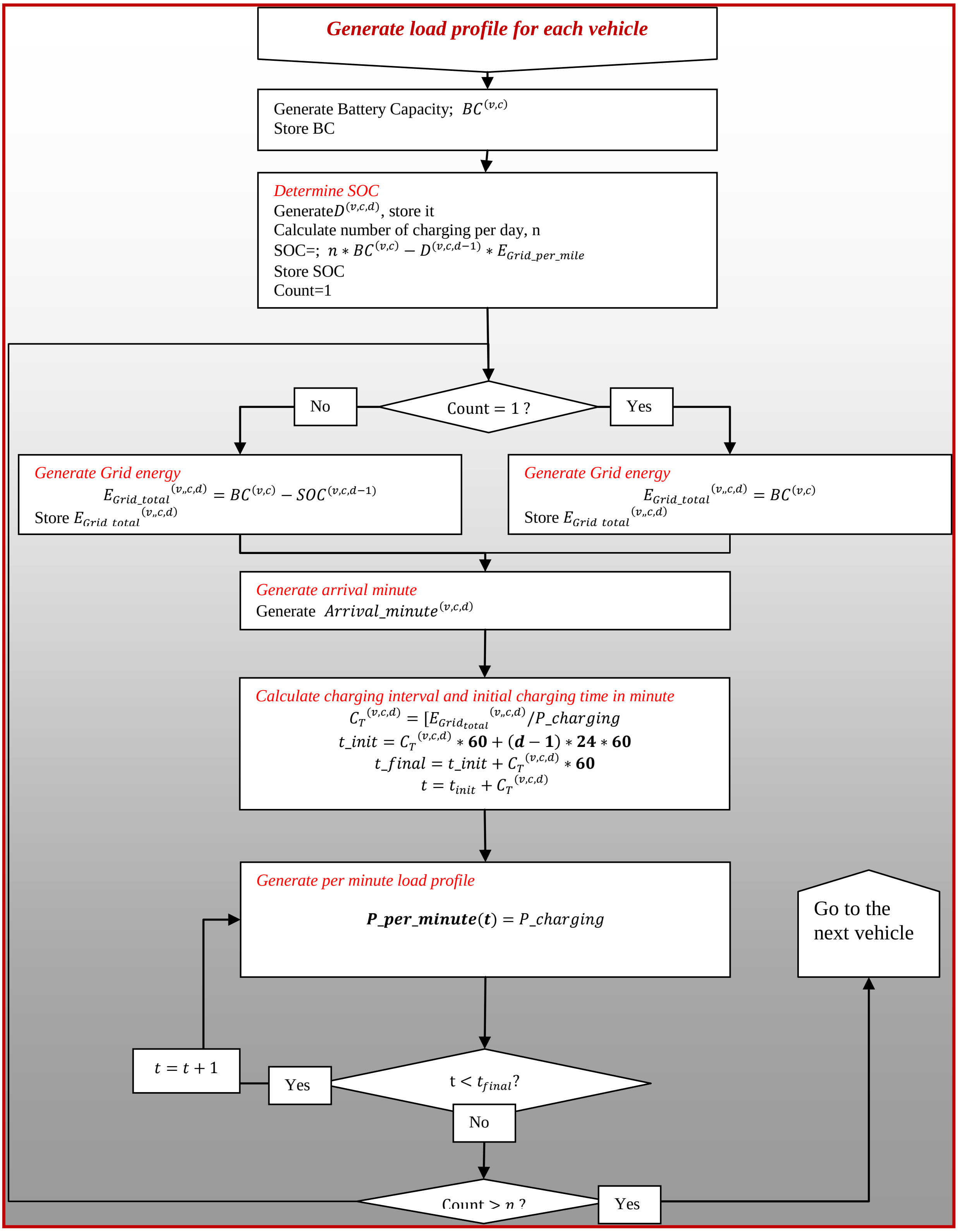


Figure 5.11: Fast charging model flow chart, detailed load profile generation algorism

Just after taking the inputs to the model, the algorithm starts by calculating the number of vehicles from each vehicle class arriving at the charging station on each hours of the day. Similar to the other two models, this model also generates and stores per minute and hurly average load profile for a week, SOC distribution, distribution of daily distance traveled and other similar parameters.

What is unique about this model is that, unlike the two residential charging models, the vehicles in this model can charge more than once in a day at the fast charging station. The result of this is that we have distribution of daily number of charging times for vehicles. In addition to this, this model also generate the distribution required number of charging poles at fast charging station which is an important parameter for an economical optimization of number of charging poles at fast charging stations. Detailed analysis will be made in chapter six: simulation, Results and analysis.

It is also important to see how the arrival minutes of vehicles in a given hour of the day are calculated as is shown in the detailed flow chart of fast charging model in Figure 5.11. For all vehicles of different classes arriving at the charging station in a given hour of the day, a probabilistic arrival minute in that particular hour is generated to determine the minute at which the charging starts in the given hour of the day.

5.3 Distribution system impact model

As discussed in various sections earlier, the penetration of PEV in the power systems can have positive or negative impacts on the power system components. In general power system components like distribution cables and transformers are vulnerable to these overloads due to the penetration of PEV with the transformer being more susceptible to overloads.

To evaluate the impact of added load due to PEVs on the system, it is necessary to model the distribution system components including distribution transformers and distribution service cables. Since we are concerned with quantifying the impacts the new loading of the system on the system components, it is expedient to use an electro-thermal model of the constituent parts of this system. The electro-thermal model allows the computation of the temperature rise of the various components of the system and subsequent evaluation of the adequacy of the system and/or the evaluation of the risk of failure [5.4]. With knowledge of the currents in the transformer windings, the temperature of the windings can be calculated using a simplified first-order electro-thermal model. From the transformer windings temperature the hotspot temperature of the transformer, loss of life, and expected life can be calculated over a planning period.

In this section impacts PEV charging on distribution transformer will be quantified with electro-thermal model. The procedure which is used to quantify transformer impacts in terms of Loss of Life (LOL) is based on *ANSI/IEEE C57.91-198 model.* The corner stone of this algorithm is to first determine the hot spot temperature of transformer winding and then to translate this into equivalent LOL of the transformer based on the standard given in *ANSI/IEEE C57.91-198* [5.5].

5.3.1 ANSI/IEEE C57.91-1981 Based Impact model

This model translates hourly loading of a transformer into expected lifetime. According to this model, the calculation of transformer aging includes two steps. These are:-

- Estimating hot spot temperature, θ_H
- Translating θ_H into transformer loss of life

The first step is to estimate the temperature of the hottest point within the transformer (the “hotspot” temperature,θ_H) for each hour in the interval of study. The hotspot temperature is a function of ambient temperatures and transformer loading [5.5].

The second step involves translating θ_H into a measure of transformer aging. Once the hotspot temperature is estimated, *IEEE Standard C57.91 [5.5]* provides a function for translating hotspot temperature into an accelerated aging factor (F_{AA}), which can be used to estimate the loss in transformer life that can result from higher temperatures and heavy loading.

5.3.2 Estimating the winding hot spot temperature

To calculate the winging hotspot temperature, θ_H, the following procedures are used:

- First, thermal time constants for the transformer oil (τ_{To}) and windings (τ_{Tw}) are calculated. Both represent the thermal inertia of the transformers. Given the weight of the transformer (w_T, in lbs.), the gallons of oil in the transformer (G_o), the temperature rise of the top-oil above ambient at rated load ($\Delta\theta_{To,R}$) and the power losses at rated load ($P_{T,R}$), thermal time constants for the transformer oil (τ_{To}) can be calculated as:

$$\boldsymbol{\tau_{To}} = \frac{(\mathbf{0.06}\boldsymbol{w_T}+\mathbf{1.93}\boldsymbol{G_o})*\Delta\boldsymbol{\theta_{To,R}}}{\boldsymbol{P_{T,R}}} \quad \text{5-21}$$

  This equation is a minor simplification of the equation for τ_{To} given in IEEE C57.91 [5.5], which provides a method for calculating a time-varying time constant. The approximation is appropriate for small time steps, which is one hour in our case. IEEE C57.91 does not provide a method for calculating the winding time constant. Following [5.4] and [5.6], the winding time constant τ_{Tw} is assumed to be small ($\tau_{Tw} = 0.25$)

- Second, the initial temperature gradients of transformer oil over ambient and hotspot over transformer oil have to be calculated in order to determine the hotspot temperature. The following equations calculate the initial temperature gradient of oil over ambient and hotspot over oil respectively for transformers:

$$\Delta\boldsymbol{\theta_{TO,0}} = \Delta\boldsymbol{\theta_{TO,R}} * \boldsymbol{A}(\boldsymbol{L_{k,0}}) \quad \text{5-22}$$

$$\Delta\boldsymbol{\theta_{H,0}} = \Delta\boldsymbol{\theta_{H,R}} * \boldsymbol{A}(\boldsymbol{L_{k,0}}) \quad \text{5-23}$$

$$\boldsymbol{A}(\boldsymbol{L_{k,h}}) = \left[\frac{\left(\frac{L_{k,h}}{L_{k,R}}\right)^2 * \left(\frac{P_{T,0}}{P_{T,R}}\right)+1}{\frac{P_{T,0}}{P_{T,R}}+1}\right]^{n_t} \quad \text{5-24}$$

  Where:

  $\Delta\theta_{TO,R} = \text{rated increase top oil temperature above ambient temperature}$

  $\Delta\theta_{H,R} = \text{rated increase hotspot temperature over top oil temperature}$

  $A(L_{k,h}) = \text{transformer loading factor at hour h}$

  $L_{k,h} = \text{Actual per hour transformer loading}$

  $L_{k,R} = \text{Rated transformer loading}$

  $P_{T,0} = No\ load\ transformer\ loss$

  $P_{T,0} = Rated\ load\ transformer\ loss$

  $n_t = constant\ for\ the\ cooing\ class\ of\ the\ transformer (= 0.8\ for\ oil/air)$

- The third step is to calculate temperature gradients for each hour. To calculate the hot spot temperature for each hour, hourly temperature increase of top-oil above ambient temperature ($\Delta\theta_{TO,h}$) and hourly temperature increase of hotspot above top-oil temperature ($\Delta\theta_{H,h}$) has to be calculated as follow:

$$\Delta\boldsymbol{\theta_{TO,h}} = \Delta\boldsymbol{\theta_{TO,h-1}} + \left(\Delta\boldsymbol{\theta_{TO,R}} * \boldsymbol{A}(\boldsymbol{L_{k,h}}) - \Delta\boldsymbol{\theta_{TO,h-1}}\right)\left(\mathbf{1} - \boldsymbol{e}^{-\Delta \boldsymbol{t}/\boldsymbol{\tau_{To}}}\right) \quad \text{5-25}$$

$$\Delta\boldsymbol{\theta_{H,h}} = \Delta\boldsymbol{\theta_{H,h-1}} + \left(\Delta\boldsymbol{\theta_{H,R}} * \boldsymbol{A}(\boldsymbol{L_{k,h}}) - \Delta\boldsymbol{\theta_{H,h-1}}\right)\left(\mathbf{1} - \boldsymbol{e}^{-\Delta \boldsymbol{t}/\boldsymbol{\tau_{Tw}}}\right) \quad \text{5-26}$$

  Where:

$\Delta\theta_{TO,h} = teprature\ gradient\ of\ top\ oil\ temperatreu\ over\ the\ ambient\ teprature\ at\ hour\ h$

$\Delta\theta_{TO,h-1} = teprature\ gradient\ of\ top\ oil\ temperatreu\ over\ the\ ambient\ teprature\ at\ hour\ h-1$

$\Delta\theta_{TO,R}$ = rated increase top oil temperature above ambient temperature

$A(L_{k,h})$ = transformer loading factor at hour h of transformer k

$\Delta t = \ lenght\ of\ time\ step\ in\ hours, for\ example, in\ the\ load\ profile\ of\ the\ transformer$

$\tau_{To} = thermal\ time\ time\ constant\ of\ the\ transfoemer$

$\Delta\theta_{H,h} = teprature\ gradient\ of\ hotspot\ temperature\ over\ top\ oil\ temperatreu\ at\ hour\ h$

$\Delta\theta_{H,h-1} = teprature\ gradient\ of\ hotspot\ temperature\ over\ top\ oil\ temperatreu\ at\ hour\ h-1$

$\tau_{Tw} = winding\ time\ constant\ of\ the\ transformer$

- The last step is to calculate the hotspot temperature with the results from the preceding two steps. From this the hourly hotspot temperature is defined as:

$$\boldsymbol{\theta_{H,h} = \theta_{A,h} + \Delta\theta_{TO,h} + \Delta\theta_{H,h}} \tag{5-27}$$

where:

$\theta_{H,h}$ =*hotspot temperature of the transformer at hour h*

$\Delta\theta_{TO,h} = temperature\ gradient\ of\ top\ oil\ temerature\ over\ ambient\ tempearature\ at\ hour\ h$

$\Delta\theta_{H,h} = temperature\ gradient\ of\ hotspot\ \ temerature\ over\ top\ oil\ tempearature\ at\ hour\ h$

$\theta_{A,h} = hourly\ ambient\ temparature$

5.3.3 Calculating Transformer Loss of Life (LOL)

Given the winding hot spot temperature $\theta_{H,h}$, IEEE C57.91 specifies that the following formula can be used to estimate per unit accelerated aging (F_{AA}) of a transformer as:

$$\boldsymbol{F_{AA}(\theta_{H,h}) = e^{\left(B/\theta_{H,R} - B/\theta_{H,h}\right)}} \tag{5-28}$$

Where B is a constant given as 15,000 in [5.4], [5.6] and $\boldsymbol{\theta_{H,R}}$ is the rated maximum hot spot temperature and $\theta_{H,h}$ is the hotspot temperature at hour h for the transformer from 5-27.

The following equation allows us to estimate the change in expected life due to thermal loading at PEV penetration level P_{PEV} over a one-year period:

$$\boldsymbol{\Delta F_{k,P_{PEV}} = \frac{1}{8760}\sum_{h=1}^{8760}\left\{F_{AA}(\theta_{H,h}(L_{k,h}(P_{PEV}))) - F_{AA}(\theta_{H,h}(L_{k,h}(0)))\right\}} \tag{5-29}$$

Where:

$\theta_{H,h}\left(L_{k,h}(P_{PEV})\right) = hotspot\ temperature\ of\ the\ transformer\ at\ P_{PEV}\ penetration\ level$

$\theta_{H,h}(L_{k,h}(0)) = hotspot\ temperature\ of\ the\ transformer\ at\ zero\ penetration\ level$

$\Delta F_{k,P_{PEV}} = change\ in\ expected\ life\ transformer\ k\ due\ to\ PEV\ charging\ at\ P_{PEV} penetration\ level$

6 CHAPTER SIX: SIMULATION, RESULTS AND ANALYSIS

6.1 Fast charging

Fast charging is one of an important part of this thesis. In this section the probabilistic fast charging model developed in chapter five is simulated and the resulting outputs are discussed. In chapter five a number of probabilistic parameters were defined which dictate the output from the models. Among these are distribution of daily distance travelled, arrival time distribution of vehicles at the fast charging stations and distribution of vehicles battery capacities in the defined ranges. In order to illustrate the power of probabilistic model compared with deterministic model, four different cases are defined. The following subsections will have a closer look at each scenarios and a number of outputs generated from the models.

6.1.1 Fast charging stations

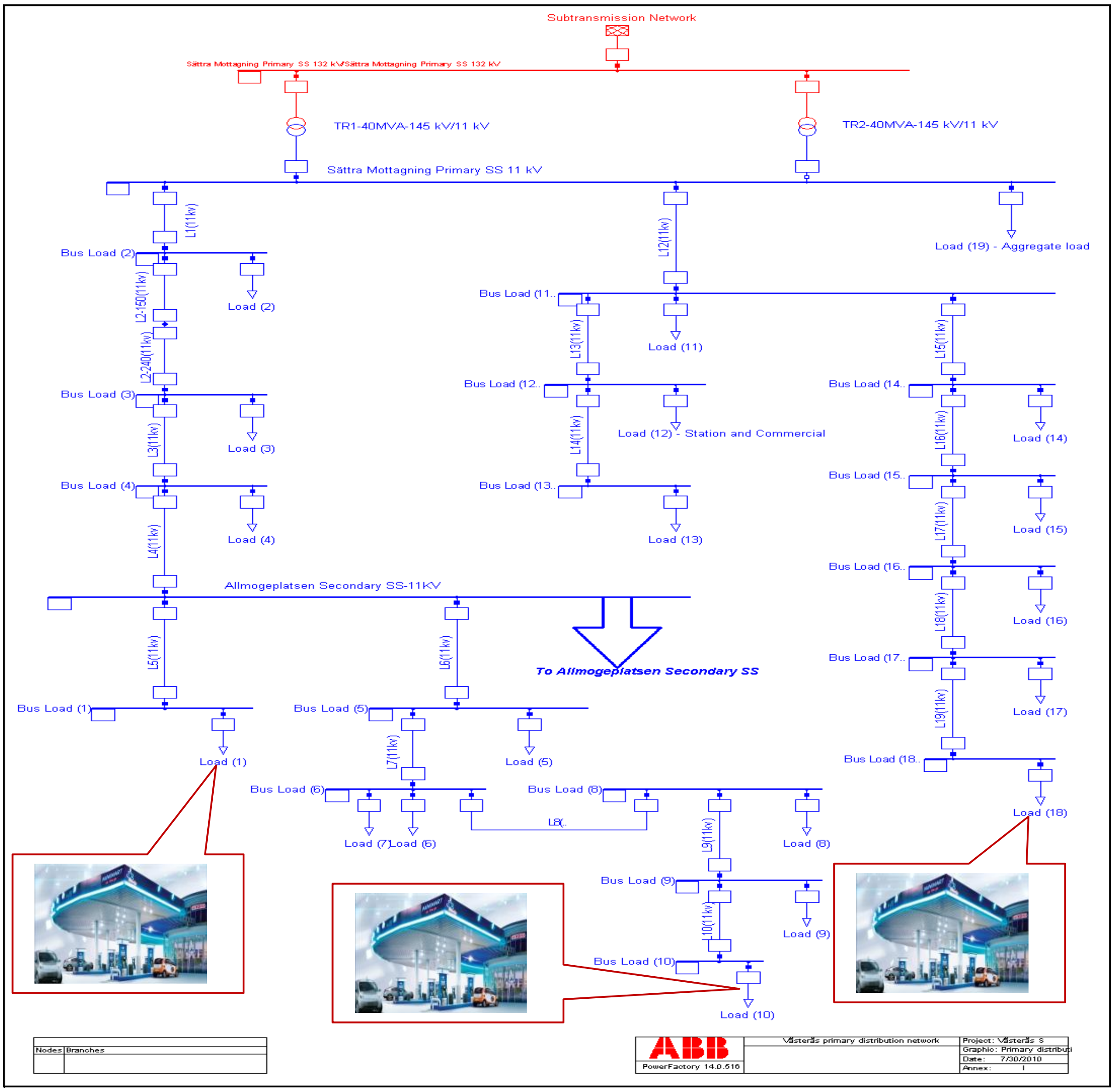


Figure 6.1: Assumed distribution of fast charging stations in the selected area of study

Figure 6.1 illustrates the primary distribution network implemented in DIgSILENT Power Factory[23] where the impacts of fast charging stations are investigated. Note that there is another secondary distribution system in this primary distribution network indicated by

[23] DigSilent Power Factory is a power system simulation tool used in the project

big arrow which illustrates ‘Allmogeplatsen’ secondary distribution network shown in Figure 6.41. All the load feeders indicated in this distribution network has its own base load profile that are generated in section 5.1.4.

As can be seen from the Figure 6.1, three fast charging stations are randomly installed in the distribution network. The charging power level from each charging poles at these charging stations are assumed to be 250KW, which is available from ABB fast charger illustrated in Figure 3.11. The number of charging poles at the charging station is not fixed. This is made purposely to have its distribution from the simulation which will intern help to optimize the required number of poles at the charging station. This will be illustrated in the upcoming sections.

6.1.2 Common inputs to all cases

One of the most important inputs to this model is vehicle arrival time distribution at each fast charging station. Figure 6.2 illustrates arrival time distribution of vehicles at each fast charging station, which is assumed to be the same for all charging stations. It is also assumed that a total of 450 vehicles arrive at each charging station every day, distributed in time, as shown in the Figure 6.2 below.

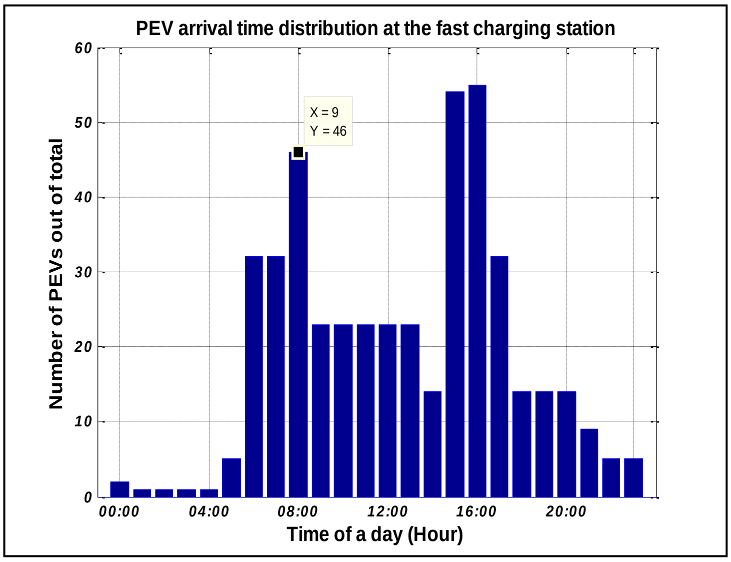


Figure 6.2: Vehicle arrival time distribution at fast charging stations

It is good to see that out of 450 vehicles arriving at the fast charging station in a given day, 46 of these vehicles arrive in the time interval between 08:00 and 09:00. This means that if all these vehicles are to start charging at the same, as in Case I, 46 charging poles are needed which will intern result in total power demand of 11.5MW.

Note also that this arrival time distribution is adapted from a statistical data which represent vehicle arrival time distribution at Statoil Bärbyleden-Oppsala petrol filing station, as is given in Figure 5.9. It is assumed that vehicle arrival time distribution at the fast charging station is the same as vehicle arrival time distribution at this petrol station.

Apart from this, it is also assumed that each vehicles charging at fast charging station require 0.2KWh energy for each km distance and all vehicles arrive at the charging station with a minimum SOC level of 10% and charged up 80% SOC (refer section 4.3.3 for allowable SOC limits).

6.1.3 Case I: All deterministic approach

6.1.3.1 Scenario definition

As stated before, there are three major random variables considered to define the cases. These are distribution of vehicle distance travelled, vehicle arrival time distribution at the fast charging stations and distribution of vehicles battery capacities. In this case all these random variables are assumed to be deterministic.

First, it is assumed that that all vehicles arriving at the fast charging station have a total battery capacity of 16KWh which represents battery capacity of ***i MiEV***[24] (refer Table 4.3 for a list vehicle battery capacities from different manufacturers). This will limit the distance the vehicle travel on a given day. With the assumed range of useable SOC, only 70% of the battery capacity is useable which enable the vehicle to travel only 40miles of distance assuming that 0.2KWh energy is required for every km distance travelled. Each vehicles are assumed to be charged only once at the charging station per day. Finally, this case assumes that all the vehicles arriving at the charging station in a given hour of the day start charging at the same time. The following subsections illustrate a number of outputs generated from the model based on the defined scenarios.

6.1.3.2 Output from the model

Figure 6.3 below shows per minute load profile from PEV charging, for one week at 250KW charging power level for the scenario defined in Case I. Note that this load profile is generated for one fast charging station only. The other two charging stations will have the same load profiles. Figure 6.4 shows the per minute load profile for one day. As can be seen from this figure, there is a high power demand of about 14MW in the time interval between 16:00 to 17:00. This high power demand is because of the deterministic assumptions made. In this time interval the total number of vehicles arriving in the fast charging station is 55 vehicles, as can be seen from Figure 6.2. If all vehicles arrive at the fast charging station just at the beginning of 16:00, for example, and start charging at the same time, this will result in a total power demand of 13.75MW. This result is the worst case scenario. However, the probability that all vehicles arriving at the charging station in a given hour start charging at the same time is very small. This is one of the main problems with the deterministic approach to model impacts of PEV charging on the power systems. All the parameters which determine the nature of the load profile including arrival minute distribution, the battery capacity, distance traveled, battery SOC level are all assumed to deterministic in this case, which resulted in the unacceptable result which may lead to a wrong conclusion.

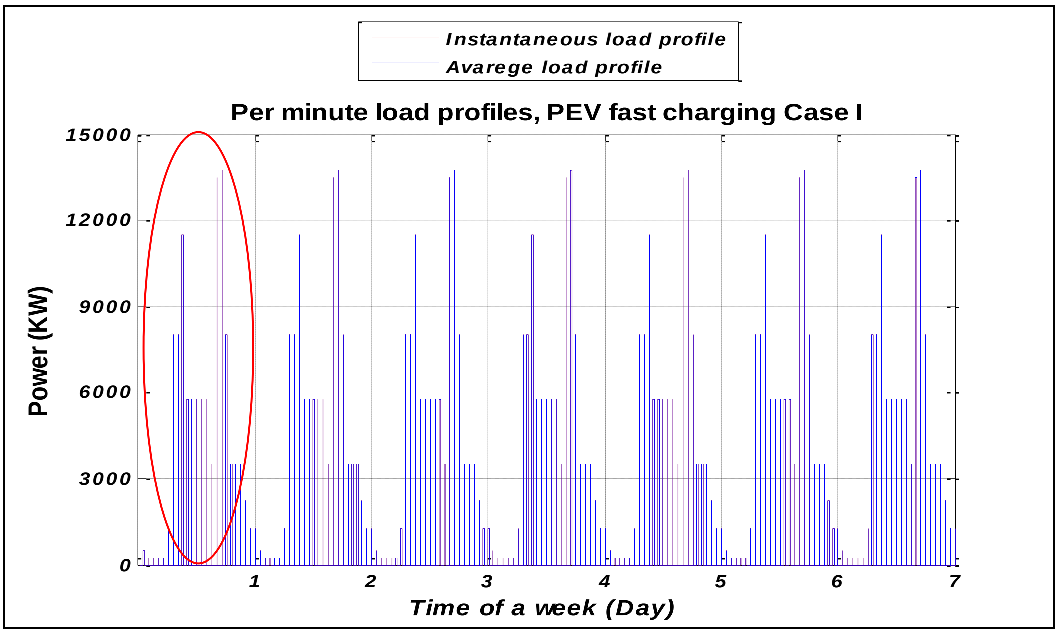


Figure 6.3: Per minute load profile for a week, PEV fast charging at 250KW

[24] Battery electric vehicle from ***Mitsubishi***

Remember that each vehicle arrive at the charging station with 10% SOC and charged up to 80% SOC. This means that only 70% of 16KWh energy is required from the charging station. The vehicles need to wait only 2.7minute to get this energy at 250KW charging power level.

