New Plug-in Electric Vehicles Charging Models Based on Demand Response Programs for System Reliability Improvement

by

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Author's Declaration

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

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

Abstract

Recent years have seen a dramatic worldwide increase in the use of plug-in electric vehicles (PEVs). Their tremendous social, economic, and environmental benefits have made PEVs highly promising alternatives to conventional automobiles powered by internal combustion engines. Continuing government initiatives and technological advances are expected to lead to an even more rapid rise in the PEV penetration in the near future. Despite the important advantages of PEVs, however, their integration also raises new concerns and presents a number of special difficulties to the power system reliability. There is in fact recognized need to address the challenges imposed by PEV charging loads, to study their adverse impact on overall system reliability, and to determine whether existing generation capacity is sufficient for accommodating these new types of loads with their high penetration levels and different uncertainty characteristics.

This thesis presents a comprehensive reliability framework for incorporating different PEV charging load models into the evaluation of generation adequacy. The proposed framework comprises special treatment and innovative models to achieve an accurate determination of the impact of PEV load models on reliability. First, a goodness-of-fit statistical analysis determines the probability distribution functions (PDFs) that best reflect the main characteristics of driver behaviour. Second, robust and detailed stochastic methods are developed for modeling different charging scenarios (uncontrolled charging and charging based on TOU pricing). These models are based on the use of a Monte Carlo simulation in conjunction with the fitted PDFs to generate and assess a large number of possible scenarios while handling the uncertainties associated with driver behaviour, penetration levels, charging levels, battery capacities, and customer response to TOU pricing.

When PEV charging loads become a significant factor in power systems and PEV charging times are uncontrolled, they are expected to cause a severe risk to system reliability, especially at higher PEV penetration and charging levels. Solutions that maintain an acceptable level of system reliability and ensure adequate generation capacity must therefore be found. Proposed in this thesis is novel reliability-based frameworks for the application of different DR programs for use with PEV charging loads. The proposed frameworks are in line with the recent trend toward investigating solutions at the demand side and exploiting the existing flexibility to help improve

reliability. The first framework is proposed for incorporating PEV charging loads to respond to dynamic critical events. The framework involves two models: the first determines the time and demand for critical system events, when system supply facilities are unable to meet PEV loads, and the second assesses the feasibility of PEV owner response to critical events. The second framework is proposed for designing time-of-use (TOU) schedules to mitigate the impact of uncontrolled PEV charging load. The proposed framework involves the use of different stochastics simulation models, visualization approaches, and expert rules that help to arrive at proper TOU schedules for PEV charging load.

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Finally, I would like to thank all my friends at the University of Waterloo, who made my life at Waterloo enjoyable.

Dedication

TO MY DEAR PARENTS

My Lord! Have mercy upon them, as they did care for me when I was little and as they still care for me when I am grown up.

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Chapter 1
Introduction

1.1 Motivation

Recent years have been marked by a dramatic increase in the use of plug-in electric vehicles (PEVs) worldwide. From 2010 through September 2016[1], global sales of PEVs exceeded two millions, with the China accounting for the largest proportion at a third of the global total, as shown in Figure 1.1. Norway has achieved the most successful deployment of PEV with 29% market share. The tendency toward PEV use is primarily the result of environmental concerns and the increasing fuel costs associated with conventional automobiles (i.e., powered by internal combustion engines). Therefore, PEVs are expected to be very promising alternatives to conventional automobiles, as PEVs have been proven to have tremendous social, economic, and environmental benefits.