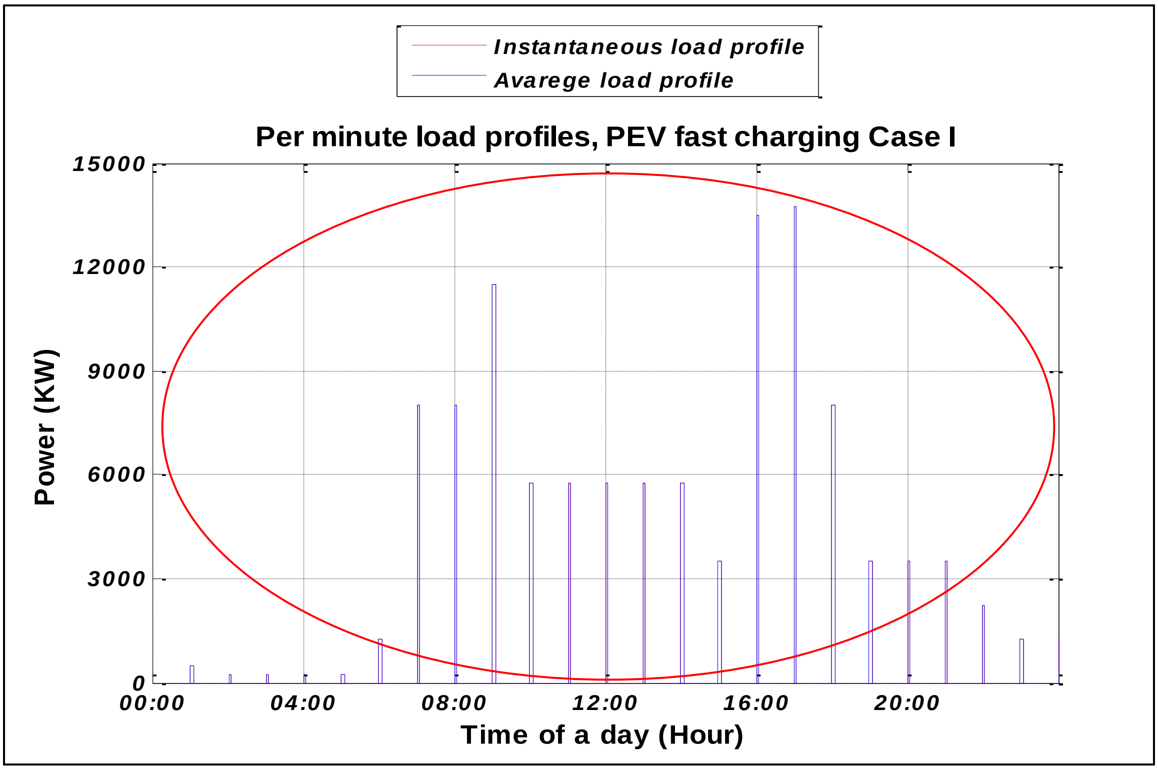


Figure 6.4: Per minute load profile for a day of the week, PEV fast charging at 250KW

The jump in power from 0MW to 14MW demand last only for 2.7minutes. This means that the charging station will be idle for the next 57.3 minutes of that hour. This is unrealistic which again shows the drawback in deterministic approach to model PEV fast charging.

The peaks in per minute load profiles seen in the preceding figures are very high. If we take hourly average load profile in each hours of the week, the peaks in the resulting load profile will very low. Averaged hourly load profiles at each charging stations are shown in Figure 6.5 and Figure 6.6.

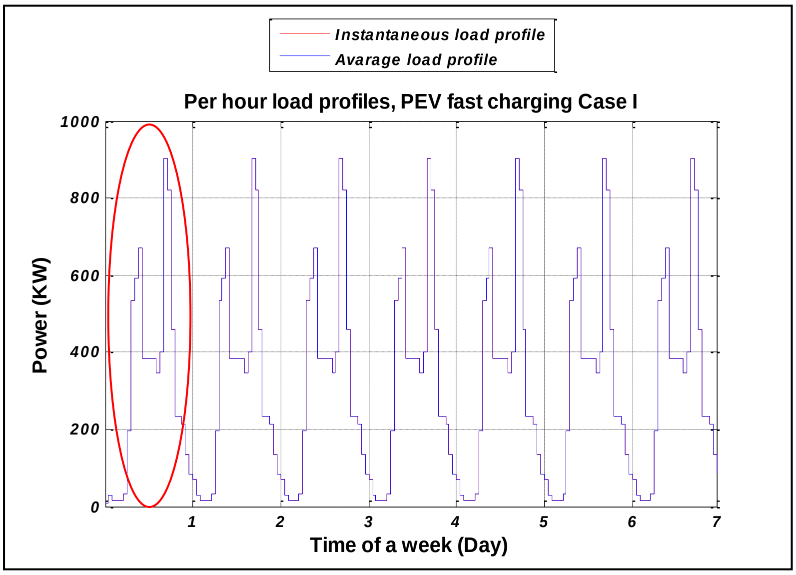


Figure 6.5: Per hour load profile for a week, PEV fast charging at 250KW

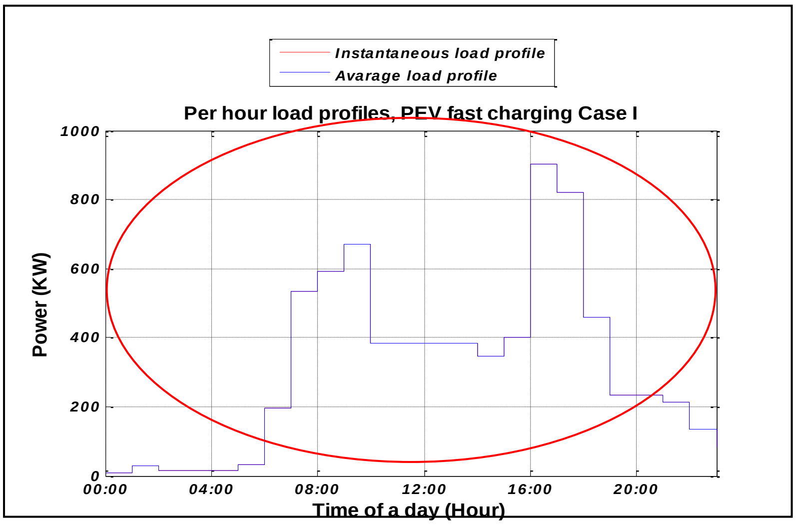


Figure 6.6: Per hour load profile of a day of the week, PEV fast charging at 250KW

Figure 6.5 shows hourly load profile for a week whereas Figure 6.6 shows per hour load profile of the first day in the week. As can be seen from these figures, the maximum power of 13.75MW seen in the per minute load profile dropped down to 0.9MW peak in an hourly load profile. This is mainly because the station is idle for most time of a given hour in a day.

It is also important to note two load profiles imbedded in each figures shown in Figure 6.3, Figure 6.4, Figure 6.5 and Figure 6.6 as shown by legends. One is an instantaneous load profile and the other is average load profile. The instantaneous load profile is the result of single simulation. On the other hand, the average load profile is generated using Monte Carlo simulation where the model is simulated a number of times and results are averaged to boost confidence in the probabilistic simulation. However, since all the parameters in this scenario are deterministic, the two results are the same and only average load profile is seen overlapped on instantaneous load profile.

As stated in the scenario definition, the number of charging poles at the charging station is not fixed. In contrast to some earlier studies, this model follows the other way round. Rather than fixing the number of charging poles, it is good to find the distribution of required number of charging poles at the fast charging station from which an economical decision can be made. Figure 6.7 shows the distribution of required number of charging poles at the fast charging station.

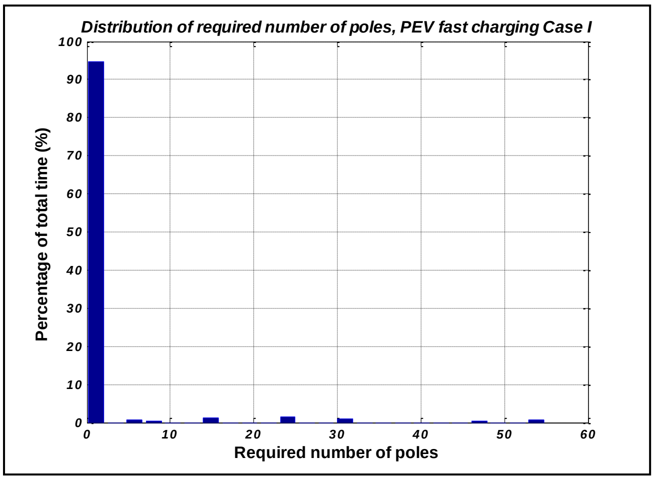


Figure 6.7: Distribution of required number of charging poles at fast charging stations

As can be seen from this figure, only 1.15 charging pole is required for 94.8% of the day. However there is some time in a day where 55 charging poles are required. Remember that the required number of charging poles depend on the number of vehicles arriving at the charging station in a given hour. It is totally uneconomical to have 55 charging poles at the fast charging station, which again shows the incapability of deterministic approach in drawing a better picture of required infrastructure at the fast charging stations.

6.1.3.3 Distribution system impact

In this section the impacts of PEV fast charging on the system bus voltage is discussed. To help us realizes differences with base voltage profiles, Figure 6.8 and Figure 6.9 illustrates the system base voltage profiles resulting from both per minute and per hour base load profiles. As can be seen from the two figures, the system is operating well within the voltage limit, i.e. ±0.05 per unit voltage before the deployment of fast charging stations shown in Figure 6.1.

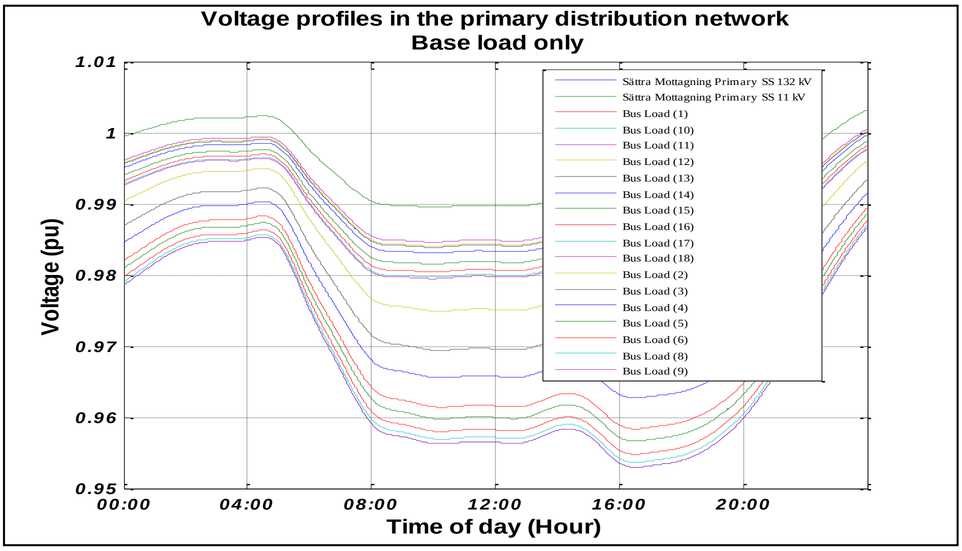


Figure 6.8: Voltage profile in the primary distribution network due to per minute and hourly base load profiles for one day

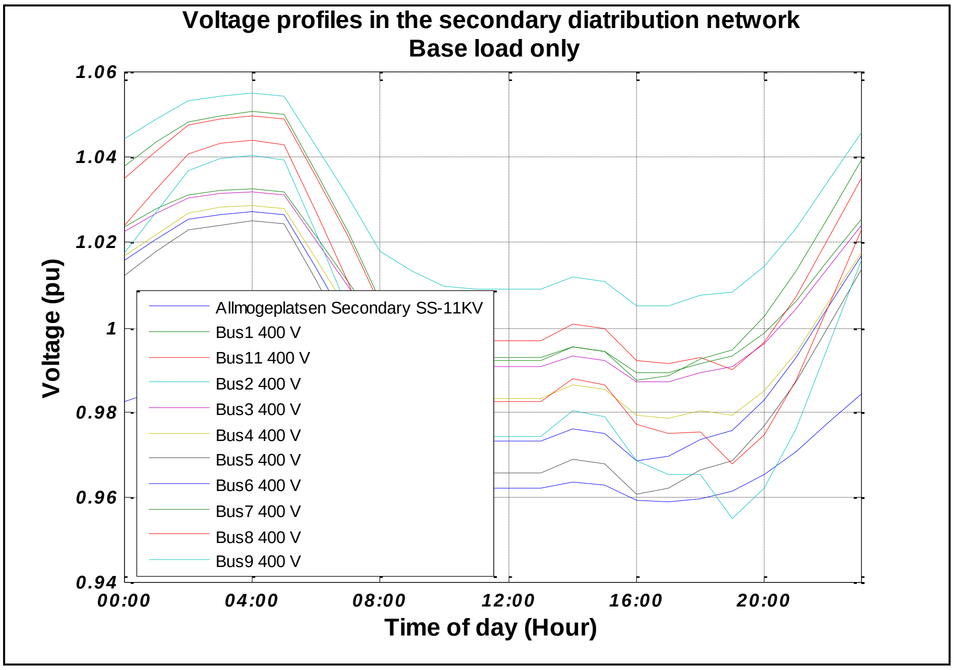


Figure 6.9: Voltage profiles in the secondary distribution network due to per minute and hourly load profiles

If the three fast charging stations are deployed in the distribution system, the result from Case I fast charging model can seriously affect the system voltage profiles. Figure 6.10 and Figure 6.11 illustrates the system voltage profiles resulting from the deployment of three fast charging stations where vehicles at these stations are all charged according to scenarios defined in Case I. Per hour voltage profiles illustrate the resulting voltage profiles when per hour load profiles are applied to the system whereas per minute voltage profiles shows the result of application of per minute load profiles in the system. As can be seen from the figures, the system voltages have gone down below an acceptable limit. It is good to see that there are no significant differences with per hour voltage profiles compared with base case. But, when it comes to per minute voltage, there are times in a day when bus voltages drop below 0.7pu. This is totally unacceptable. And once more this shows the problem in the deterministic approach to model the impacts PEV charging on the power system. What we see from these figures are the worst case scenarios.

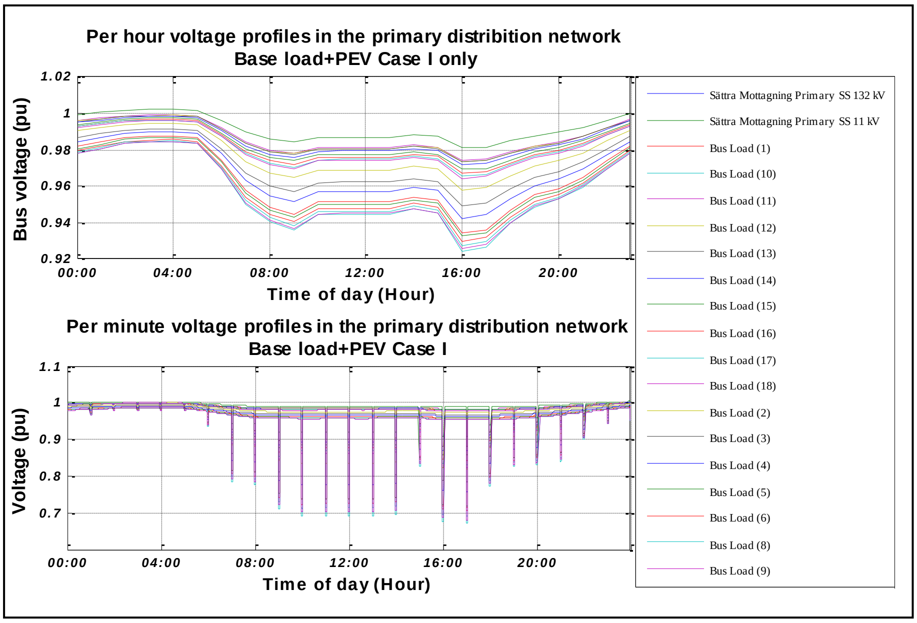


Figure 6.10: Voltage profiles in the primary distribution network resulting from the deployment of three fast charging stations

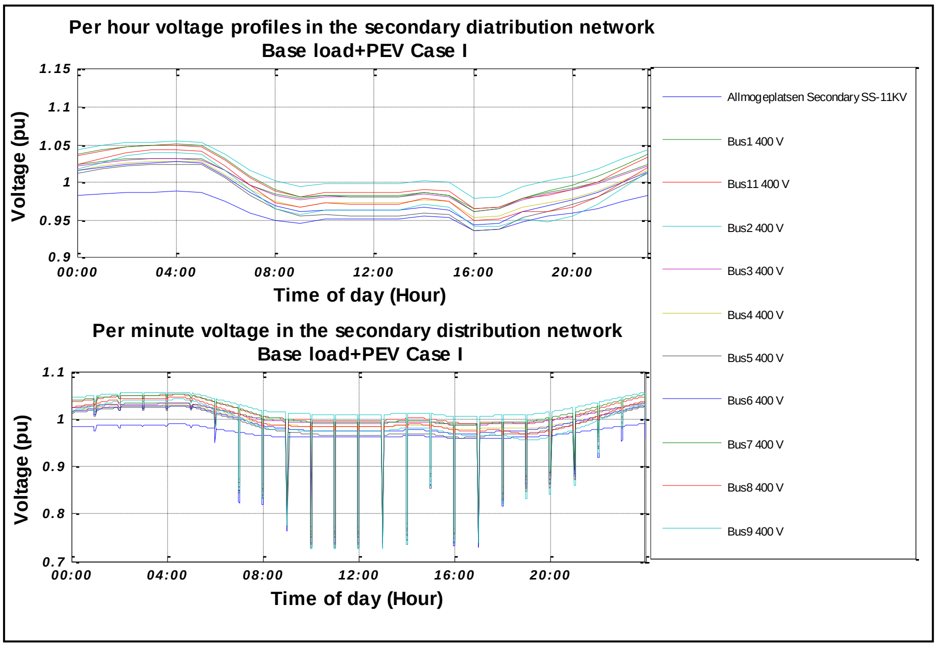


Figure 6.11: Voltage profiles in the secondary distribution network resulting from the deployment of three fast charging stations

6.1.4 Case II: Stochastic-Deterministic

6.1.4.1 Scenario definition

Similar to the scenario defied in Case I, there are three main parameters which dictated the output from this model. These are the battery capacity, arrival time distribution and distribution of daily distance travelled by vehicles. The first two parameters are made deterministic as in Case I and distribution of daily distance traveled is made probabilistic.

Similar to Case I, battery capacities of all vehicles in this simulation are assumed to fixed to represent the battery capacity of '***i MiEV'*** pure electric vehicle from ***Mitsubishi*** which has a total battery capacity of 16KWh[25]. Taking the arrival time distribution of vehicles at charging station given in Figure 6.2, it is assumed that all vehicles that arrive at the charging station in a given hour start charging at the same time. The duration of charging will be determined by the charging power level and the required energy from the grid which is a function of daily distance travelled and SOC level.

Distribution of daily vehicle distance travelled is the only random variable in this model. Its value depends on statistics. The statistical daily distance distribution for PEVs is taken from [6.1]. According this study the driving pattern studies in USA showed that in average vehicles traveled 12000 miles per year. Out of all the vehicles 50% of them travelled 25 miles or less per day and 78% of these traveled 45 miles per day or less. This statistics also showed that on average all vehicles travelled 32 miles per day.

This statistical data is one source of randomness in the model. Hence the model is simulated to satisfy this requirement. The probabilistic distribution of daily distance travelled will in turn affect the vehicle's daily energy requirement, SOC distribution, charging interval distribution and other important parameters. It is important to note at this point that daily energy requirement, SOC level and charging interval are all probabilistic and they will have their own distribution as will be evident soon.

6.1.4.2 Output from the model

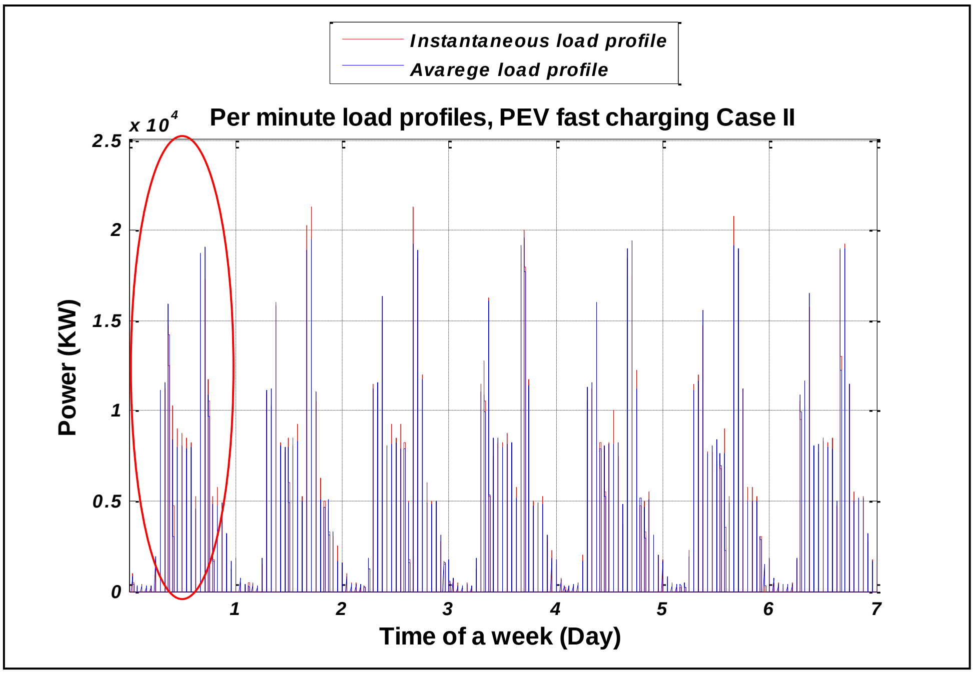


Figure 6.12: Per minute load profile for a week, PEV fast charging at 250KW

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[25] Refer Table 4.3 for the list of battery capacities for different vehicles

Figure 6.12 shows the per minute load profile of PEVs at one of the fast charging station for one week for the scenario defined in Case II. Whereas Figure 6.13 shows per minute load profile of the first day of the week given in Figure 6.12 above.

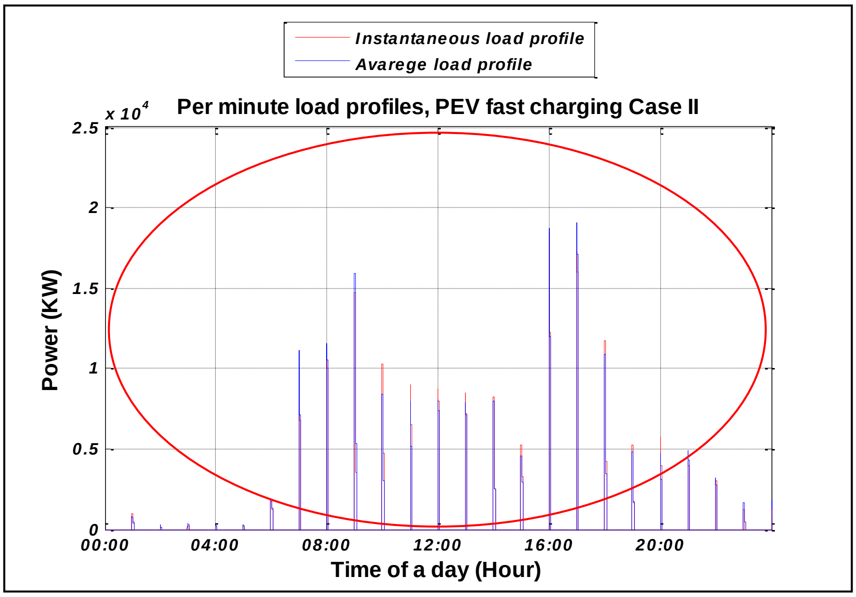

Figure 6.13: Per minute load profile for a day of the week, PEV fast charging at 250KW

It is important to see two important differences between the per minute load profiles of Case I and Case II. The first one is the difference between non Monte Carlo instantaneous per minute load profile and Monte Car averaged load profiles. As can be seen from the figures, there is a slight difference between non Monte Carlo load profile shown in red and Monte Carlo load profile shown in blue. The second important difference is the peak power in the per minute load profiles. In Case I, the maximum power observed was about 14MW whereas in Case II the maximum power is near 20MW, which is a difference of 6MW compared with Case I.

As we recall from the scenario definition of Case I, the vehicle travel a fixed distance of 40miles where as the daily distance distribution in Case II is governed by the statistical distribution defined in the scenario. The distribution daily distance traveled generated in the model is shown in Figure 6.14 below.

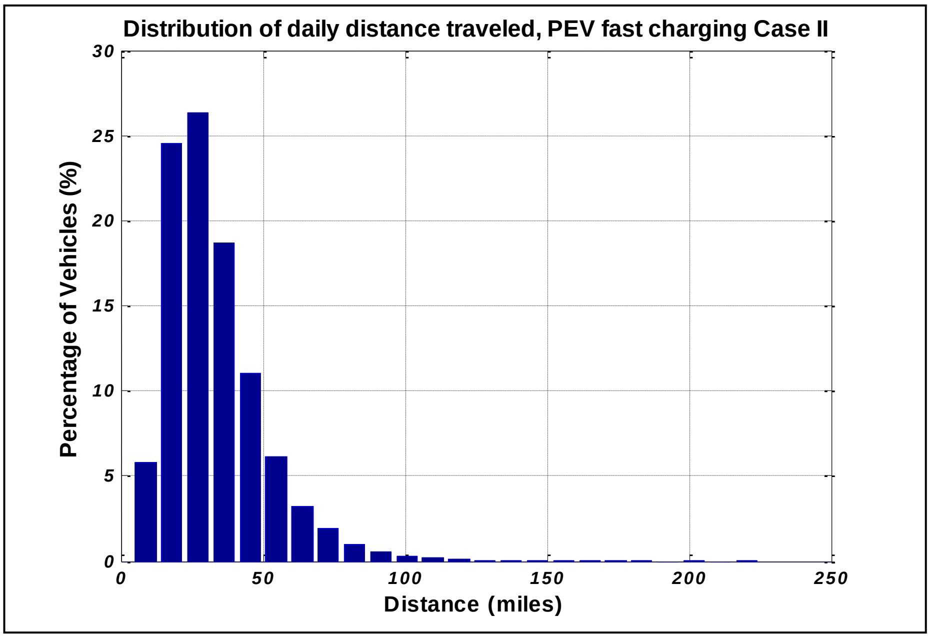

Figure 6.14: Simulated distribution of daily distance travelled used in the model

The distribution of simulated distance travelled generated in the model shows the match between the simulation and the given statistical data. As can be seen from Figure 6.14 above, about 80% of the vehicles travel 40miles or less and about 58% of the vehicles travel 30 miles or less. At the same time, the simulated vehicles in this scenario travel about 12,019 miles annual distance travelled and average of 32.87 miles covered in a day. This is one of the factors for the difference seen between the two cases as the daily distance travelled is totally probabilistic.

It is also evident from the scenario definition of Case I that all vehicles visit the charging station only once per day. However in Case II, a given vehicle can visit the charging station more than once as long as it needs more energy to cover its daily distance. As we discussed earlier, the driver can travel only 40miles with the full useable battery capacity. However as can be seen from the probabilistic distribution of vehicle distance travelled in Figure 6.14 above, there are some vehicles which travel more than 100 miles in a day. This makes the vehicle to come to charging station more than once to recharge their battery or use another alternative energy source to cover the remaining distance or park the vehicle. But the model assumes that vehicles can visit the charging station more than once to recharge its battery to cover the last remaining distance. Figure 6.15 below show the probabilistic distribution of the number of times the vehicles come to charging station to recharge their batteries.

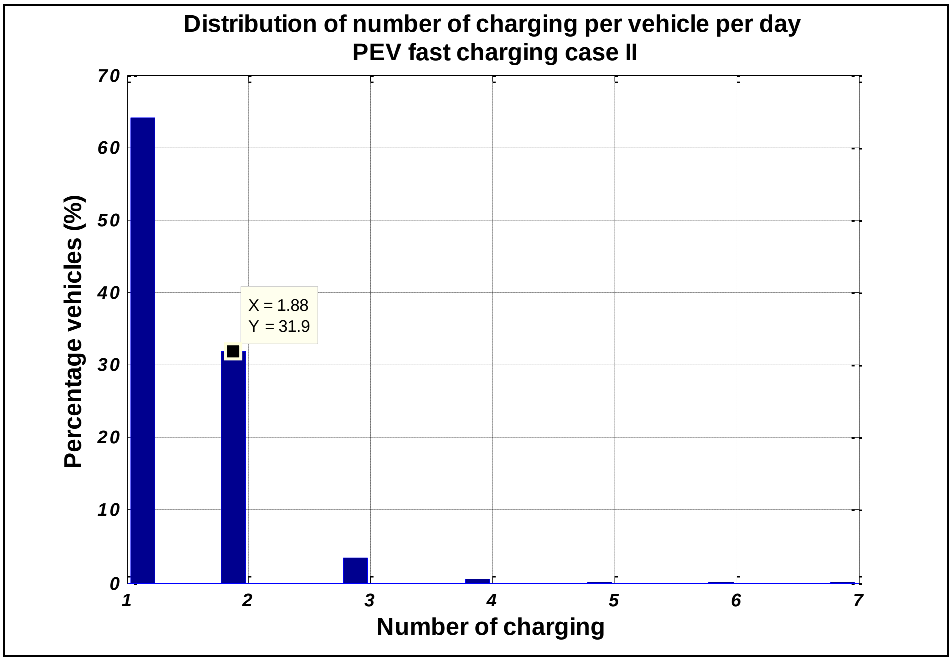

Figure 6.15: Probabilistic distribution of required number of charging per vehicle per day

As can be seen from this figure, about 65% of the vehicles come to the charging station only once per day, 31.7% come twice per day, 3.5% come three times in a day and 0.5% came four times per day out of the total number vehicles arriving at the charging station in a given day which is 450 in this case. This is the second important factor that made the peak to rise in Case II.

Considering the average per hour load profiles at the fast charging stations, the results from Case I and II are almost similar as can be seen from Figure 6.16 and Figure 6.17 below.

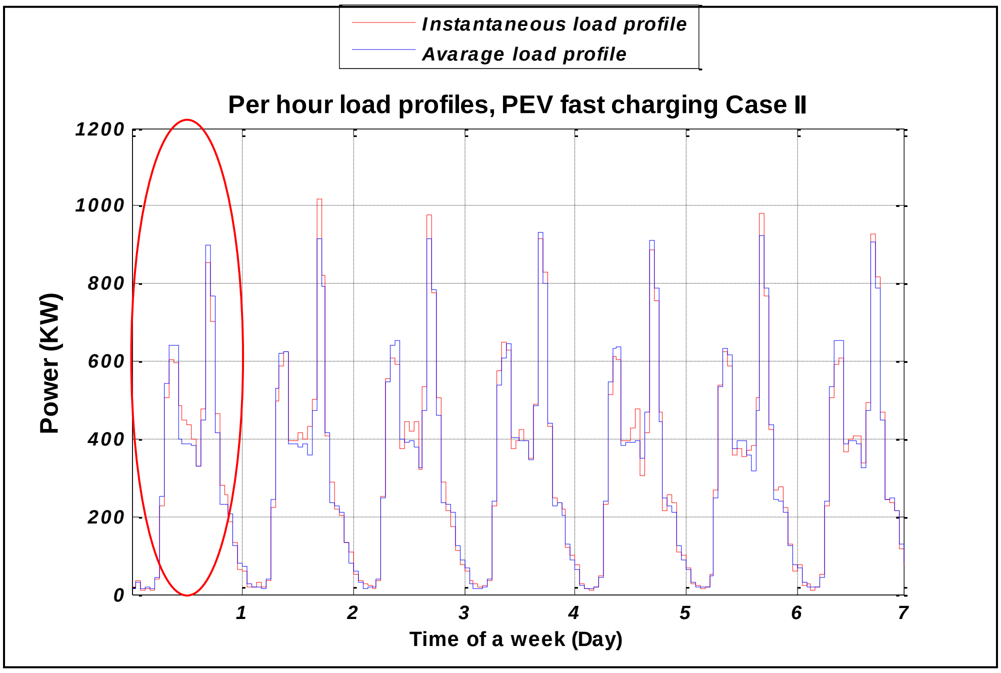

Figure 6.16: Per hour load profile for a week, PEV fast charging at 250KW

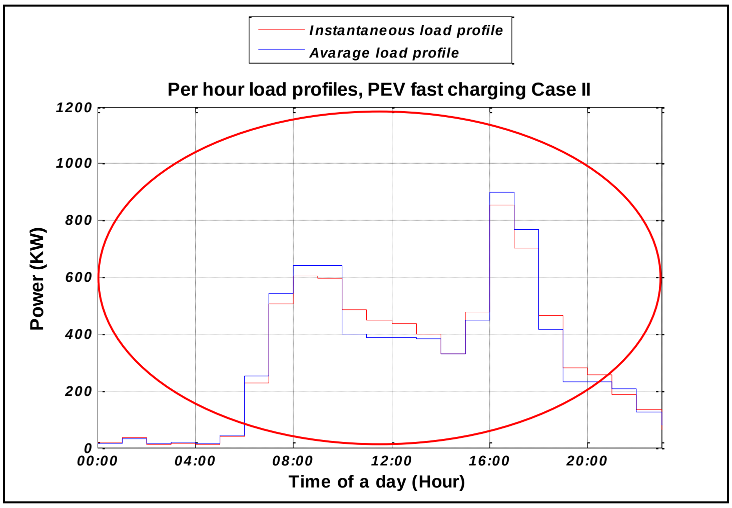

Figure 6.17: Per hour load profile for a day of the week, PEV fast charging at 250KW

As can be seen from Figure 6.16 and Figure 6.17, there is no significant difference in hourly load profiles generated in Case II and that seen in Case I, especially if we compare the average peak power in the two cases. One difference is the difference between non Monte Carlo instantaneous result and Monte Carlo average result. This difference resulted in from the probabilistic distribution of daily distance travelled.

The other important distinction between Case I and II is the distribution of SOC level of the batteries. As we recall from Case I, vehicles came to the fast charging station with a fixed SOC of 10% whereas the SOC levels of vehicles coming to charging station in Case II are probabilistically distributed as a function of daily distance traveled. In case two, it assumed that vehicles can get as much energy as they need from the grid any time. Hence at the end of the day there is a probability that some amount of energy is left in the battery for the next day. Figure 6.18 shows the distribution energy left in the battery at the end of the day to be used the next day. This is what we call it SOC distribution of vehicles.

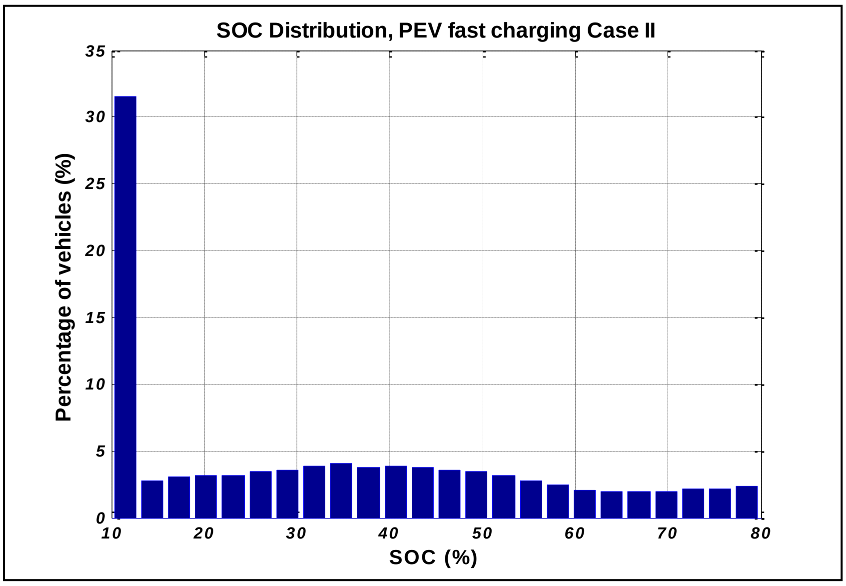

Figure 6.18: Distribution of SOC levels

As can be seen from Figure 6.18, about 31.5% the vehicles come to charging station with the SOC level of about 11.5%, which just above the minimum and about 2.3% the vehicles come with an OSC level of 78.5%. The rest of the vehicles come to the charging station with an SOC level in between this range as can be seen from the distribution.

The SOC levels of vehicles coming to the charging station will determine how long it takes to fully recharge the battery. In other word, since all the vehicles have the same battery capacity, the charging time needed for each vehicle at the fast charging station is a function of its SOC level. Figure 6.19 shows the probabilistic distribution of required charging time.

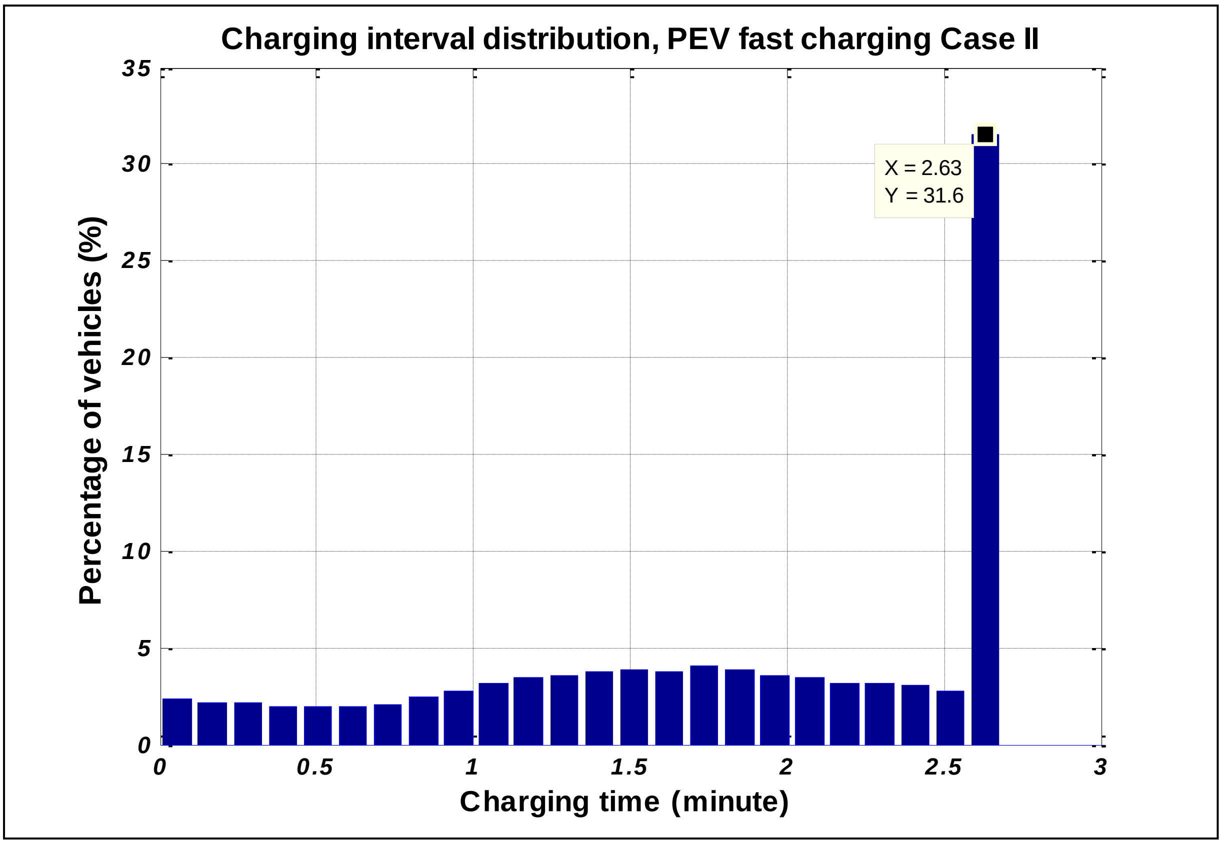

Figure 6.19: PEV charging time interval distribution

As can be seen from this figure, about 31.5% the vehicles charge in about 2.63minutes and about 2.41% the vehicles charge their battery in about 3.3second. The remaining vehicles can fully charge their vehicles in between these intervals. At this point it is important to see the inverse relationship between vehicle charging time and SOC; the higher the SOC level the less time required to recharge the vehicles and vice versa.

The last important thing to note is to compare the distribution of required number of charging poles at charging stations in Case I and II. If we have a look at the distribution of required number of charging poles at the charging stations shown in Figure 6.7 and Figure 6.20, we have increased number charging poles in Case II than in Case I. In Case I the maximum required number pole was 55 while in Case II, the maximum required number of pole is 85 as can be seen the figures. This is because of the same reason stated above that a given vehicle can come more than once per day that will increase the number of vehicles at the charging station in a given hour of a day.

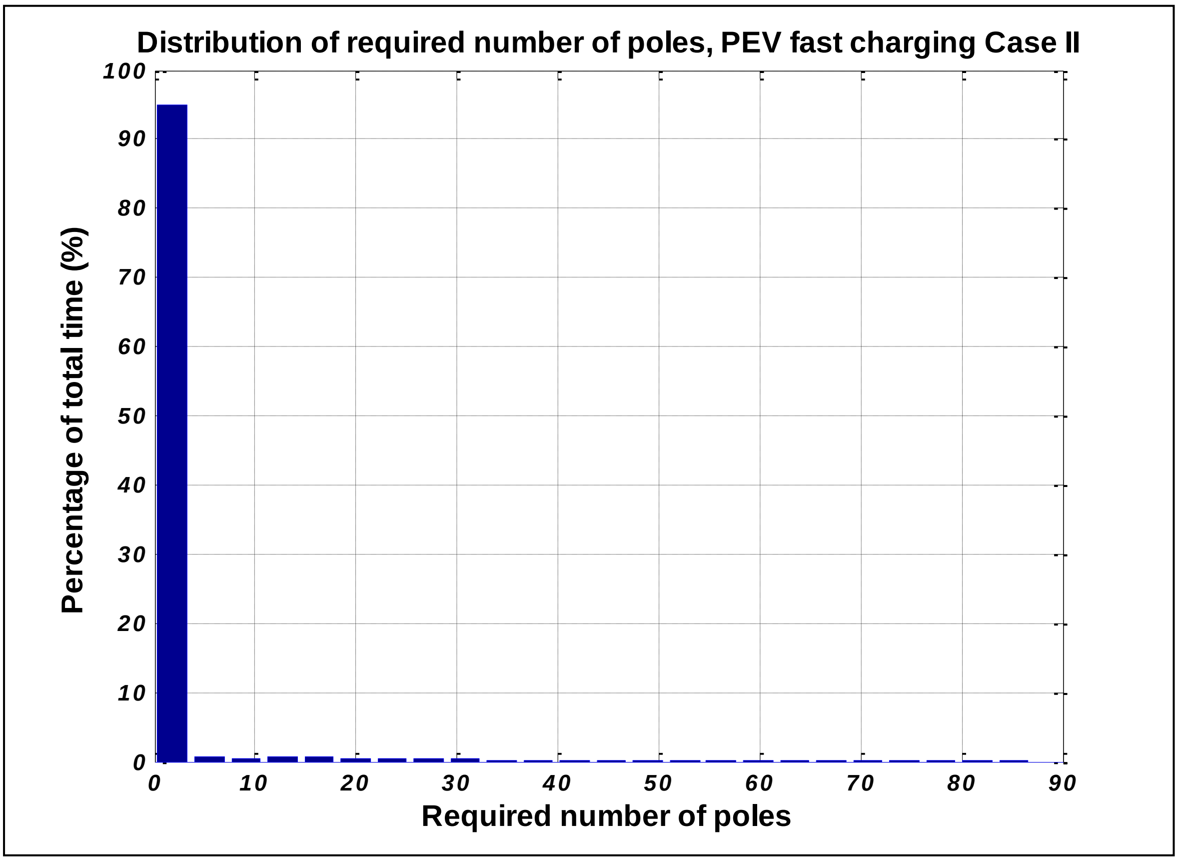

Figure 6.20: Distribution of required number of charging poles at the charging station

Notice that, a close look at the results in Figure 6.7 and Figure 6.20 reveals that the time at which vehicles start charging determines the required number of charging poles at the fast charging station. In both case I and II, the underlying assumption was that all vehicles arriving at the charging station in a given hour of a day start charging at the same time. This is not realistic and as we stated earlier the probability that all the vehicles in the given hour arrive at the same time is less probable. Hence this kind of deterministic assumption on the vehicle arrival time leads to a wrong conclusion.

6.1.4.3 Distribution system impact

Similar to Case I, if the load profiles from PEV fast charging stations are added on the system base load profiles, it can seriously affect the system buss voltages as shown in Figure 6.21 and Figure 6.22. These figures shows voltage profiles at the system buses resulting from the deployment of three fast charging stations in the system where vehicles are charged according to scenarios defined in Case II. As can be seen from the figures, there is some time in a day where bus voltage drop below 0.6pu. This is more serious than Case I charging model. This mainly because of increased power demand from vehicles due to increased number of charging per day resulting from increased daily distance travelled.

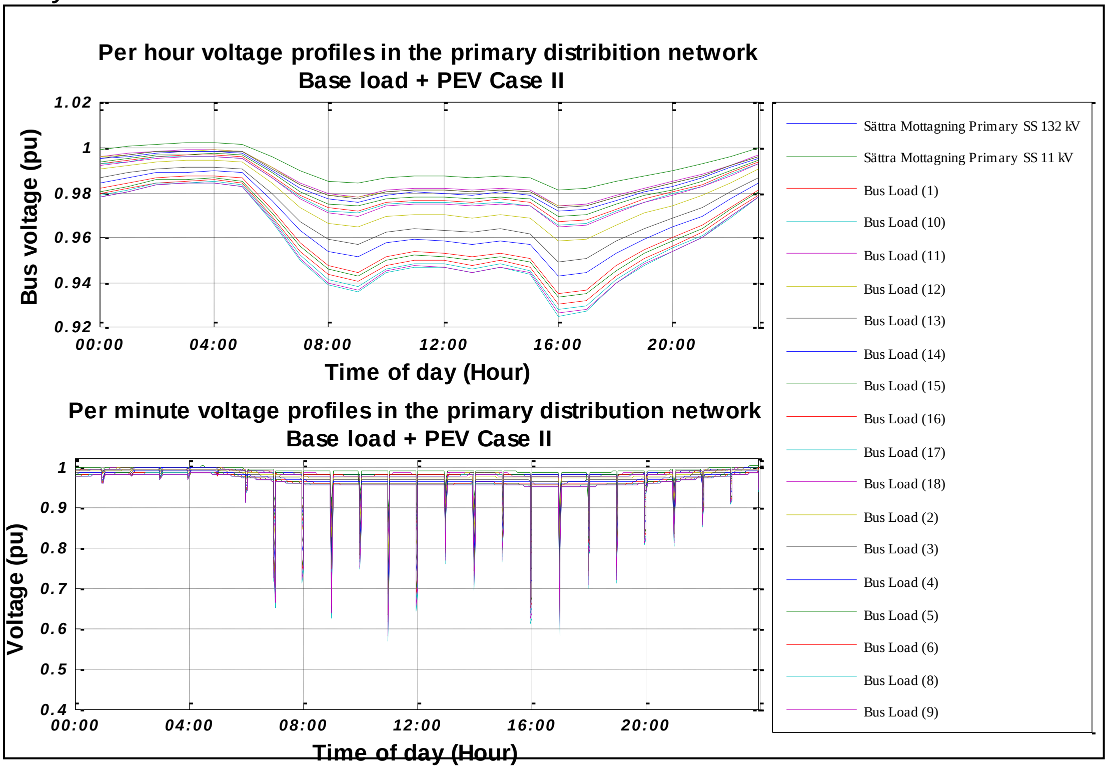

Figure 6.21: Bus voltage profiles in the primary distribution network resulting from the deployment of three fast charging stations

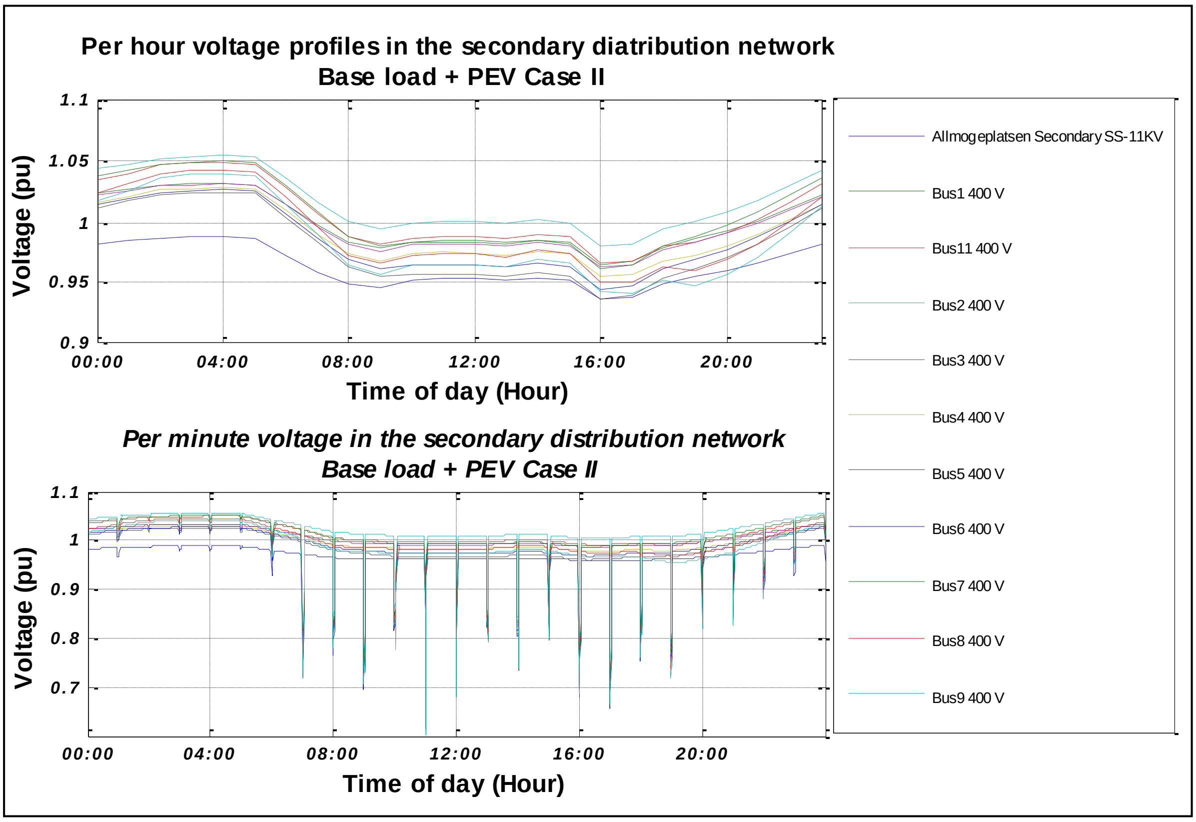

Figure 6.22: Bus voltage profiles in the secondary distribution system resulting from the deployment of three fast charging stations

6.1.5 Case III: Stochastic-Deterministic

6.1.5.1 Scenario definition

Similar to the scenarios defied in Case I and II, the total battery capacity of all the vehicles in the simulation are assumed fixed to 16KWh, which is a represent the battery capacity of '***i MiEV'*** pure electric vehicle from ***Mitsubishi.***

In addition to this, the distribution of daily distance by each vehicle assumed to be that defined for Case II. This is probabilistically distributed statistical distance. The statistical daily distance distribution for PEVs is taken from [6.1]. According this study the driving pattern studies in USA showed that in average vehicles traveled 12000 miles per year. Out of all the vehicles 50% of them travelled 25 miles or less per day and 78% of these traveled 45 miles per day or less. This statistics also showed that on average all vehicles travelled 32 miles per day.

The most important probabilistic parameter that distinguishes Case III from the other two cases discussed above is the distribution of arrival minute distribution. As we discussed it before, we know the distribution of vehicles arrival time at charging station in each hours of the day as illustrated in Figure 6.2.For example, we know the number of PEVs arriving at the fast charging station between 08:00 and 09:00. As is shown in Figure 6.2, 46 vehicles arrive at the fast charging station in this interval. It not appropriate to assume all 46 vehicles arrive at the fast charging station at the same time, this is not probable. What is most important is to know that vehicles can arrive at the charging station at any minutes in that time interval. Hence normally distributed arrival minute of vehicles in a given hour is assumed. This is what we called it vehicles 'arrival minute distribution' in a given hour. This important point is considered in this case that exponentially changed the output from the model as will be illustrated soon. This is a better realistic approach and shows the power of probabilistic to model PEV charging at the fast charging stations.

6.1.5.2 Output from the model

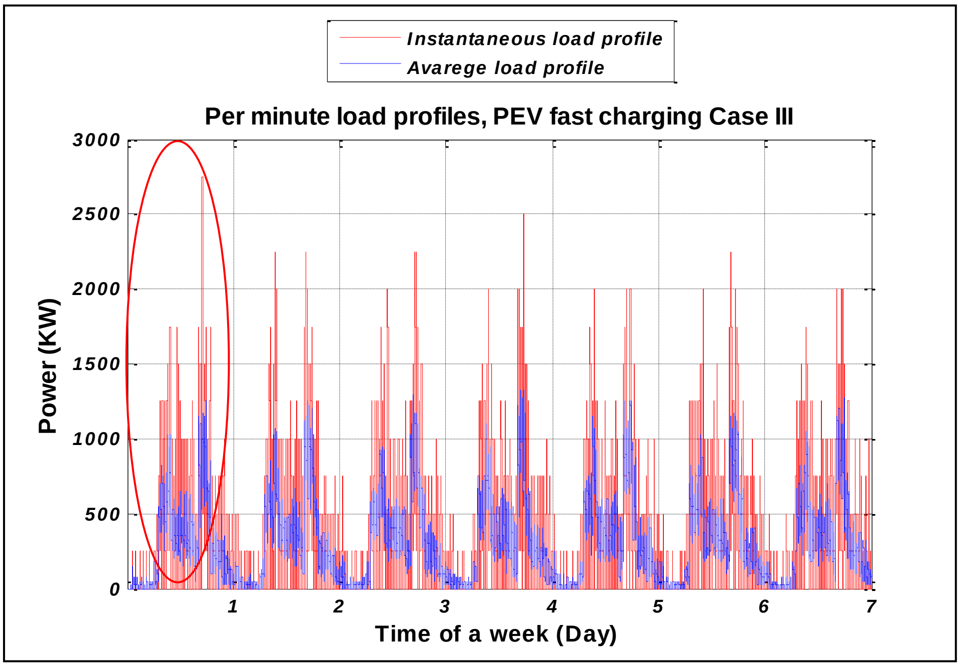

Figure 6.23: Per minute load profile for a week, PEV fast charging at 250KW

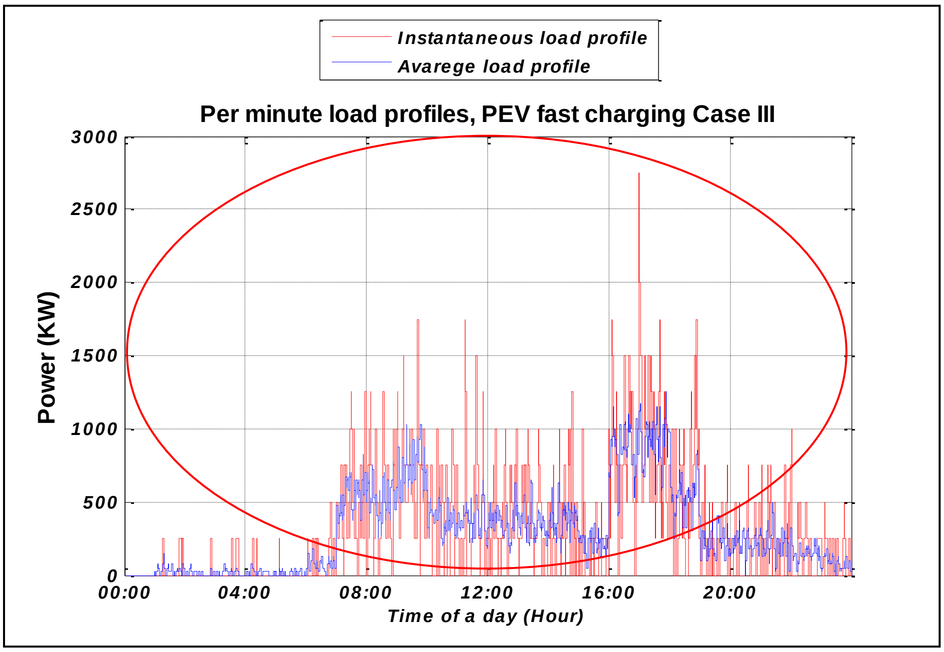

Figure 6.24: Per minute load profile for a day in the week, PEV fast charging at 250KW

Figure 6.23 and Figure 6.24 shows per minute load profiles for a week and per minute load profiles of the first day in the week respectively. There are two important things to note from these results. The first one is the peak power of the load profile. As can be seen from Figure 6.23, the maximum power demand in the week from one fast charging station is 2.5MW and the average peak power is about 1.4MW. If we compare this with the maximum power demand defined in Case II and shown in Figure 6.12 which is more than 20MW, we can see a significant difference between the two cases. The maximum power demand generated from the fast charging stations in Case III in a week is about ten times less than that generated in Case II. This sounds logical and feels realistic and is indeed an important tool for a professional decision. This again shows the power of probabilistic approach to model the impacts PEV fast charging on the power systems.

The second important difference to note is non Monte Carlo instantaneous load profile and averaged Monte Carlo load profiles. As the number random variables increases in the model, the result from the simulation varies every time we run the simulation. Hence that is why we see the deference between load profile generated from single simulation and that generated from a number of simulations with a Monte Carlo simulation. Monte Carlo simulation is used to run the model a number of times and generate the average load profiles from the results.

Figure 6.25 and Figure 6.26 shows per hour load profiles for a week and a day in the week. As can be seen from these figures, the load profiles are similar with that shown in Case II. This is because the number of vehicles arriving at the fast charging station in a given hours of a day are the same. Plus, the distribution of daily distance travelled by each vehicle is similar. The only difference is the charging intervals. In Case II vehicles start charging at same time whereas in Case III the charging intervals are probabilistically distributed. This doesn’t make significant change on average power in that interval of time but it does affect per minute load profile significantly as illustrated in the figures.

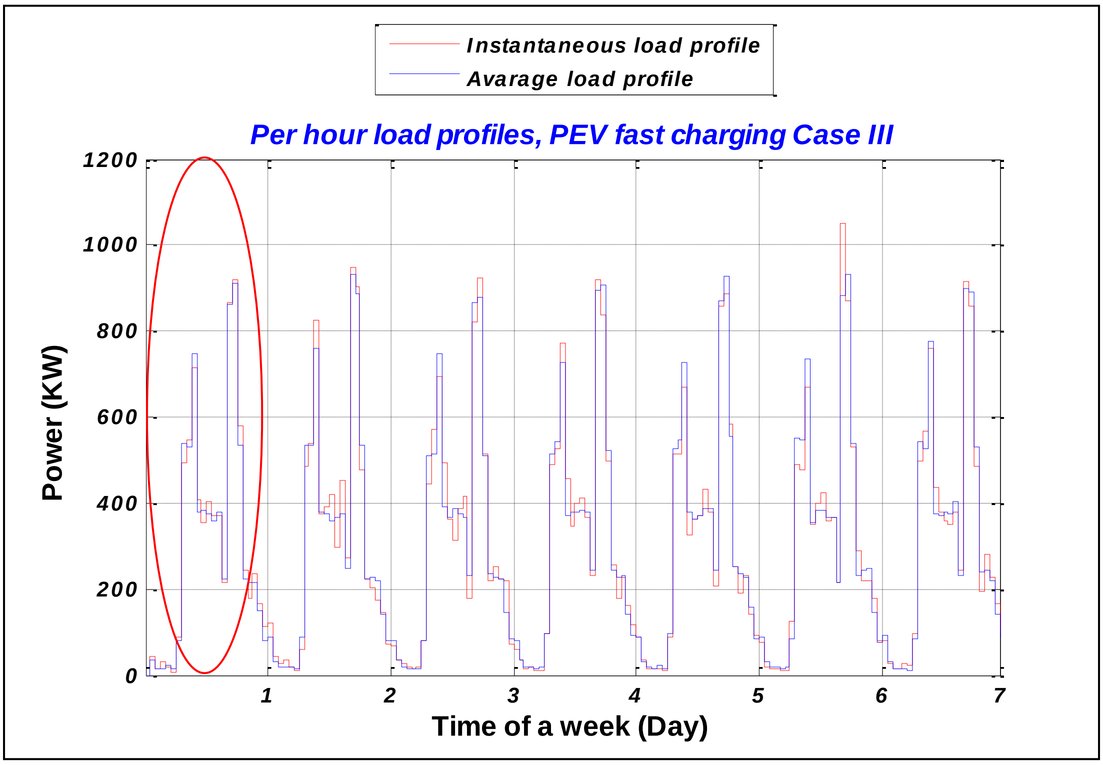

Figure 6.25: Per hour load profile foe a week, PEV fast charging at 250KW

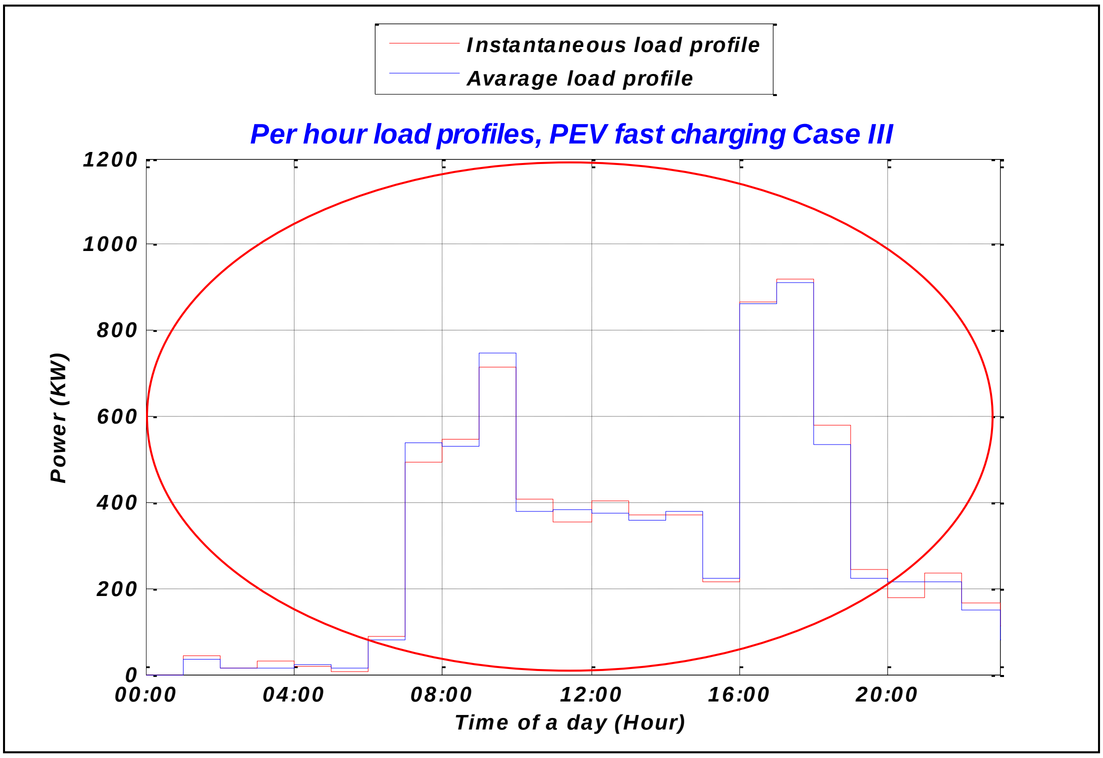

Figure 6.26: Per hour load profile for a day in the week, PEV fast charging at 250KW

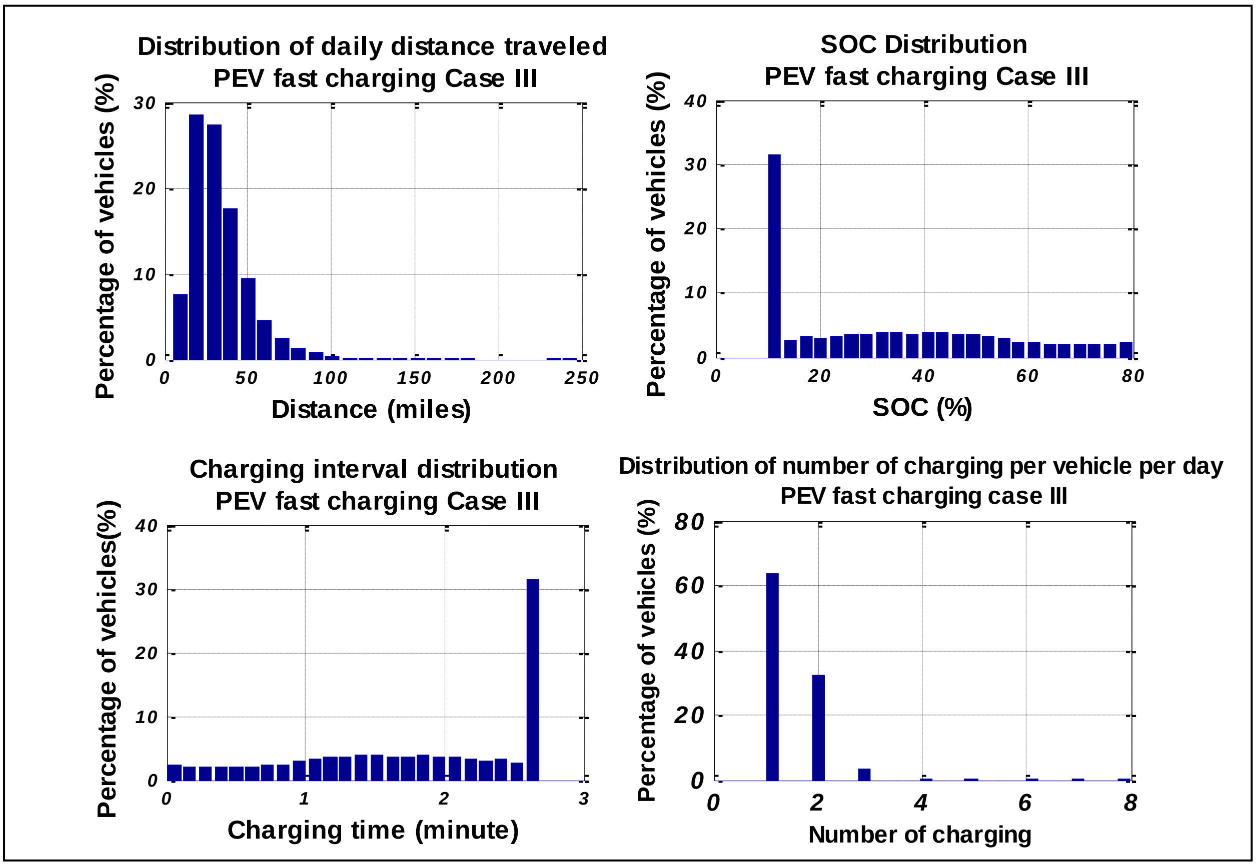

Figure 6.27: Distribution of distance traveled, SOC, charging interval and required number of charging per vehicles per day

Figure 6.27 illustrates probabilistic distribution of daily distance traveled, distribution of SOC levels, distribution of charging time interval and distribution of number of charging per vehicles per day. These distributions are similar to the corresponding distributions shown in Case II. The reason behind this is the daily distance travelled. We know that distribution of daily distance travelled for both cases is taken from statistical data which is the same. And as we made it clear before, vehicle's SOC level is a function of daily distance travelled provided that the battery capacity is fixed as in our case. And we have also discussed that required charging time is inversely proportional to battery SOC level and the required number of charging per day is also a function of daily distance travelled. These are the main source of similarities between the results in the two cases.

However there is one exceptional and important difference between Case II and Case III as can be seen in Figure 6.28. This is the distribution of required number of charging poles at fast charging stations.

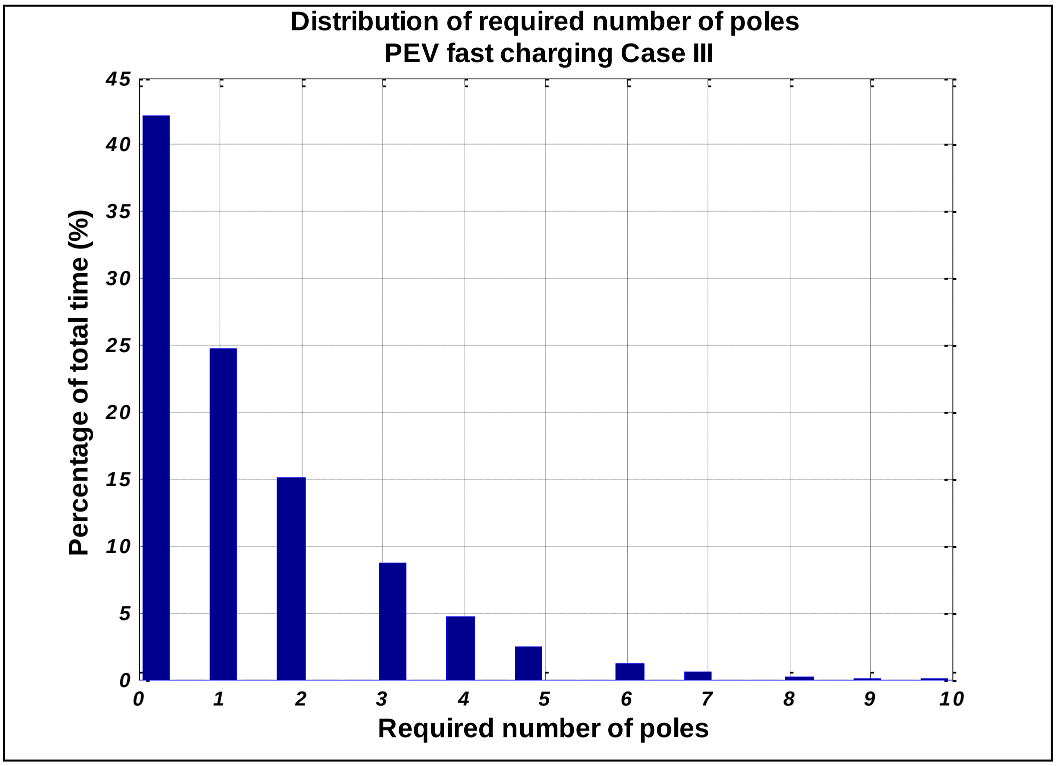

Figure 6.28: Distribution of required number of poles at fast charging stations

As can be seen from Figure 6.28, the decline in the required number of charging poles at the charging station is amazing. Figure 6.20 shows that a maximum of 85 required charging poles if all vehicles are to charge on arrival in Case II. This can be compared with a maximum of 10 charging poles in Case III if all the vehicles are to start charging on arrival. AS a result, an economical decision on the required number of charging poles at the fast charging stations can be made based on the distribution shown in Figure 6.28. For example, if we decided to have only four charging poles at each fast charging station defined in Figure 6.1, 95.54% of vehicles can be charged on arrival. Only 4.46% of vehicles out of 450, in our case, have to wait for some time. Similar conclusion can be drawn if we decide to have one, two three or any other number of charging poles as can seen from Figure 6.28. This is the beauty of probabilistic modeling. That is why we did not fix the required number of charging poles at the fast charging station. An important economic decision can be made based on the distribution of required charging poles as we have just seen.

6.1.5.3 Distribution system impact

Figure 6.29 and Figure 6.30 illustrates system bus voltage profiles, at both primary and secondary distribution level, resulting from the deployment of three fast charging stations. This is a more realistic voltage profile as it is the result Case III PEV charging model which is a more acceptable model. As can be seen from the figures, the voltage hardly drops below 0.9pu in the primary distribution. Almost all system voltages are above 0.9pu in the secondary distribution network.

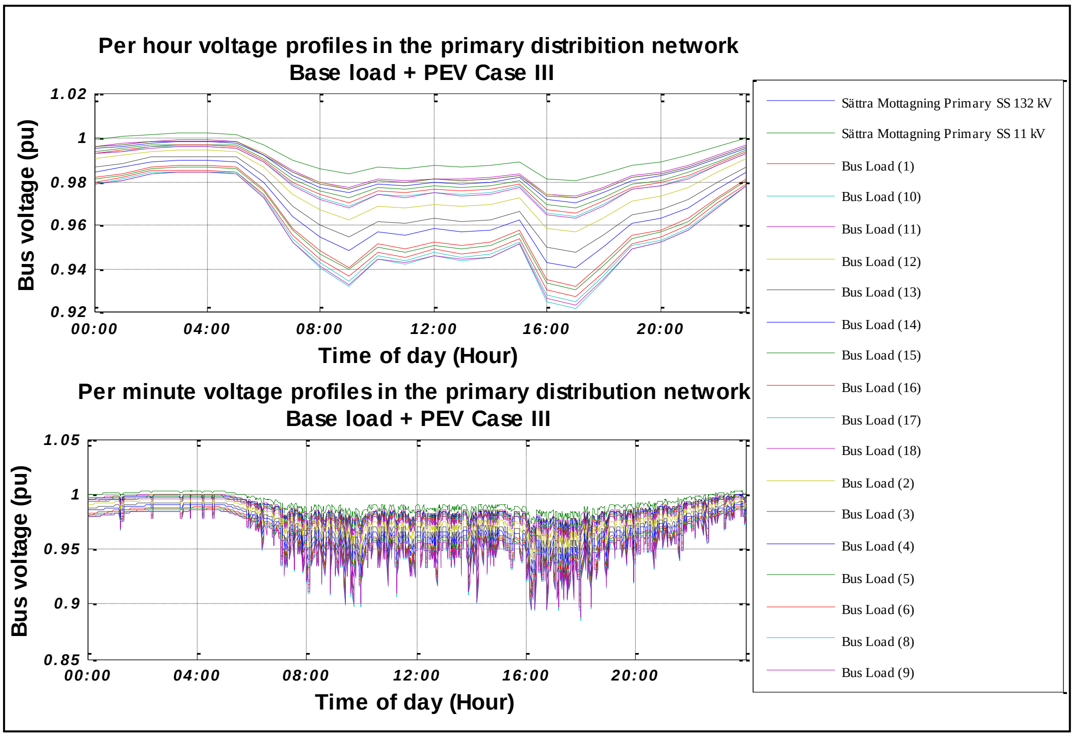

Figure 6.29: Bus voltage profiles of primary distribution network resulting from the deployment of three fast charging stations

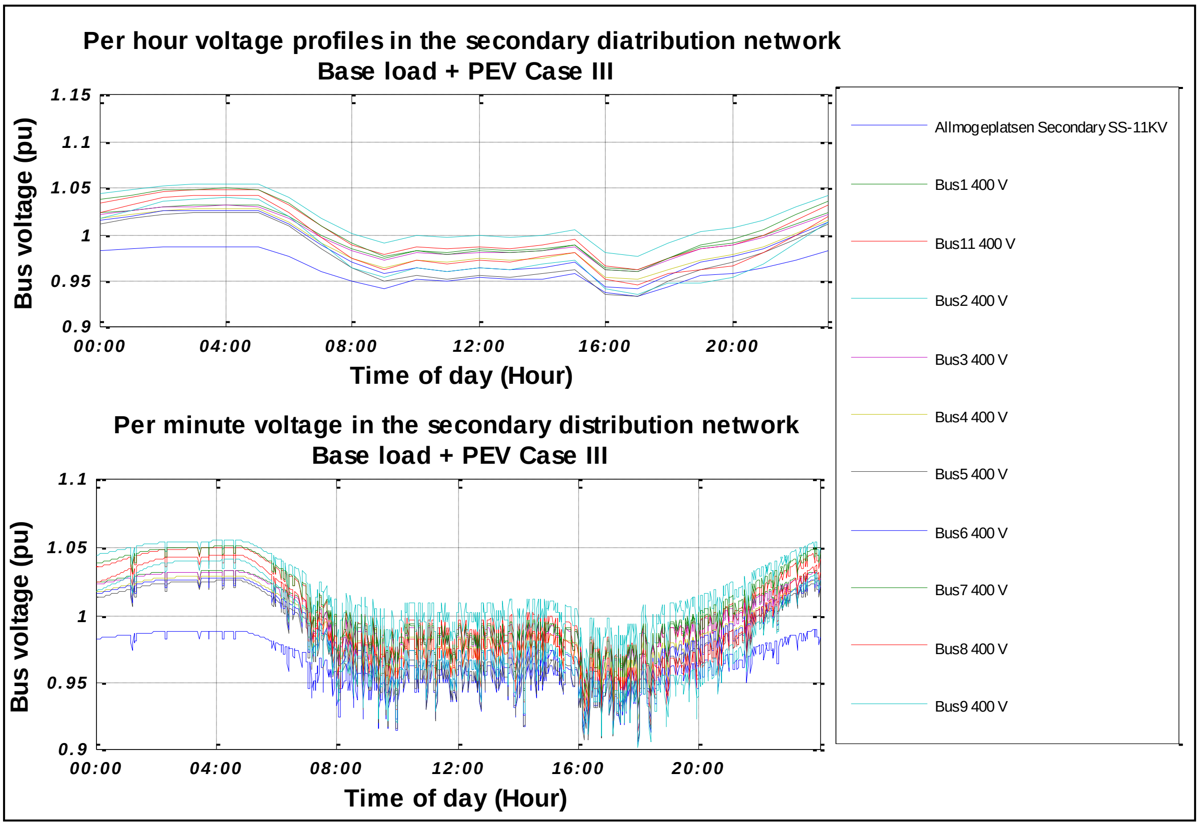

Figure 6.30: Bus voltage profiles in the secondary distribution network resulting from the deployment of three fast charging stations

6.1.6 Case IV: All Stochastic

6.1.6.1 Scenario definition

From Case III, we have seen the capability of probabilistic model in drawing a better picture of PEV fast charging and their impacts on power systems with a fixed battery capacity, probabilistically distributed daily distance traveled and arrival minute distribution. This case, Case IV, is an extension of Case III which includes more varieties of vehicles coming to the charging stations. This is to say in the preceding three defined cases, all vehicles coming to the charging station have identical battery capacity. But now in Case IV, we wanted to incorporate classes of vehicles which have ranges of battery capacities that can represent wider classes of PEVs which are on the market today. The model distinguishes these classes of vehicles based on their battery capacities.

This model assumes the same distribution daily distance travelled and arrival minute distribution as was done in Case III. It introduces the third random variable to incorporate wider ranges of vehicles in the simulation to have a better feeling of their impacts on the power system. This third random parameter is vehicle's battery capacities. Table 6.1 shows the defined range of battery capacities for each class based on data given in Table 4.3 and Table 9.5.

The battery capacities of fully electric vehicles today on the market ranges from 8.4KWh of ATX from ALKE and 55.00KWh of Roadster of TESLA as illustrated in Table 4.3. Hence this scenario defines four ranges of battery capacities, as shown in Table 6.1, to represent vehicle class defined in Table 5.1.

Table 6.1: Distribution of vehicles battery capacities to represent classes of vehicles

Class	$BC^{(c)}{}_{max}[KWh]$	$BC^{(c)}{}_{min}[KWh]$
1	20	10
2	30	20
3	40	30
4	50	40

6.1.6.2 Output from the model

Figure 6.31 and Figure 6.32 shows per minute load profiles of PEV fast charging at 250KW for a week and first day of the week respectively. As can be seen from the figures, there is no significant increase in the per minute peak load profile compared with that shown in Figure 6.23 and Figure 6.24 of Case III. This is because the charging power levels in both cases are the same. The only difference between the two cases is the increases of the battery capacity in Case IV.

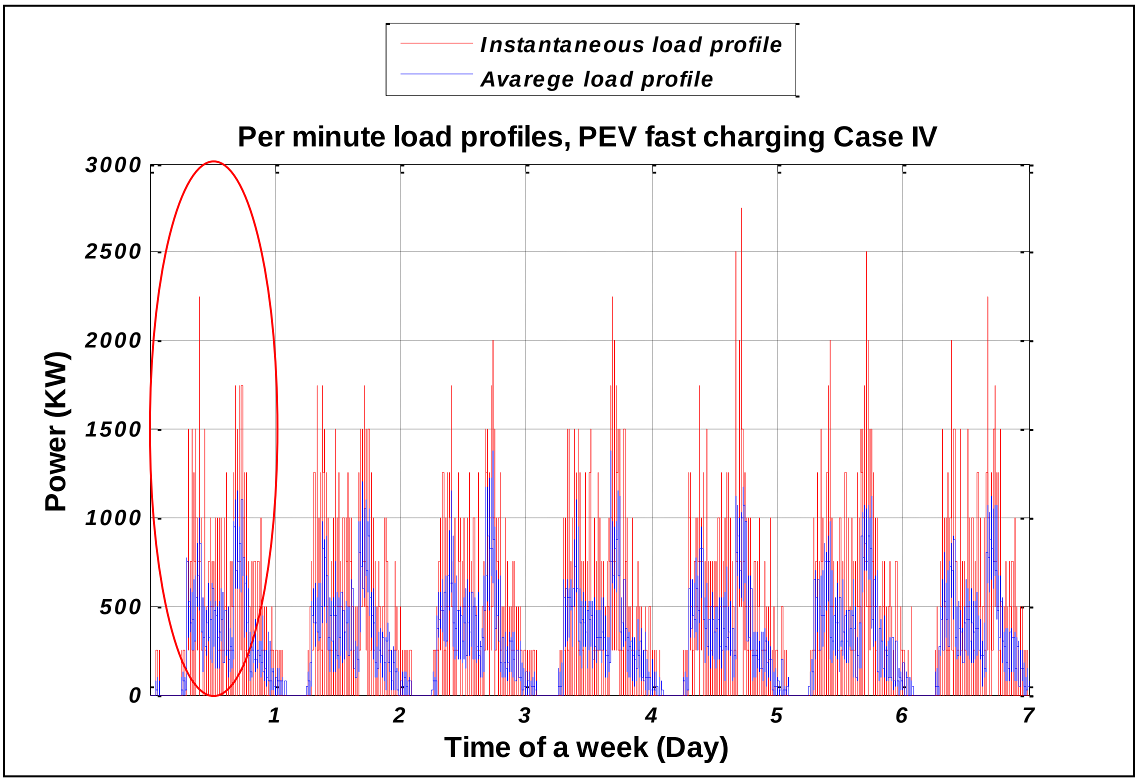

Figure 6.31: Per minute load profile for a week, PEV fast charging at 250KW

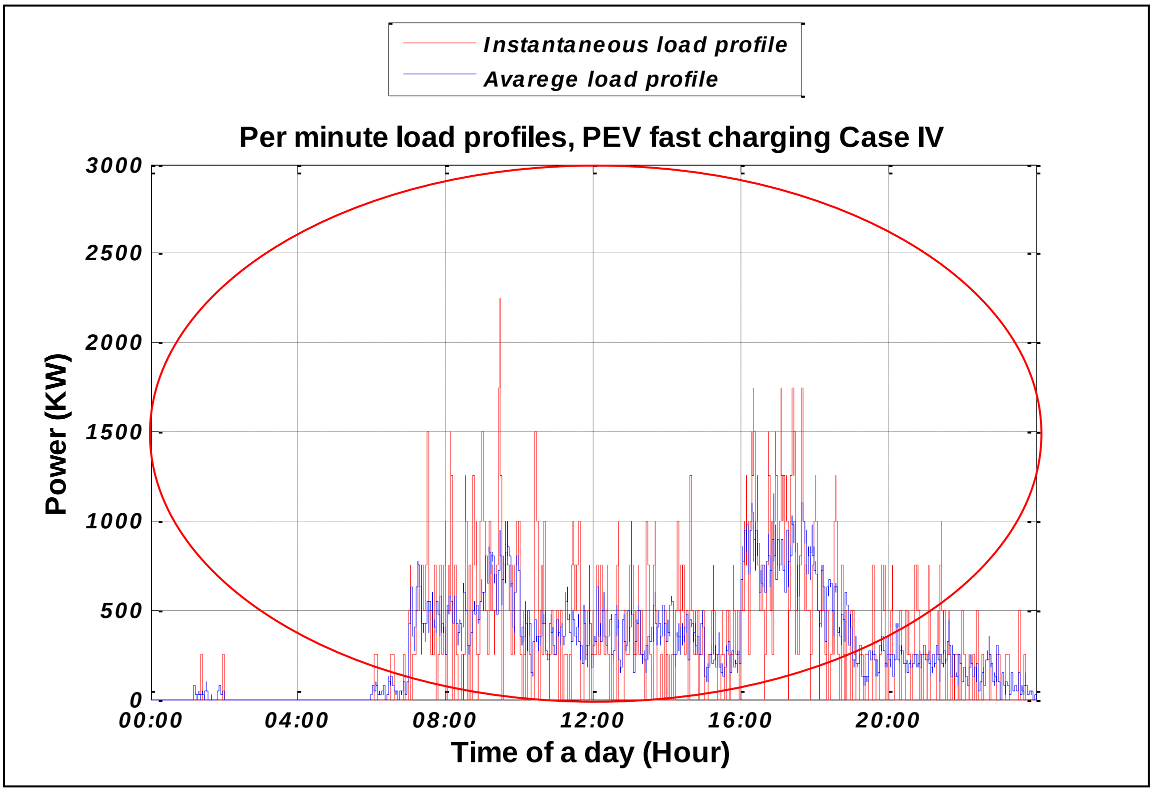

Figure 6.32: Per minute load profile for a day in the week, PEV fast charging at 250KW

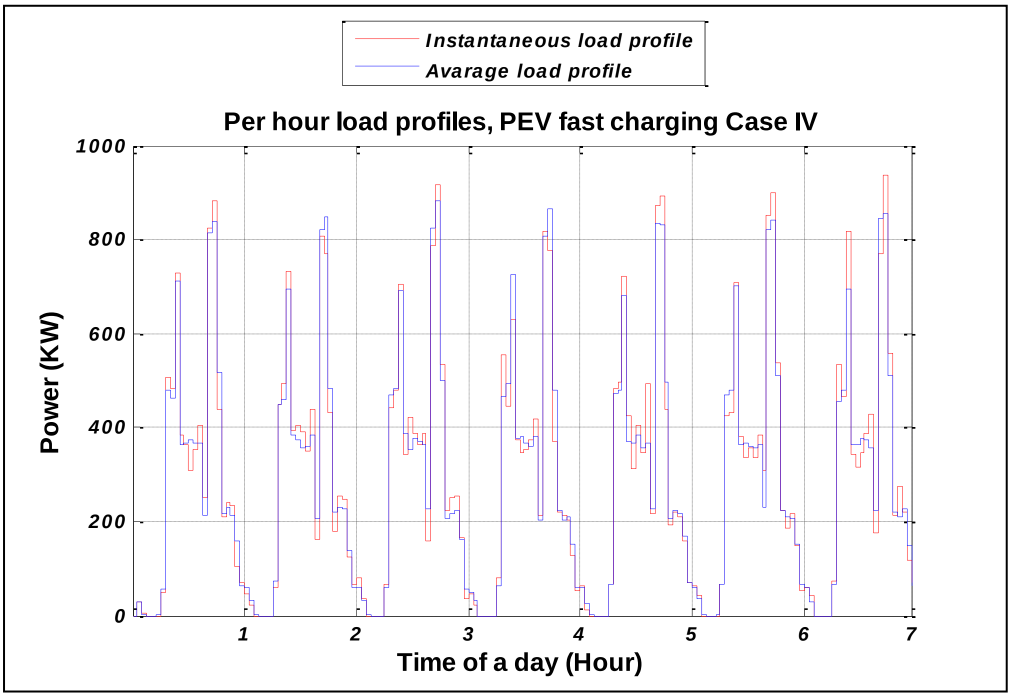

Figure 6.33: Per hour load profile for a week, PEV fast charging at 250KW

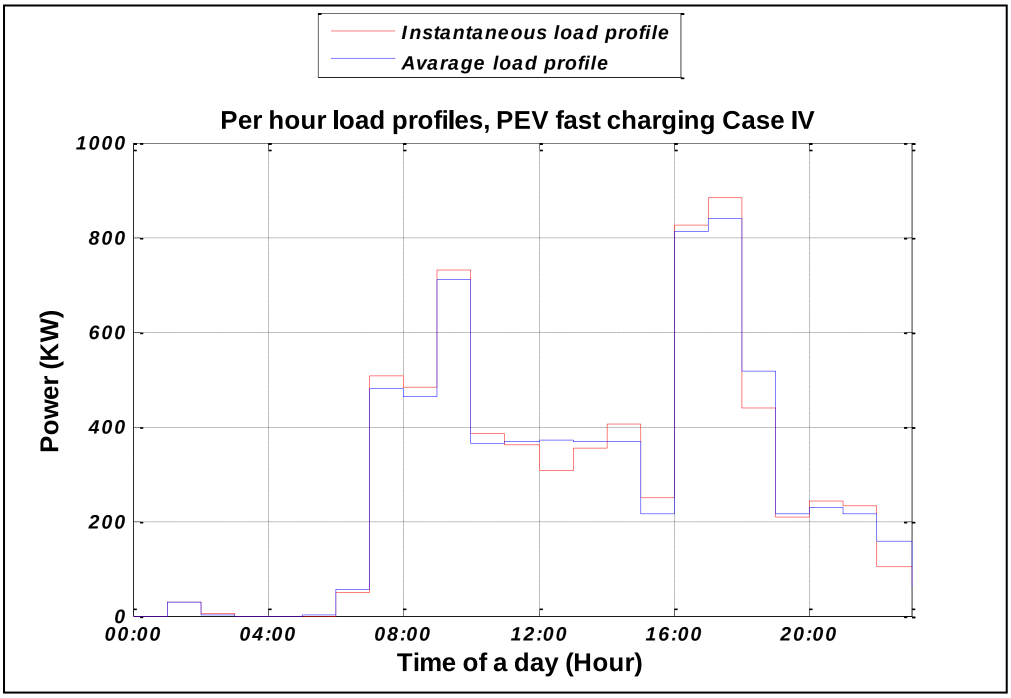

Figure 6.34: Per hour load profile for a day in the week, PEV fast charging at 250KW

Figure 6.33 and Figure 6.34 shows per hour load profiles for a week and the first day of the week respectively. Compared with the results shown in Figure 6.25 and Figure 6.26 of Case III, the results are almost the same since daily energy requirement by each vehicle, which is a function of daily distance traveled, is not changed. However, if compare per minute load profiles in Case III and Case IV, we can seen a reduction in the concentration of peak power in Case IV. This is mainly because as a result increased battery capacities, the number of times that vehicles come to the fast charging station to recharge their batteries is reduced as can be seen in Figure 6.37.

The distribution of daily distance travelled in Case IV is similar to that shown in Figure 6.14 and Figure 6.27 for Case II and III respectively. This is because there is no change the statistical data. They all depend on the statistical distance defined in the scenarios of Case II and III. However there is a change in the distribution of SOC and distribution charging time interval as shown in Figure 6.35.

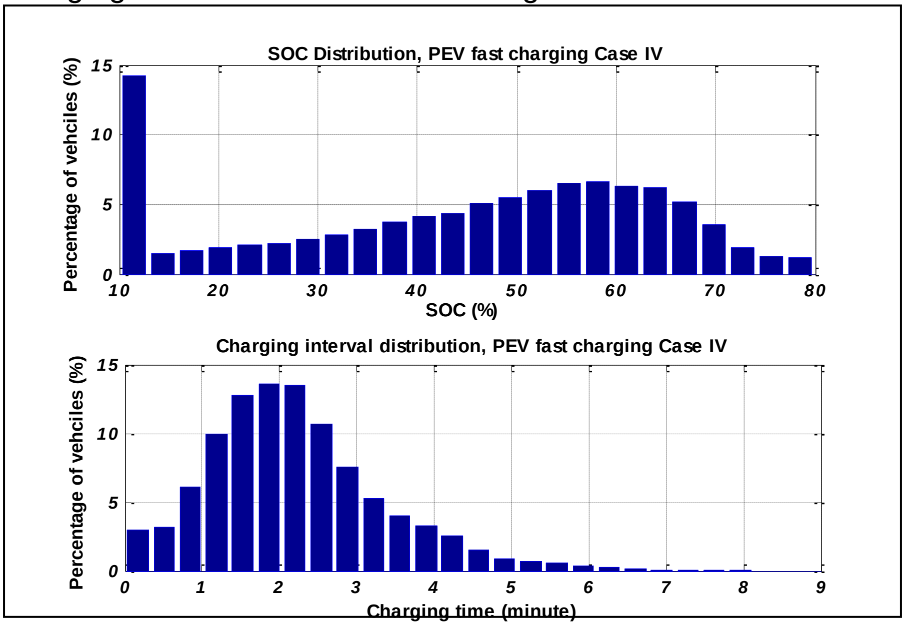

Figure 6.35: Distribution of SOC and charging time interval, PEV fast charging at 250KW

As can be seen from Figure 6.35, the charging time interval has increased to the maximum value of about 8 minute. This is mainly because of distribution of increased battery capacities introduced in Case IV. However, in average the charging time is still about 2 minutes. The distribution of battery capacities used in the model, that made these parameters to vary, is shown in Figure 6.36.

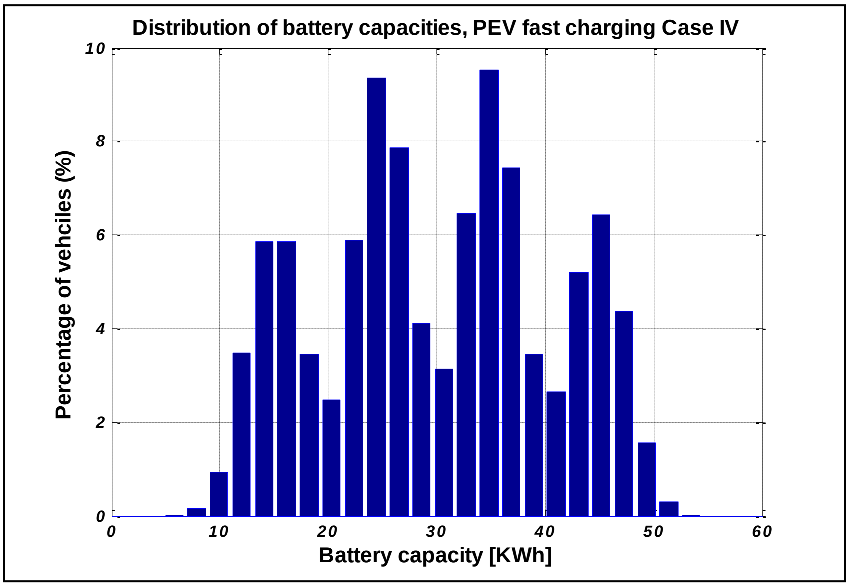

Figure 6.36: Distribution of battery capacities used in the model, PEV fast charging at 250KW

As can be seen from the distribution of vehicles used in the model, we can see that the range of vehicle's battery capacity varies from a minimum of 7KWh to a maximum of 53KWh. However the average value of total battery capacity is 29.99KWh.

Figure 6.37 shows the distribution of required number of charging poles at the fast charging stations and required number of charging per vehicles per day. As we can see from the figure, the utilization the fast charging station has increased. This is to say, if we decide to have four charging poles at the fast charging station, 88.41% of vehicles out of total can be charged on arrival in Case IV compared to 95.54% of Case III. From this we can see that as the battery capacity increases, the charging poles that we need at the charging stations need to grow with it since increased battery capacity increases charging time intervals, if vehicles are to charge on arrival.

In addition to this, Figure 6.37 also shows that the required number of charging per vehicle per day is almost the same as that of Case III with a maximum value of 8 times per day.

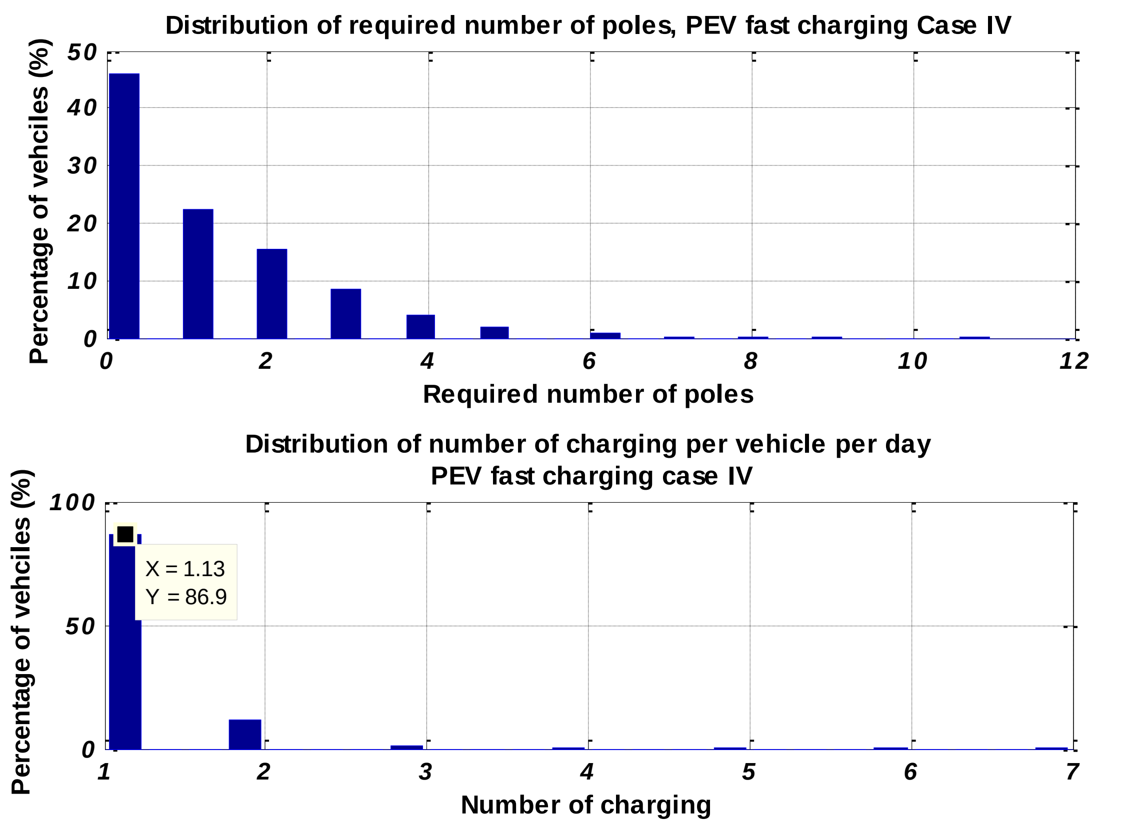

Figure 6.37: Distribution required number of poles and required number of charging per day per vehicles

6.1.6.3 Distribution system impact

This is the most realistic impacts of PEV fast charging on the distribution system's bus voltages. This is mainly because the voltage profiles are the result of totally probabilistic approach. Figure 6.38 and Figure 6.39 illustrates bus voltage profiles both in the primary and secondary distribution network due to the deployment of three fast charging stations. These system bus voltage profiles are similar to those generated in Case III. The only difference is that the system is more stresses in this case due to increases battery capacity and hence increased energy demand.

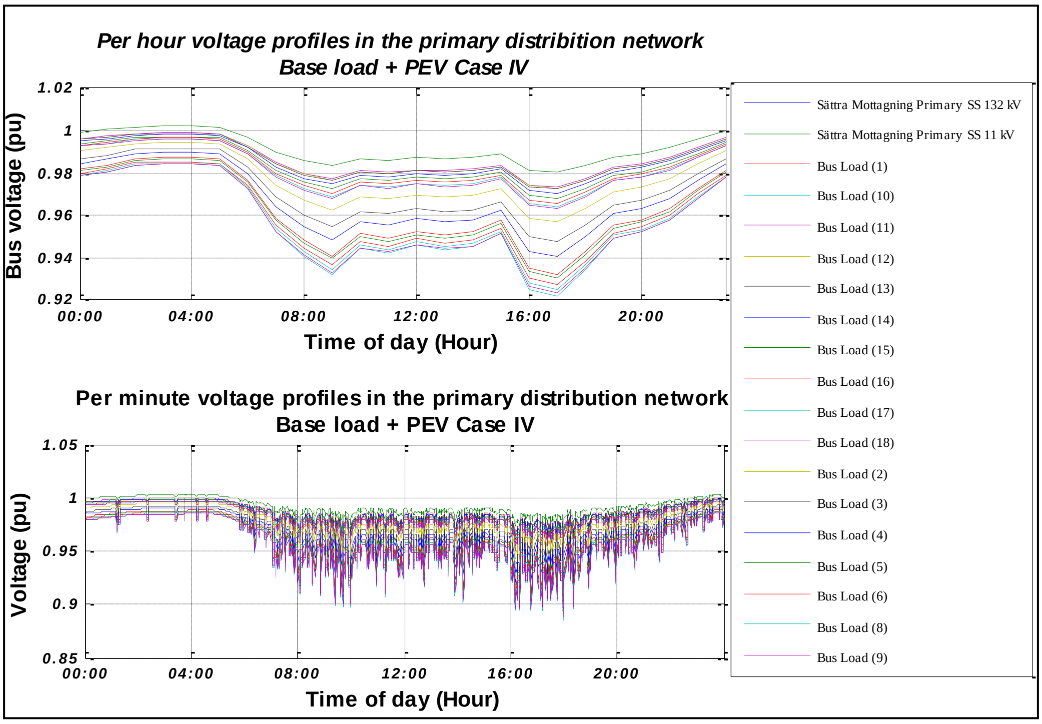

Figure 6.38: Bus voltage profiles in the primary distribution network due the deployment of three fast charging stations

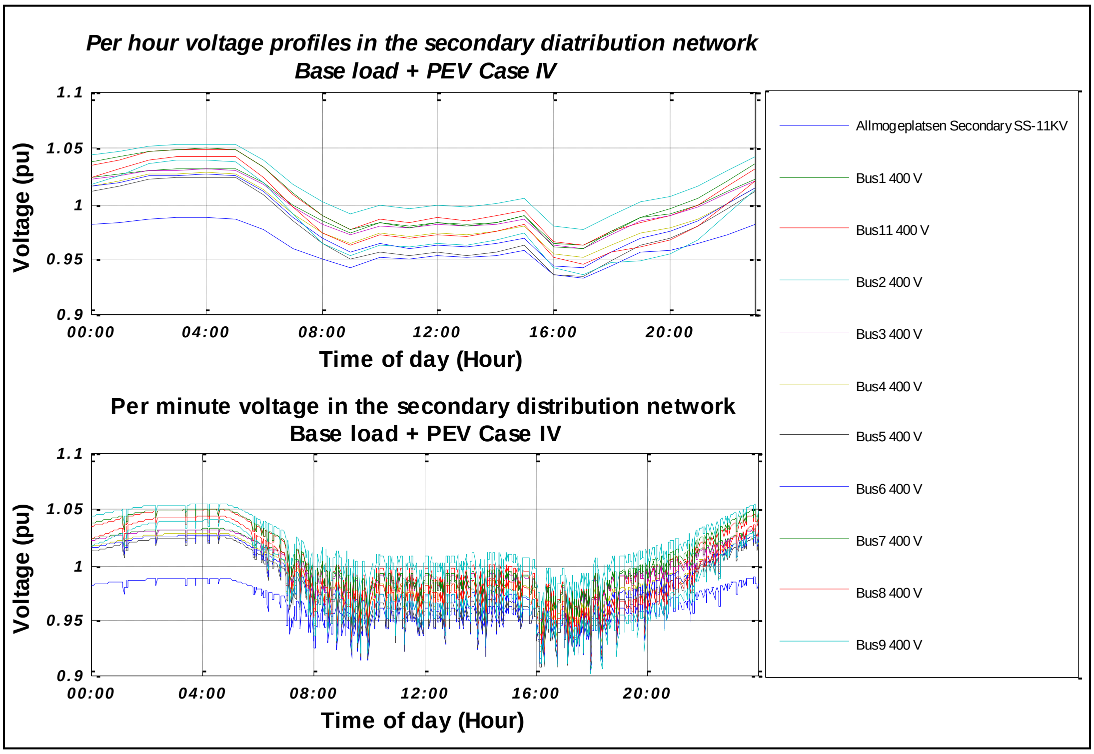

Figure 6.39: Bus voltage profiles in the secondary distribution network due to the deployment of three fast charging stations in the system

6.2 Optimizing energy storage system

We have illustrated the impacts of fast charging on the system bus voltages in the preceding sections. No one can tolerate this drop in the voltage levels of the system. If fast charging station is to be deployed, their impacts on the system parameters will be inevitable. Therefore, we need to have a way to overcome this problem.

As we have seen from the voltage profiles and the load profiles resulting from fast charging of PEVs, the jump in the high power demand which result in voltage deep lasts only for a short interval of time estimated in minutes. As a result, energy storage devices, which can provide high power during a short interval of time, are important to be installed at the fast charging stations. The installed high power energy carriers can dump their energy, stored during light load, during a high demand time to save the system from voltage dip. Figure 4.4 illustrates a number of energy carriers that can provide high power during a short interval time. Among these energy carriers are advanced flywheels and ultracapacitors. If, for example, we have an advanced flywheel in the vicinity of fast charging station that can store energy during the light load period, we can use this energy during high demand times at the charging station to save the system from voltage deep.

The question will be how to size the energy storage capacity to be used. This is a tricky question to answer. However knowing the length of the day during which the voltage drops below the allowable limit can give us a good initial gauss on the size of energy storage device. The duration of voltage dip throughout the day varies from bus to bus. Figure 6.40 shows the percentage time distribution of voltage dip at one of the bus in the primary distribution network. As can be seen from this figure, the bus voltage at this location is above 0.95pu for about 76.85% of the day. The voltage of this specific bus drops below the limit only for 23.18% of the day as can be seen from Figure 6.40. This is just one way to have a good initial gauss on the optimum size of storage device at fast charging stations. Further study is needed to establish the relationship between the size of energy storage devices and voltage dip in the distribution network.

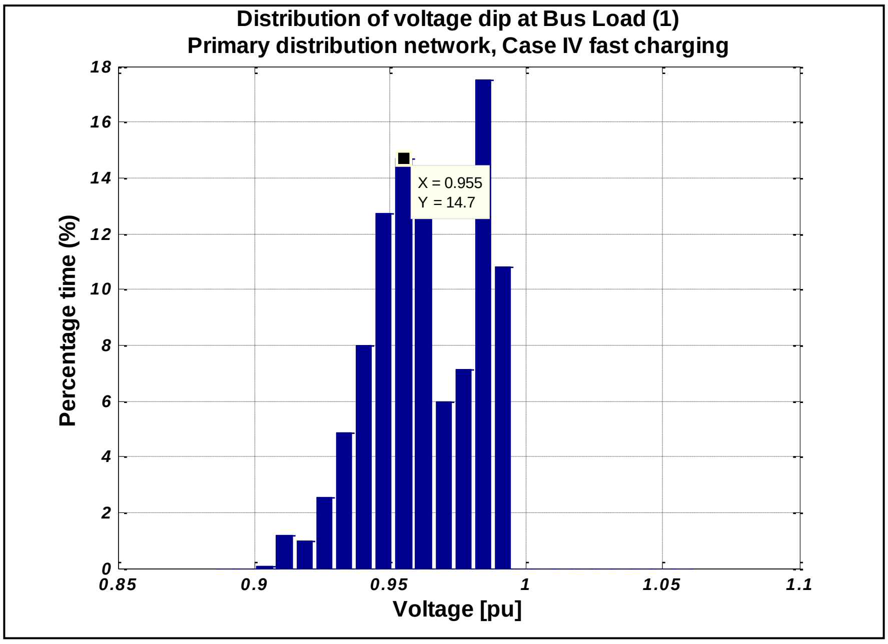

Figure 6.40: Duration of voltage dips at Bus Load (1) in the primary distribution network

6.3 Residential charging

6.3.1 Selected region of study

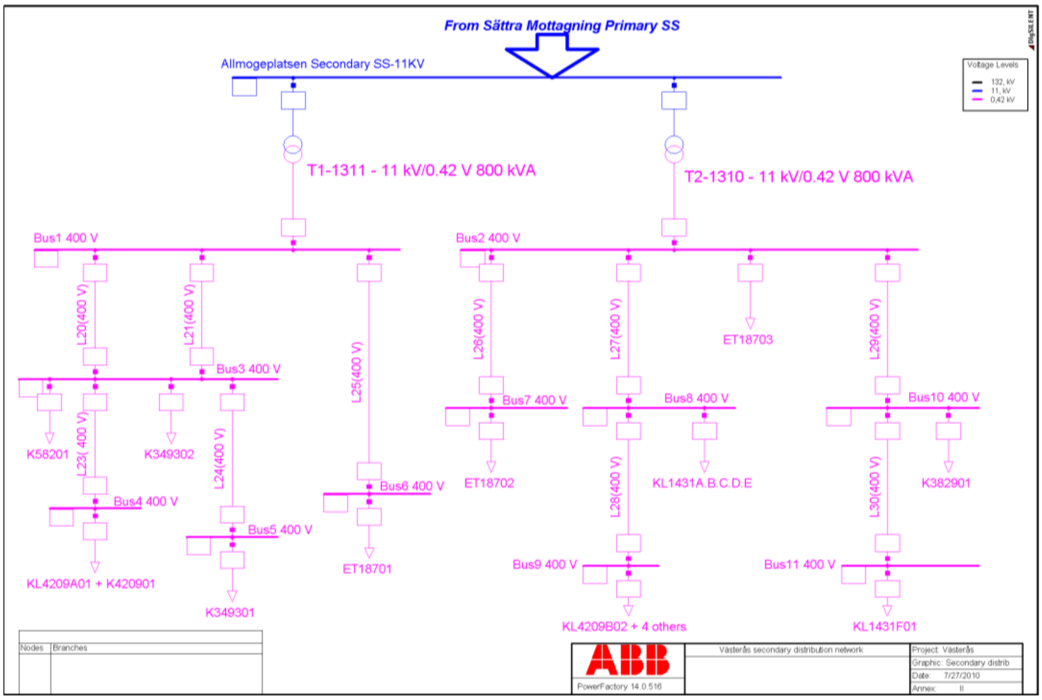

Figure 6.41: Selected residential charging area

Figure 6.41 illustrates the area selected for residential charging where PEVs are to be deployed. It shows the secondary distribution network demonstrated in Figure 4.3. This network is characterized by different groups of customers at each load feeders. This consists of residential, commercial and mixed types. There are two distribution transformers in this distribution network which steps down voltage from 11KV to 400V. Each transformers supply both residential, commercial and mixed load types.

There are two primary objectives of this section. The first one is to demonstrate some important results from both Case I and Case II residential charging models including distribution of battery capacities, daily distance travelled, arrival and departure times, SOC and charging times. The second important objective is to illustrate the impacts of residential charging on the distribution transformer loading and transformer loss of life.

6.3.2 Common inputs to the models

The first two important common input parameters are the total number vehicle population in the selected residential area and penetration levels of PEVs. For this particular study, a total of 450 total vehicle population and different penetration levels of PEVs out of the total including 10%, 25%, 50%, 75% and 100% are all considered. It is also assumed that, based on number of residential houses on each transformers, 180 vehicles are distributed on transformer 1(T1-1311-11 kV/0.42 V 800 kVA) and the remaining 270 vehicles distributed on transformer 2(T2-1310 - 11 kV/0.42 V 800 kVA).

Similar to fast charging models discussed in the preceding section, there are three important probabilistic parameters which dictate the output from the residential charging models. These are distribution of vehicle battery capacities, daily distance travelled and arrival time distribution.

The first two parameters, distribution of battery capacities and daily distance travelled, are assumed to be the same as that used in Case IV of fast charging model. What is unique in the residential charging models is the arrival time distribution. Table 6.2 illustrates distribution of arrival and departure time of vehicles from and to work respectively. As can be seen from this table, arrival and departure times of vehicles are expressed in terms of mean and variance departure and arrival time for both weekdays and weekend.

Table 6.2: Statistical distribution of daily arrival and departure time of vehicles

	Departure		Arrival	
Parameter	Weekday	Weekend	Weekday	Weekend
$\mu_T^{(p)}$	7	9	18	15
$\left(\sigma_T^{(p)}\right)^2$	3	6	3	6

Residential charging model is built on the basis that all the vehicles in the simulation are charged at home when they come back home from work every day and charging will commence on arrival from work[26]. It is important to note that residential charging may not necessarily mean charging during night time. It is a probabilistic term. The vehicle can charge at home as long as it is parked at home. The parking time of vehicle at home is probabilistic and depends on the data given in Table 6.2.

In the following subsections, outputs from two residential charging models and their impacts on the distribution transformer will be discussed. The two models, Case I and Case II residential charging models mainly differ on the available residential charging power level to charge PEVs at home.

6.3.3 Case I: Charge on parking interval

6.3.3.1 Scenario definition

In this charging model, the charging power varies from day to day which is a function of parking interval[27], available residential charging voltage level and daily energy requirement from each vehicle which is a function of daily distance traveled. The daily parking times of vehicles are functions of daily arrival and departure times which are probabilistic in nature as shown in Table 6.2. Once the daily arrival and departure times of PEVs on a given day are determined, the parking interval and hence the charging time interval in this case, will be the difference between the two. The charging voltage level is assumed to be 230V, single phase and the maximum charging current available from the charging circuit is assumed to be 16A. Note that the daily vehicle's charging power level is random which can vary from day to day depending on the charging interval and required energy. If in case the required charging current demand exceeds the maximum current, the model has the capability to limit the current to the circuit's maximum.

6.3.3.2 Output from the model

To have a clear understanding of outputs from this model, it important to understand how the probabilistic input parameters, which dictate the output from the models, are distributed and manipulated to be used in the model. Figure 6.42 illustrates the distribution of vehicle battery capacities, daily distance travelled, daily arrival and departure times of vehicles where all are generated during the simulation to determine the outputs from the model for 100% penetration levels of PEVs. It is important to note that the simulated input parameters match with the statistics defined in the scenarios.

[26] It is important to note at this point that if delayed charging is needed to provide ancillary service to the grid, the model can allow this. However, in the following section delayed charging is not considered. It is assumed that vehicles start charging on arrival from work.

[27] The time interval between vehicle arrival time on day (d) and departure time on day (d+1)

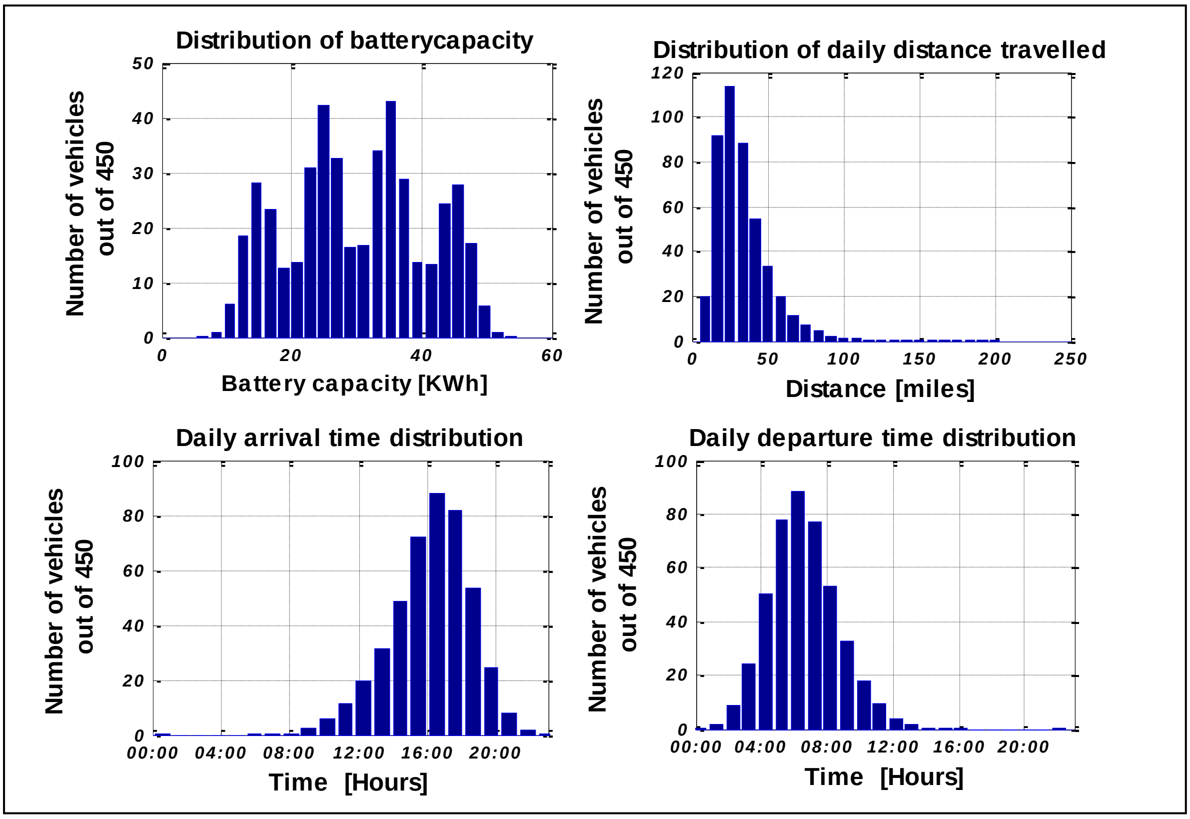

Figure 6.42: Simulated distribution of probabilistic parameters used in the model

These probabilistically distributed input parameters to the model dictate all aspects of outputs from the model. Figure 6.43 shows one example output from the model which illustrates daily charging interval of vehicle at home. It is in this charging interval that this model charges PEVs at home. As can be seen from the figure, about 35 vehicles out of 450 are parking at home for about 10 hour before going to work the next day. This is very important. As stated before, the charging circuit has maximum current capacity. There is a probability that the current demand from PEVs may exceed this limit due to short interval and high energy demand. In this case the model limits the current demand to the maximum demand and the vehicle may leave home partially charged. These current demands from vehicles are tracked in the model and the result is plotted in Figure 6.44. As can be seen from the figure, almost all the vehicles have daily current demand below the maximum circuit capacity and hence all are fully charged when leaving to work next day.

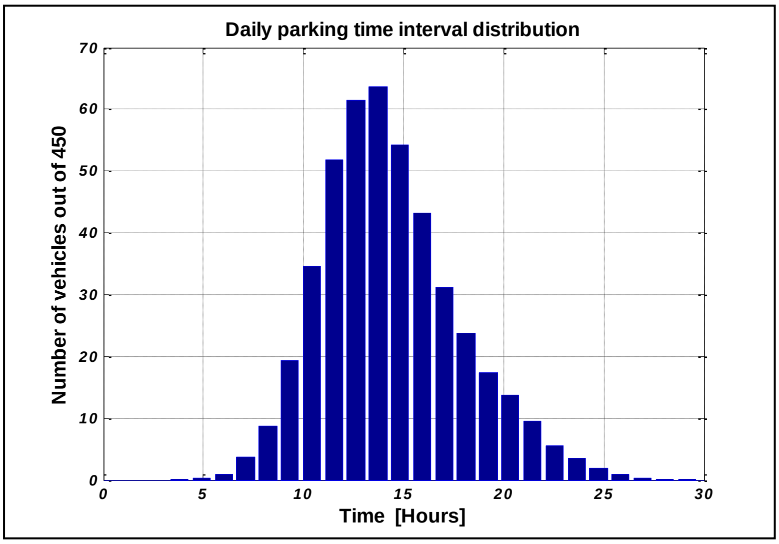

Figure 6.43: Distribution of daily parking interval of vehicles at home

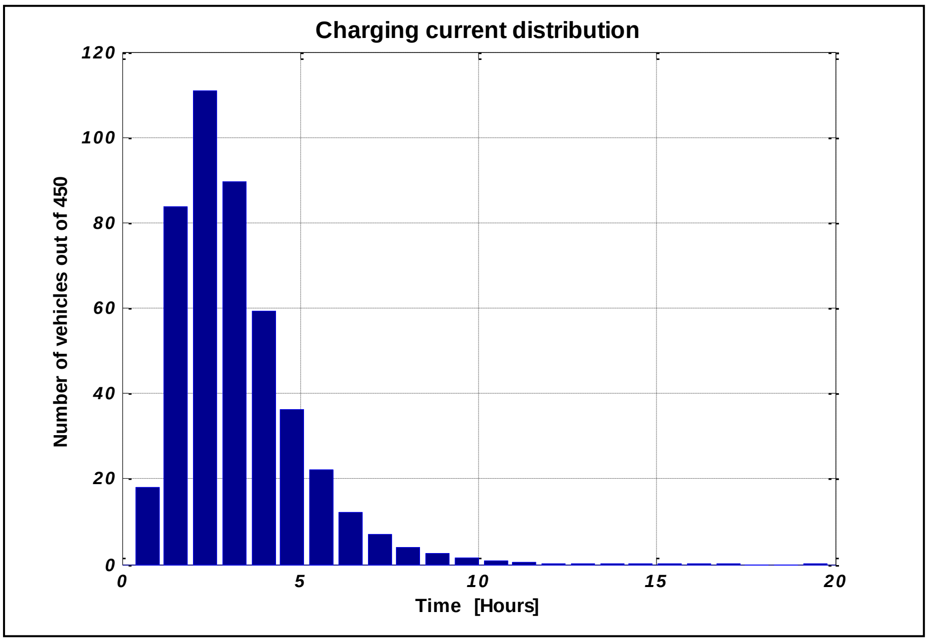

Figure 6.44: Distribution of daily current demand from vehicles

Charging PEVs over such an extended period of time at home means that the daily energy demand from vehicles will be distributed over longer time interval which in turn lower power demand from the grid. This is where the main advantage of Case I residential model lies. Figure 6.45 illustrates per minute and per hour load profiles due to Case I residential charging for different penetration levels.

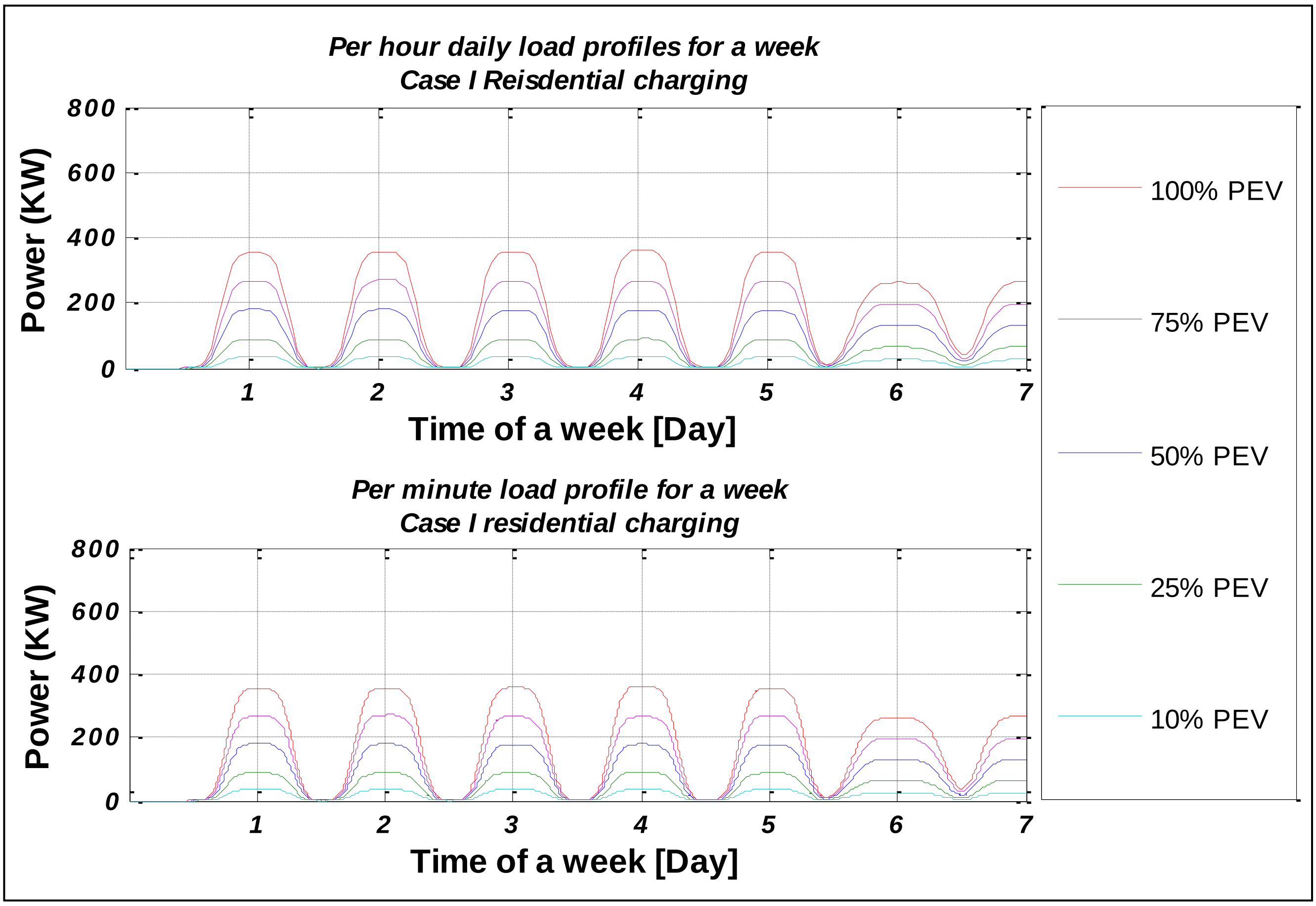

Figure 6.45: Per hour and per minute load profiles for a week, PEV residential charging only

Unlike fast charging models, per minute and per hour load profiles of residential charging are almost the same. This is mainly because of the charging time interval. In residential charging, PEVs are charged in order of hours whereas in fast charging, charging interval is in an order of few minutes.

One of an interesting result from residential charging is the SOC distribution. Figure 6.46 shows the simulated distribution of daily SOC levels. We know that SOC levels of all vehicles in the models cannot be lower than 10%, which is a minimum allowable value. However this figure shows an SOC level of even much lower, about -30%. What does this negative SOC mean? In residential charging models, we have assumed that vehicles can only be charged once per day, which is during parking interval at home. However it happened that some vehicles travelled beyond the capability of their battery as a result of probabilistic daily distance travelled. In this case, the only option for vehicles to finish the remaining distance is either to recharge outside home such as fast charging stations or use a hybrid energy source. Neither of these alternatives is considered in this model[28]. This is purposely done to give an indication of required charging infrastructures outside home and the range of battery capacities to be used if fully electric vehicles are to stay on the road.

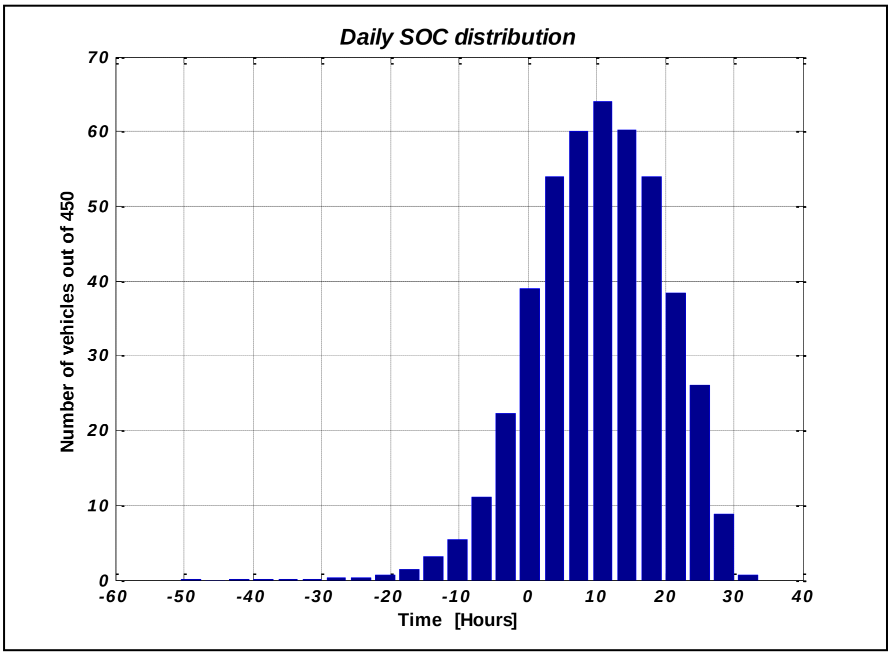

Figure 6.46: Daily SOC distribution of vehicles

6.3.3.3 Distribution system impact

Figure 6.47 shows the loadings of both distribution transformers at each penetration levels of PEVs. As can be seen from the figure, no transformer limit is exceeded even at 100% penetration level.

[28] Remember that charging multiple times per day is considered in fast charging models

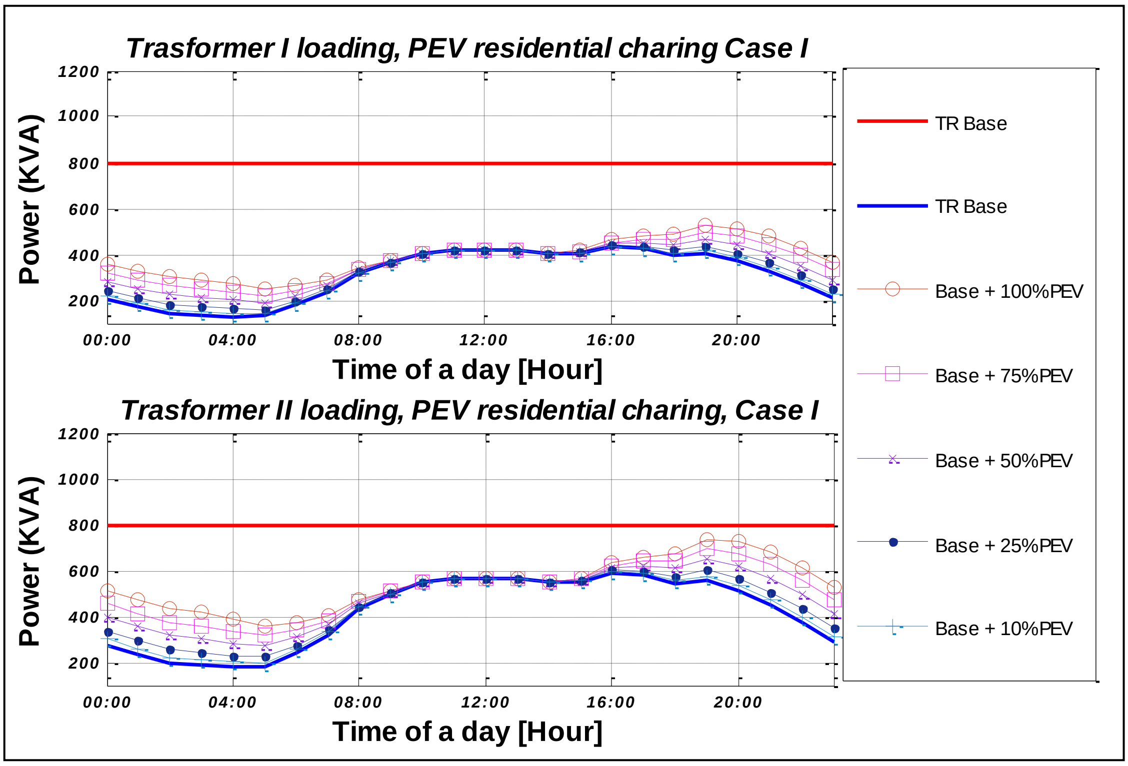

Figure 6.47: Transformer loadings resulting from PEV residential charging

However transformer loadings are increased due to added power demand from the vehicles. The increased loading of the transformer will result increased winding currents, which will intern result in increased transformer temperature. This increased winding current resulting from increased transformer loading can be used to find the hottest point in the transformer using the model described in section 5.3.2. Figure 6.48 shows the hotspot temperature of both transformers resulting from different transformer loading conditions. Note that hotspot temperature is calculated by assuming an ambient temperature of 30°C throughout the day in both Case I and Case II models.

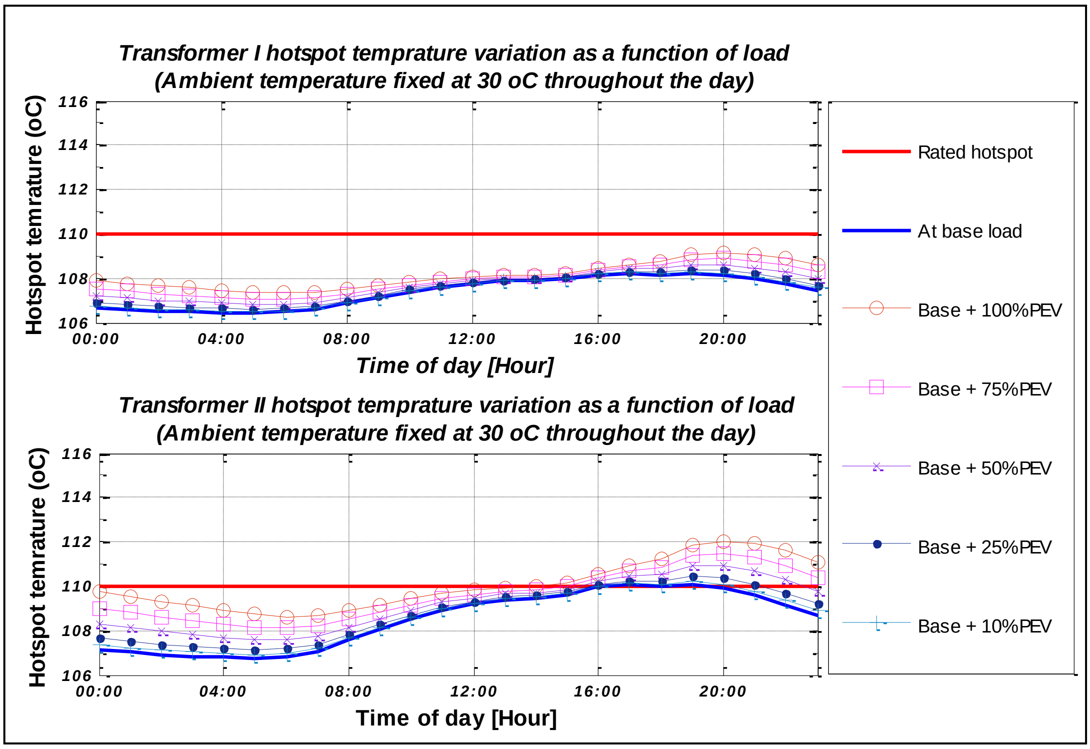

Figure 6.48: Hot spot temperature profiles of transformers resulting from different loading condition of transformers

As can be seen from Figure 6.48, the hotspot temperature of Transformer II exceeds its rated hot spot temperature, which is 110 ^{o}C, sometime during the day. Hence necessary arrangements by providing cooling system, has to be made to limits these impacts of the transformers. Once the hotspot temperature profile is determined for each transformer, accelerated aging factor (AAF) of the transformers can be calculated based on the model discussed in section 5.3.3. The calculated accelerated AAF is illustrated in Figure 6.49. This can be translated into transformer loss of (LOL) as indicated in section 5.3.3.

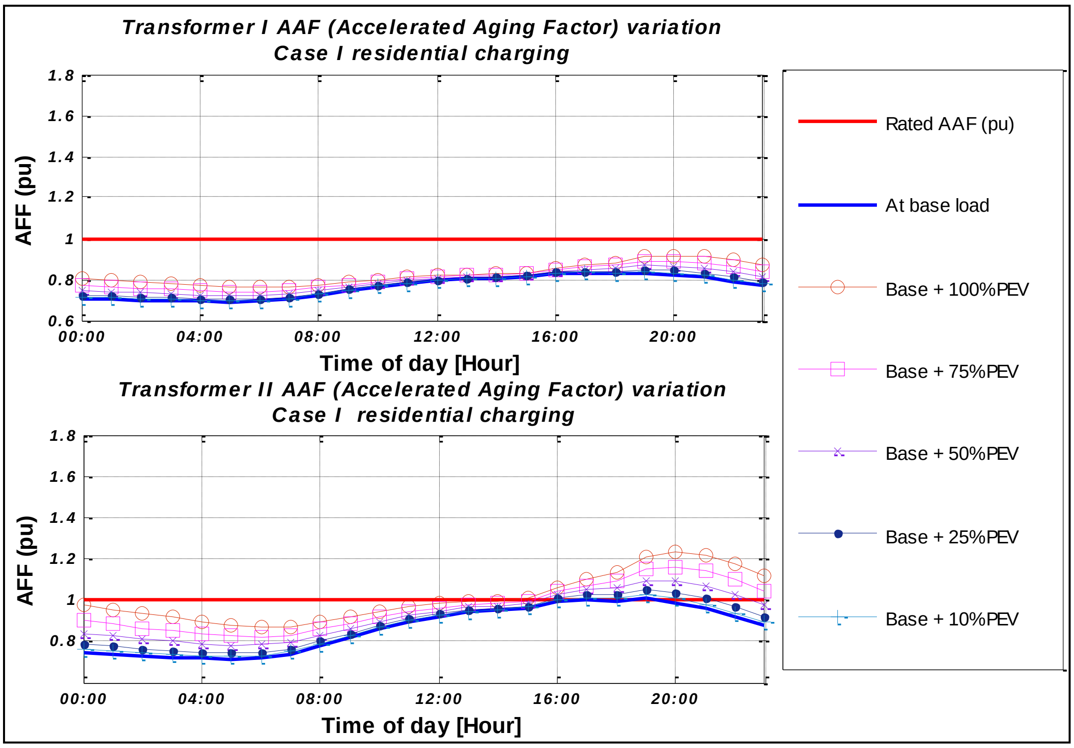

Figure 6.49: Transformers Accelerated Aging Factors

6.3.4 Case II: Fixed power charging

6.3.4.1 Scenario definition

Similar to residential charging Case I, this case uses the same distribution of battery capacity, arrival and departure time distribution and distribution of daily distance travelled by each vehicle. Apart from this, it also uses the same data as was used in Case I on total vehicle population in the study area, penetration levels and distribution of PEVs on each transformer.

The main difference between the two cases stem from the way they charge PEVs. In Case I, required energy, charging voltage level and parking interval of vehicles were used to determine the charging power levels. However, in Case II residential charging model the fixed charging power level and required grid energy from vehicles determines the charging time interval. As a result, this model assumes a charging power level of 3.3KW that represents residential charging power level of LAMPO2 discussed in section 3.5.1.

6.3.4.2 Output from the model

Since Case I and Case II residential charging models use the same data source on battery capacities, daily distance travelled, arrival and departure time distribution, they both have similar distribution of battery capacities, daily distance travelled, arrival and departure times and SOCs. However they have differences on generated load profiles and charging time distribution as illustrated in Figure 6.50 and Figure 6.51.

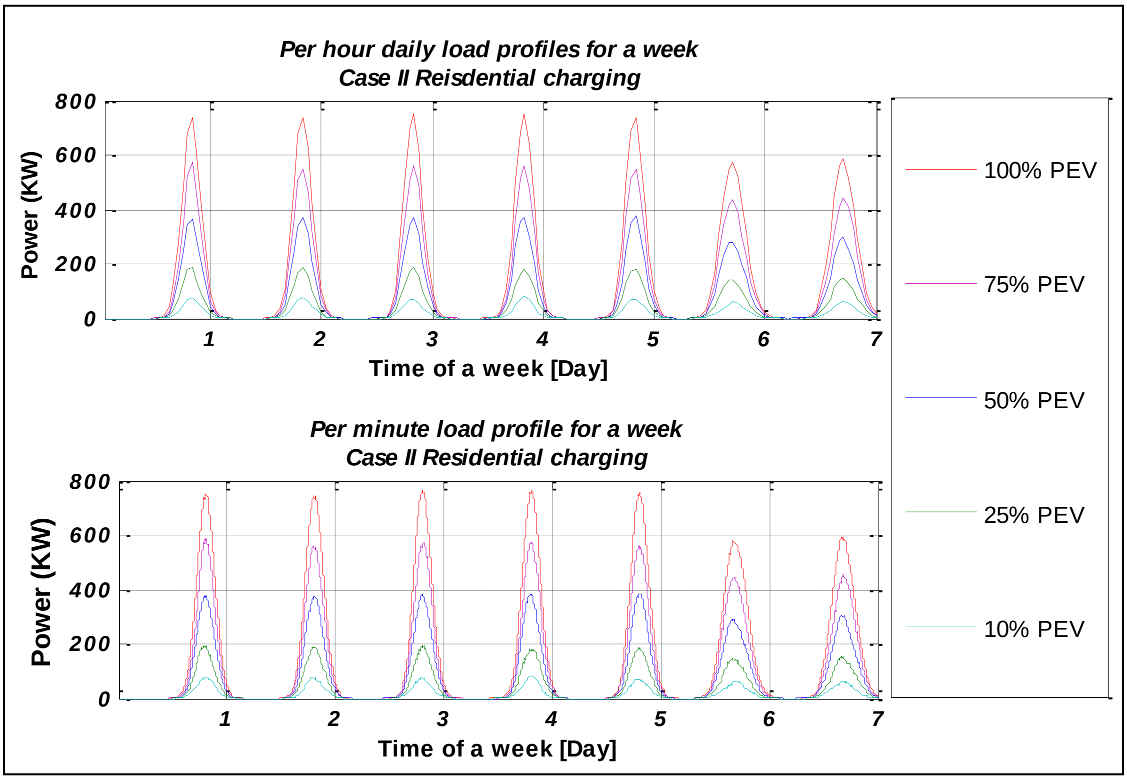

Figure 6.50: PEV hourly and per minute load profiles for a week, load due to PEV charging only

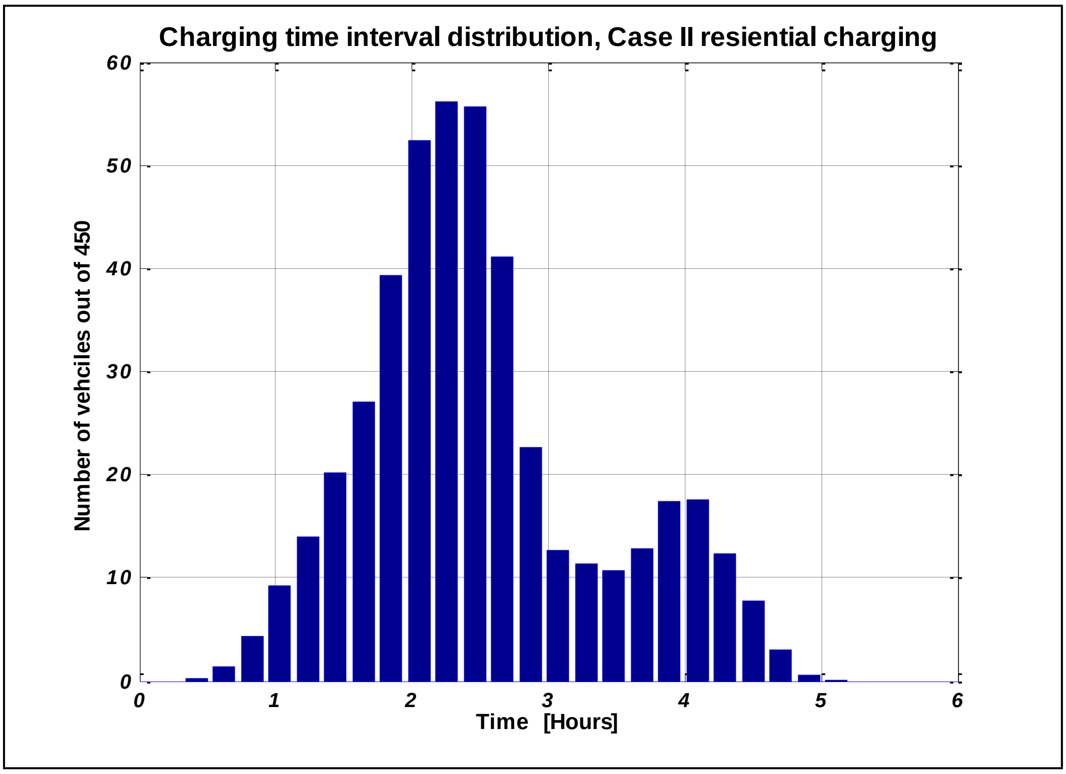

Figure 6.51: Charging time interval distribution, residential charging Case II

Figure 6.50 shows per minute and per hour load profiles generated due to PEV charging only. Note that per minute and per hour load profiles are similar. Compared with the same load profiles generated in Case I residential charging, we can observe an increased peak load in each penetration level in Case II residential charging model. This can be explained by a shorter charging time interval illustrated in Figure 6.51 compared with the parking interval and hence the charging time interval illustrated in Figure 6.43

for Case I. As we have discussed it before, the distribution of daily distance travelled and battery capacities are the same in both cases. This means that we have the same grid energy demand from PEVs in both cases. But this energy is required to be supplied in a shorter charging time interval in Case II than it is in Case I. This increases the peak power demand in Case II residential charging model.

6.3.4.3 Distribution system impact

As stated before, the smaller charging time of vehicles at a fixed power level has resulted in a higher peak power demand. This will intern increase the transformer loadings as shown in Figure 6.52. From this figure one can see that apart from increased transformer loadings, the rating of TR II is exceeded at 100% and 75% PEV penetration. This needs controlling the charging of PEVs in some way to protect the transformer from damage.

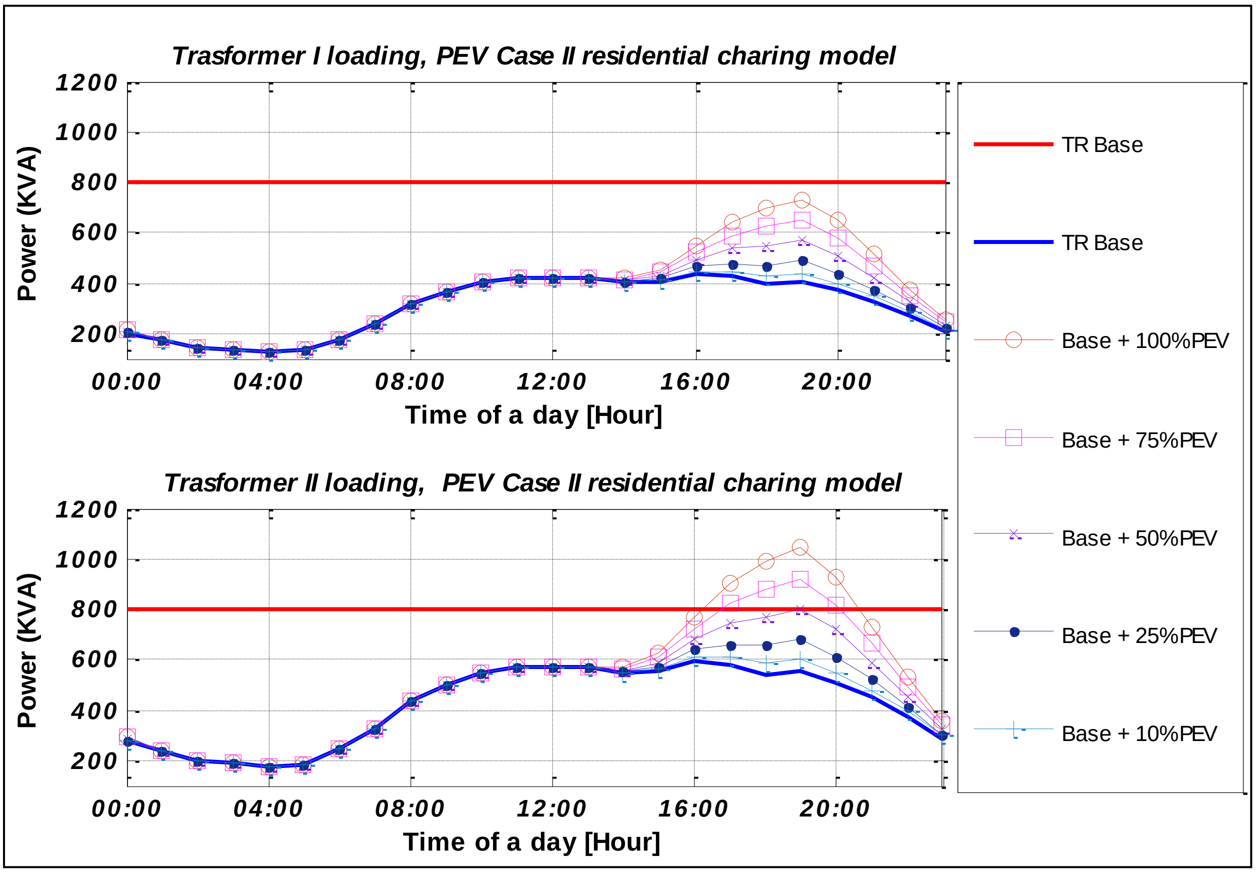

Figure 6.52: Transformer loadings resulting from Case II residential charging

The increased transformer loading results in increased transformer current which will intern result increased transformer winding temperature. Figure 6.53 illustrates transformer hotspot temperature variation as a function transformer loading.

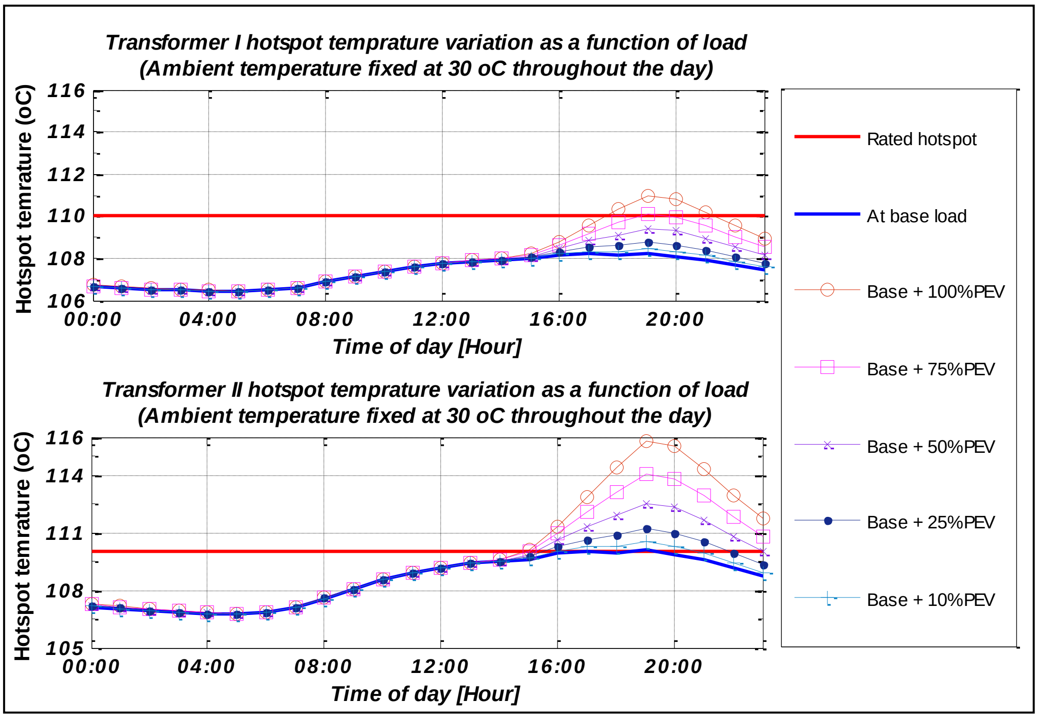

Figure 6.53: Distribution transformer hotspot temperature profiles resulting from Case II residential charging

As can be seen from Figure 6.53, the temperature of the hottest point in the transformer has exceeded the rated hotspot temperature of the transformer. In TR II, the limit is exceeded at all penetration levels whereas in TR I it is exceeded only 100% PEV penetration level. Compare this result with that shown in Figure 6.48 where this limit is not exceeded for TR I and in TR II the hotspot temperature is lower than that shown in Figure 6.53.

Similar to Case I residential charging model, this hotspot temperature variation can be translated into equivalent accelerated aging factor (AAF) of the transformer as shown in Figure 6.54 below. From this we can see that transformers loss life is faster in Case II residential charging than in Case I.

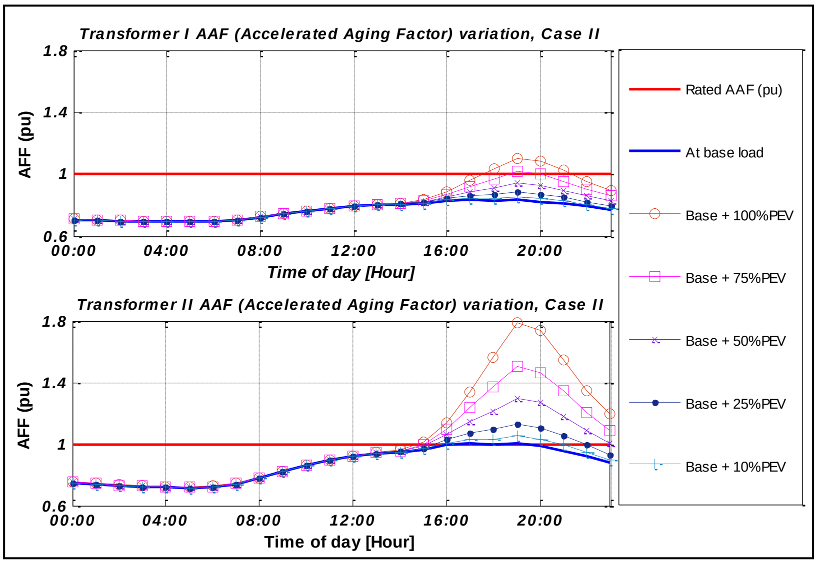

Figure 6.54: Accelerated Aging Factors of transformers resulting from Case II residential fast charging

7 CHAPTER SEVEN: CONCLUSIONS AND FUTURE WORK

7.1 Conclusions

One of the most important achievements of this diploma work are the probabilistic models developed to quantify charging patterns of PEVs both at residential areas and public fast charging stations. All the charging models developed can be used in any system provided that required input data for the model are available.

In the fast charging models, deterministic approach is compared with probabilistic approach. The result showed the incapability of deterministic approach in drawing a good picture of PEV charging patterns. From this it is concluded that probabilistic approach is the best way to quantify the impacts of PEV charging on the power system.

Distribution of number of charging per day of PEVs at the fast charging stations is the second most important outputs from the fast charging models. From this distribution a good initial estimation on the required charging infrastructures outside residential areas can be made.

The third important result is the distribution of required number of charging poles at the fast charging stations. From this distribution an economic decision can be made on the optimum required number of charging poles at fast charging stations.

What is also important from fast charging models is impact of fast charging on the system bus voltage. From the distribution of voltage profiles at system buses, an important clue to establish the relationship between optimum sizing of required energy storage devices at fast charging station can be made.

Important conclusion can also be drawn from residential charging models. As we have discussed, residential Case I charging model, which charges PEVs over an extended parking interval gives a more sound and acceptable results. Hence it can best be used to quantify charging patterns of PEVs in residential areas.

There are a number of outputs from residential charging models. Among these is distribution of SOC levels. This SOC distribution curve can be used for an optimum sizing of battery capacities to be used in the mass penetration of PEVs to be deployed in the market. At the same time, this same distribution can also be used to a relationship between required infrastructures outside residential areas, daily distance traveled and battery capacities to be used in the vehicle fleet.

Using load profiles from fast charging models and base load profiles of selected area of study, impacts of fast charging on the system bus voltage can be made. In addition to this, using the load profiles generated from residential charging models along with system base load profiles, impact analysis on the distribution transformer loadings, variation of hotspot temperature and variation of accelerated aging factor (AAF) can be made.

Note that impact analysis of fast charging stations on the distribution bus voltages is carried out in **DIgSILENT** Power Factory. And all PEV charging models of both residential and fast charging are developed using **MATLAB** programming language.

7.2 Future work

There are a number of things need to be considered in the future. Among these is ***clustering*** of PEV charging. As we have seen, the models developed in this thesis consider residential charging and charging at the fast charging stations independently. We have not considered charging vehicles at industrial premises, commercial areas, parking areas, road side charging poles and similar other charging alternatives. A given vehicle can be charge at different charging areas on a given day depending on a given circumstances. In this case, there must be a way to cluster or integrate the behaviors of PEV charging to have more sound loading profiles from PEV charging.

From the distribution of bus voltages, we can have a good initial estimation on the required size of energy storage. However, for a more accurate result further investigation to establish a mathematical relationship between voltage distribution at system bus and required energy storage has to have to be done.

As we have seen, the distribution of number of charging per day gives a good indication of required charging infrastructures outside residential premises. Further study need to be carried out to formulate this distribution with the required charging infrastructure outside residential areas. In addition to this, we have also observed the relationship between number of charging per day and battery sizes. As we have seen from this, there is a strong relationship between distribution of battery capacities, required number of charging per day and required charging infrastructures outside residential premises. Extended studies need to be taken to establish this relationship.

Much need to done in Monte Carlo simulation. As we have seen in the models, there are a number of parameters that dictate the output from the models. Among these are distribution of daily distance travelled, distribution of required battery capacities, distribution of vehicle population in each class and arrival time distribution of vehicles. First, it is very important to figure out a way to mach a given statistics with appropriate distribution. Once the perfect distributions that matches the statistics is determined, it important to figure out the relationship between the parameters, if there is any. Each parameters need to be taken into account to finally determine Monte Carlo loop needed to solve the whole system with a certain degree of confidence level. This parameter relationship, to establish degree of confidence in the simulation is not taken into account in this thesis work. Further work need to be done to establish this relation.

8 CHAPTER NINE: REFERENCES

[1.1] Percent of world oil consumption used for transportation: Available at http://cadlab6.mit.edu/2.009.wiki/anchor/index.php?title=Percent_of_world_oil_consumption_used_for_transportation

[1.2] U.S Energy Information Administration, Crude oil Supply and Disposition: Available at http://tonto.eia.doe.gov/dnav/pet/pet_sum_crdsnd_adc_mbblpd_m.htm

[1.3] Consumption Vs discovery of oil: Available at http://www.transitionkeighley.org.uk/peakOil.html

[1.4] U.S Energy Information Administration, Weekly Inputs, Utilization and Production: Available at http://tonto.eia.doe.gov/dnav/pet/pet_pnp_wiup_dcu_nus_w.htm

[1.5] Curtis Aaron Roe, ''Power System Level Impacts of Plug-In Hybrid Vehicles'', Georgia Institute of Technology August 2009: http://www.pserc.org/cgi-pserc/getbig/publicatio/reports/2009report/meliopoulos_phev_pserc_report_t-34_2009.pdf

[1.6] U.S Energy Information Administration, World Crude oil price: Available at http://tonto.eia.doe.gov/dnav/pet/pet_pri_wco_k_w.htm

[1.7] Annual Oil Market Chronology: Available at http://www.eia.doe.gov/cabs/AOMC/Full.html

[1.8] U.S. Department of Transportation, 2006: Available at http://climate.dot.gov/about/transportations-role/overview.html

[1.9] Global Warming Art: Available at http://www.globalwarmingart.com/wiki/File:Major_greenhouse_gas_trends_png

[1.10] Sakis Meliopoulos, Jerome Meisel, George Cokkinides, Thomas Overbye; ''Power System Level Impacts of Plug-In Hybrid Vehicles'', Power Systems Engineering Research Center, October 2009: Available at www.pserc.wisc.edu/.../meliopoulos_phev_pserc_report_t-34_2009.pdf

[1.11] Patricia Sandmeier, Simon Felsenstein; '' Electric vehicle infrastructure ABB Market potentials'', ABB Internal report, October 2009

[2.1] Patricia Sandmeier, Simon Felsenstein; '' Electric vehicle infrastructure ABB Market potentials'', ABB Internal report, October 2009

[2.2] Sakis Meliopoulos, Jerome Meisel, George Cokkinides, Thomas Overbye; ''Power System Level Impacts of Plug-In Hybrid Vehicles'', Power Systems Engineering Research Center, October 2009: Available at www.pserc.wisc.edu/.../meliopoulos_phev_pserc_report_t-34_2009.pdf

[2.3] ALEC N. BROOKS, San Carlos, SVEN H. THESEN; "Vehicle to Grid Demonstration and Evaluation Program'', PG&E and Tesla Motors:; Available at http://www.spinnovation.com/sn/Articles_on_V2G/PG_and_E_and_Tesla_Motors_-_Vehicle_to_Grid_Demonstration_and_Evaluation_Program.pdf

[2.4] K. Parks, P. Denholm, and T. Markel: ''Costs and Emissions Associated with Plug-In Hybrid Electric Vehicle Charging in the Xcel Energy Colorado Service Territory'', National Renewable Energy Laboratory, *Technical Report NREL*/TP-640-41410 , May 2007; Available at: http://www.nrel.gov/docs/fy07osti/41410.pdf

[2.5] Michael Kintner-Meyer, Kevin Schneider, Robert Pratt: ''Impacts Assessment of Plug-In Hybrid Vehicles on Electric Utilities and Regional U.S. Power Grids Part 1: Technical Analysis'' from http://www.pnl.gov/energy/eed/etd/pdfs/phev_feasibility_analysis_combined.pdf

[2.6] Chris Farmer, Paul Hines, Jonathan Dowds, and Seth Blumsack: ''Modeling the Impact of Increasing PHEV Loads on the Distribution Infrastructure'', Available at http://www.cems.uvm.edu/~phines/publications/2010/farmer_2010_phev_distribution.pdf

[3.1] Liam Kelly, ''Vehicle Impacts on Distribution Networks in British Columbia'', University of Victoria 2009

[3.2] Chris Farmer, Paul Hines, Jonathan Dowds, and Seth Blumsack: ''Modeling the Impact of Increasing PHEV Loads on the Distribution Infrastructure'', Available at http://www.cems.uvm.edu/~phines/publications/2010/farmer_2010_phev_distribution.pdf

[3.3] Curtis Aaron Roe, ''Power System Level Impacts of Plug-In Hybrid Vehicles'', Georgia Institute of Technology August 2009: http://www.pserc.org/cgi-pserc/getbig/publicatio/reports/2009report/meliopoulos_phev_pserc_report_t-34_2009.pdf

[3.4] William H. Kersting , ''Distribution System Modeling and Analysis'', New Mexico State University Las Cruces, New Mexico, CRC Press,

[3.5] Eduard Stolz - Park&Charge , www.protoscar.com; ''Strategy for European EV & PHEV conductive charging infrastructure: analysis of the situation''; September 10th, 2009; Available at: http://www.park-charge.ch/documents/EV_infrastructure_strategy.pdf

[3.6] http://en.wikipedia.org

[3.7] Françoise Nemry, Guillaume Leduc, Almudena Muñoz; '' Plug-in Hybrid and Battery-Electric Vehicles: State of the research and development and comparative analysis of energy and cost efficiency''; © European Communities, 2009; Available at: http://ftp.jrc.es/EURdoc/JRC54699_TN.pdf

[3.8] Patricia Sandmeier, Simon Felsenstein,; '' Electric vehicle infrastructure ABB Market potentials Electric vehicle infrastructure, using the Swiss example''; ABB Sales Switzerland Business Development, October 2009; ABB Internal report

[3.9] PRESS RELEASE, Protoscar LAMPO2 : the electric sporty show car boasting "fast-charge" capability; Available at: http://www.protoscar.com/pdf/LAMPO2/LAMPO2_Press_Release.pdf

[3.10] http://www.protoscar.com/

[3.11] http://www.japanfs.org/ja/pages/028973.html

[3.12] Level III Fast Charging Stations, Available at: http://akerwade.indigofiles.com/AkerWade_EVFC_Specsheet.pdf

[3.13] Sakis Meliopoulos, Jerome Meisel, George Cokkinides, Thomas Overbye; ''Power System Level Impacts of Plug-In Hybrid Vehicles'', Power Systems Engineering Research Center, October 2009: Available at www.pserc.wisc.edu/.../meliopoulos_phev_pserc_report_t-34_2009.pdf

[3.14] Kevin Morrow, Donald Karner, James Francfort; ''U.S. Department of Energy Vehicle Technologies Program – Advanced Vehicle Testing Activity 'Plug-in

Hybrid Electric Vehicle Charging Infrastructure Review''; U.S. Department of Energy, November 2008; Available at: http://avt.inel.gov/pdf/phev/phevInfrastructureReport08.pdf

[4.1] ABB Internal Report, PHEV Impact Task Force

[4.2] A. Perujo, B. Ciuffo; '' Potential Impact of Electric Vehicles on the Electric Supply System, A case study for the Province of Milan, Italy''; JRS Technical Notes, EUR 23975 EN 2009; Available at: http://www.cars21.com/files/papers/Potential%20Impact%20of%20Electric%20Vehicle.pdf

[4.3] Patricia Sandmeier, Simon Felsenstein,; '' Electric vehicle infrastructure ABB Market potentials Electric vehicle infrastructure, using the Swiss example''; ABB Sales Switzerland Business Development, October 2009; ABB Internal report

[4.4] Françoise Nemry, Guillaume Leduc, Almudena Muñoz; '' Plug-in Hybrid and Battery-Electric Vehicles: State of the research and development and comparative analysis of energy and cost efficiency''; © European Communities, 2009; Available at: http://ftp.jrc.es/EURdoc/JRC54699_TN.pdf

[4.5] Sakis Meliopoulos, Jerome Meisel, George Cokkinides, Thomas Overbye; ''Power System Level Impacts of Plug-In Hybrid Vehicles'', Power Systems Engineering Research Center, October 2009: Available at www.pserc.wisc.edu/.../meliopoulos_phev_pserc_report_t-34_2009.pdf

[5.1] A report prepared by the Reliability Test System Task Force of the Application of Probability Methods Subcommittee, ''The IEEE Reliability Test System -1996'', IEEE Transactions on Power Systems, Vol. 14, NO. 3, August 1999

[5.2] Public Service Electric and Gas Company (PSE&G), ''PSE&G Load Profiling Methodology'', Available at: http://www.pseg.com/customer/energy/pdf/TPS_LoadProfiling.pdf

[5.3] Sakis Meliopoulos, Jerome Meisel, George Cokkinides, Thomas Overbye; ''Power System Level Impacts of Plug-In Hybrid Vehicles'', Power Systems Engineering Research Center, October 2009: Available at www.pserc.wisc.edu/.../meliopoulos_phev_pserc_report_t-34_2009.pdf

[5.4] Chris Farmer, Paul Hines, Jonathan Dowds, and Seth Blumsack: ''Modeling the Impact of Increasing PHEV Loads on the Distribution Infrastructure'', Available at http://www.cems.uvm.edu/~phines/publications/2010/farmer_2010_phev_distribution.pdf

[5.5] ANSI/I EEE C57.91-1981, ''American National Standards, guide for loading mineral-oil-immersed overhead and pad mounted distribution transformer'', Revision of ANSI C57.91-1974

[5.6] ABB Internal report, ''PHEV Task Force''

[6.1] Sakis Meliopoulos, Jerome Meisel, George Cokkinides, Thomas Overbye; ''Power System Level Impacts of Plug-In Hybrid Vehicles'', Power Systems Engineering Research Center, October 2009: Available at www.pserc.wisc.edu/.../meliopoulos_phev_pserc_report_t-34_2009.pdf

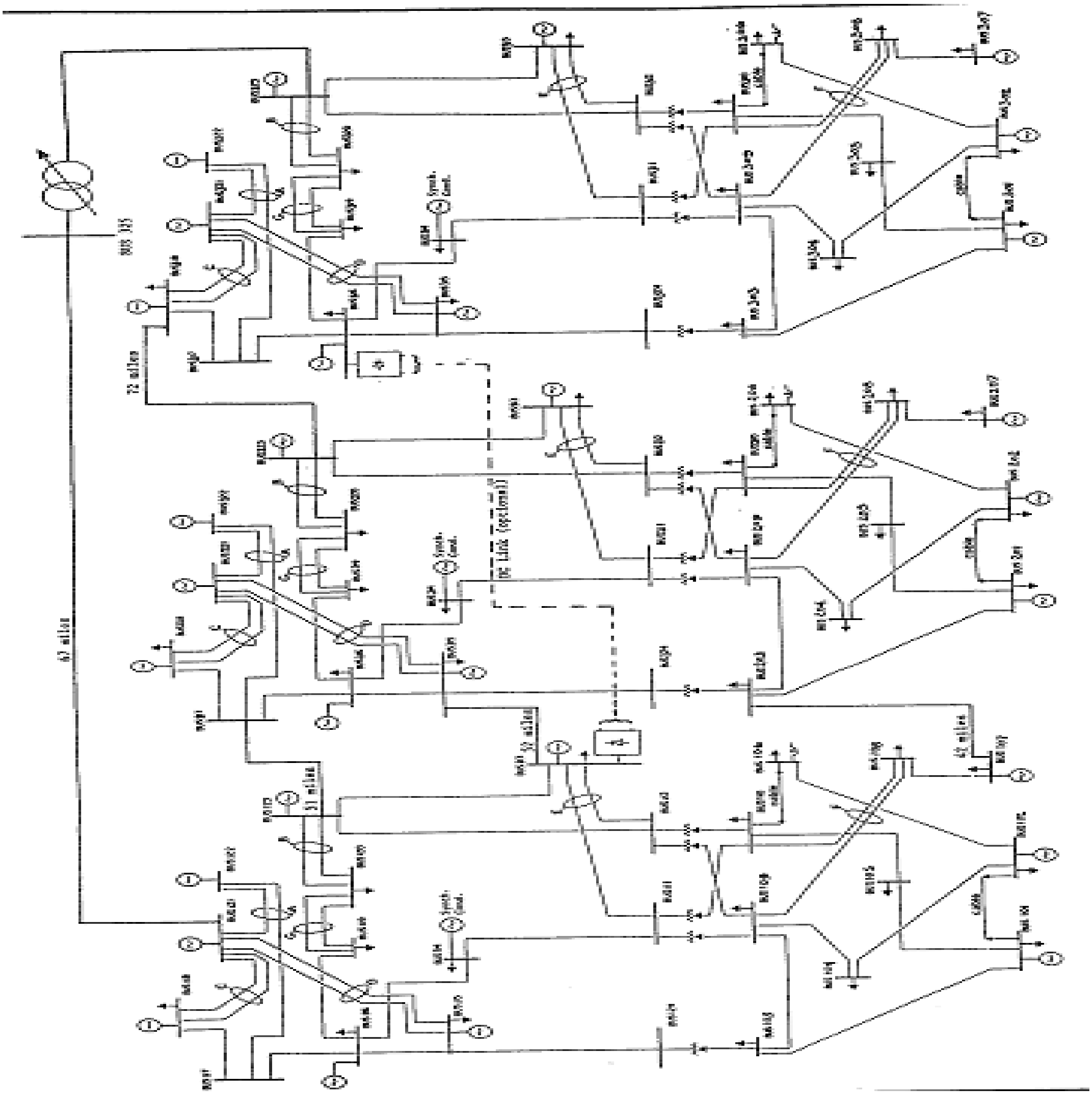

Figure 9.1: IEEE RTS-96 network topology

Table 9.1: Weekly Peak Load in Percent of annual peak

Week	Peak load (%)	Week	Peak load (%)
1	86.2	27	75,5
2	90.0	28	81,6
3	87.8	29	80,1
4	83,4	30	88,0
5	88,0	31	72,2
6	84,1	32	77,6
7	83,2	33	80,0
8	80,6	34	72,9
9	74,0	35	72,6
10	73,7	36	70,5
11	71,5	37	78,0
12	72,7	38	69,5
13	70,4	39	72,4
14	75,0	40	72,4
15	72,1	41	74,3
16	80,0	42	74,4
17	75,4	43	80,0
18	83,7	44	88,1
19	87,0	45	88,5
20	88,0	46	90,9
21	85,6	47	94,0
22	81,1	48	89,0
23	90,0	49	94,2
24	88,7	50	97,0
25	89,6	51	100
26	86,1	52	95,2

Table 9.2: Daily load in Percent of Weekly Peak

Day	Peak Load (%)
Monday	93
Tuesday	100
Wednesday	98
Thursday	96
Friday	94
Saturday	77
Sunday	75

Table 9.3: Hourly peak load in Percent of daily Peak

	Winter weeks		Summer weeks		Spring/fall weeks	
	1-8 & 44-52		18-30		9-17 & 31-43	
Hour	Week day	Weekend	Weekday	Weekend	Weekday	Weekend
12-1 am	67	78	64	74	63	65
1-2	63	72	60	70	62	73
2-3	60	68	58	66	60	69
3-4	59	66	56	65	58	66

4-5	59	64	56	64	59	65
5-6	60	65	58	62	65	65
6-7	74	66	64	62	72	68
7-8	86	70	76	66	85	74
8-9	85	80	87	81	95	83
9-10	96	88	95	86	99	89
10-11	96	90	99	91	100	92
11-noon	95	91	100	93	99	94
Noon-1pm	95	90	99	93	99	94
1-2	95	88	100	92	92	90
2-3	93	87	100	91	90	90
3-4	94	87	97	91	88	86
4-5	99	91	96	92	90	85
5-6	100	100	96	94	92	88
6-7	100	99	93	95	96	92
7-8	96	97	92	95	98	100
8-9	91	94	92	100	96	97
9-10	83	92	93	93	90	95
10-11	73	87	87	88	80	90
11-12	63	81	72	80	70	85

Table 9.4: List of expected PHEVs (non-exhaustive) [4.4]

Manufacturer	Model	Category	Architecture	Fuel	AER (km)	Battery type	Battery energy storage (kWh)	Vehicle cost (indicative)	Expected date
Audi	A1 Sportback	Berline (sport)			50-100	Li-ion			2011
BYD Auto	BYD F3DM	Medium/big	Parallel	Gasoline	100	$LiFePO_4$	20	€11350-14670	China (2008); 2011 in the EU
BYD Auto	BYD F6DM	Medium/big	Parallel	Gasoline	100	$LiFePO_4$	20	€17938-21525	China (2008) and 2010 in the US
Chrysler	Chrysler 200 C EV	Medium/big	Series	Gasoline	64	Li-ion	27		2010 USA; 2013 EU
Chrysler	Chrysler Jeep Wrangler EV	Medium/big	Series		64	Li-ion			2010 USA; 2013 EU
Chrysler	Chrysler Town&Country	Minivans	Series		64	Li-ion			2010 USA; 2013 EU
Chrysler	Chrysler Jeep Patriot EV	SUV			64	Li-ion			2010 USA; 2013 EU
Fisker	Fisker Karma	Berline (sport)	Series		80	Li-ion	22	€55000	2010
Ford	Volvo V70	Medium/big (break)		Diesel	50	Li-ion	11.3		2012
Ford	Escape	SUV	Series-Parallel		50	Li-ion			
GM	Chevrolet Volt	Medium/big	Series	Gasoline/E85	64	Li-ion	16	€28700	2010
GM	Opel Ampera	Medium/big	Series	Gasoline	60	Li-ion	16	€35000	2011
GM	Cadillac Converj	Medium/big	Series		64	Li-ion	16		
GM	Saturn Vue Green Line	SUV			16	Li-ion		$40000	2011 (USA)
Hyundai	Blue-Will concept car	Berline (sport)		Gasoline	60	Li-ion			2012
Toyota	Prius	Medium/big	Split	Gasoline	50	Li-ion		$48000	
VW	Golf VI Twin-Drive	Medium/big	Series	Diesel	50	Li-ion	16		2010

Table 9.5: List of expected BEVs (non-exhaustive) [4.4]

Manufacturer	Model	Category	AER (km)	Battery type	Energy Storage (kWh)	Vehicle cost (indicative)	Market introduction (target)
BMW	Mini E	Small	240	Li-Ion	35 (28 usable)		Leasing Plan, NY, CA, London and New Jersey
BYD Auto	BYD e6 EV	Berline	400	$LiFePO_4$	72		
Chery Automobile	S18 EV	Small	150	Li-Ion	40	$14600	End 2009 (China)
Chrysler	Chrysler Dodge Circuit EV	Berline (sport)	241-322	Li-Ion	26		2010 USA-2013 UE
CODA Automotive	CodaEV	Berline	145-195	Li-Ion		$45000	
Daimler	Smart Fortwo Brabus Electric	Small	115				
Fiat	Fiat-Fiorino Micro-Vett	Small	70-130 (depending on the model)	Li-Ion	22	€29900 (low-cost version)	
Fiat	Fiat E500	Small	110	Li-Ion	22	Aprox €27000	
Fiat	Fiat Pallio Electric	Small/medium	128	Ni-MH			Brasil
Ford	Focus EV	Berline	160				2011 in the US
Mitsubishi	MiEV	Small	140-160 (MY2006) (160)	Li-Ion	16/20		Japan (2009); EU and US (2010)
NICE/Fiat	Micro-Vett e500	Small	120	Li-Ion	18		
Nissan	Nissan EV		160	Li-Ion		$28000-30000	2010 mass production in Japan and US
Pininfarina	Buecar aka B0	Small	250	Li-MP+ supercapacitor			2010 in Italy
PSA	Citroen C1 eléctrico (conversión)	Small	112			€18882	
Renault	Fluence EV	Berline					2011
Renault	be bop ZE	Small (Kangoo)	100 (up to 150 soon)	Li-Ion	15	€13000 (including 5000 subsidies)	2010-2011
Rudolph Perfect Roadster	Spyder	Berline (sport)	125 (80 km/h)	Li-Poly	16	€60000 ($83000)	
Subaru	R1e EV	Small	80	Li-Ion		€13000-16000	2009 Japan
Subaru	Plug-in Stella concept	Small	90	Li-Ion	9	Aprox. €35000	2009-2010
Tata Motors	Indica EV	Small	200	Li-Ion			2009
Tesla Motors	Roadster	Berline (sport)	360 (combined cycle)	Li-Ion	56	$109000	Available in US and Europe
Tesla Motors	Model S	Berline (sport)	257-483	Li-Ion	42-70	Aprox €36000	
Think	City EV	Small	180	Li-Ion or zebra	28.3	Around €25000 in France	2010 in the US
Toyota	FT-EV	Small (IQ)	80				
ZENN	City Zenn	Small	400	Li-Ion			2010