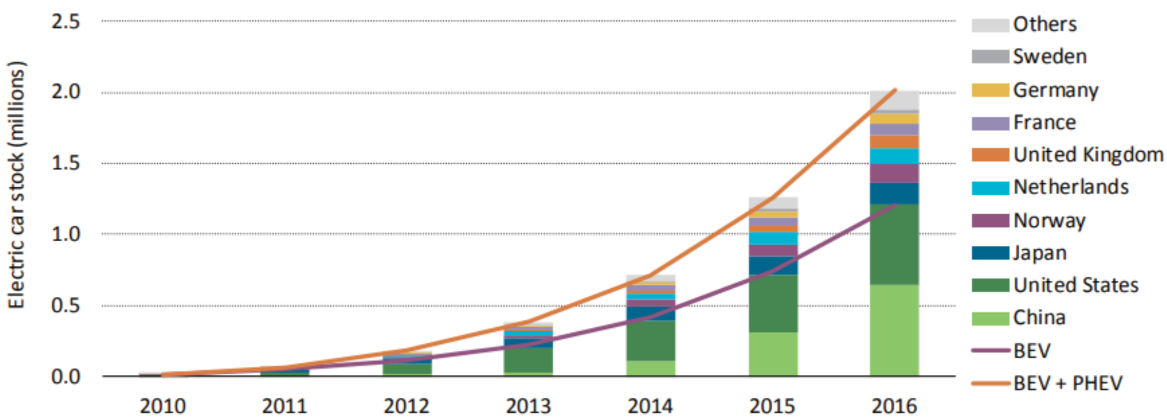


Figure 1.1 Global Cumulative PEVs sold 2010-2016 [1]

The continuation of government initiatives and increases in technological developments are expected to lead to a rapid rise in PEV penetration. Different research organizations estimated a high PEV market penetration level over the next few decades. For example, the Electric Power Research Institute (EPRI) [2] estimated the market share of PEVs in the U.S. to become more than 50% in 2030 and the National Renewable Energy Laboratory (NREL) [3] estimated a 50% global market penetration level of PEVs in 2050.

Despite the important advantages of PEVs, however, their integration also raises new concerns and presents a number of special difficulties related to the analysis of power system reliability. These issues arise from two main areas in which the behaviour of PEV loads is fundamentally different from that of conventional loads. First, a PEV charging load is comparatively larger than that of typical house appliances, which means that the energy consumed by PEVs is expected to represent a considerable draw on electrical power networks. Second, PEV loads involve both types of uncertainties: aleatory (i.e., the intrinsic randomness of driver behaviour) and epistemic (i.e., lack of knowledge about penetration levels, technological developments, and charging infrastructures).

Numerous studies have explored the development of PEV charging load models and their implementation in relation to a variety of power system problems [4]–[12]. For example, a great deal of previous research was focused on investigating the implementation of PEVs into distribution systems with regard to short- and long-term planning problems [5]–[8]; dynamic performance of a power system [9]; economic and financial analyses [10] ; and electricity market polices and opportunities [11], [12]. Thus far, however, very little attention has been paid to the assessment of the effect of PEV inclusion on power system reliability, and to the adequacy of generating capacity in particular. There is in fact recognized need to address the challenges imposed by PEV charging loads, to study their adverse impact on overall system reliability, and to determine whether existing generation capacity is sufficient for accommodating these new types of loads with their high penetration levels and different uncertainty characteristics. To this end, a need exists to establish a comprehensive reliability framework that involves consideration of 1) adequate representation of the elements that characterize the charging process, 2) suitable and sufficient data about the relevant elements, 3) the development of an appropriate model that takes into account the inherent variability and randomness associated with PEV profiles, and 4) the creation of a robust reliability method for incorporating the significant features of PEV charging models with different system characteristics (e.g., inherent component failures and load variations) and for anticipating their impact on reliability. Such a framework would provide essential assistance for system planners and decision-makers so that they can properly quantify the effect of PEVs on system reliability, decide on the correct actions and upgrades required for their grid, and update their policies to accommodate PEV charging loads.

When PEV charging loads become a significant factor in power systems and PEV charging times are uncontrolled, they represent a severe risk to generation reliability, especially at higher PEV penetration and charging levels. Solutions that maintain an acceptable level of system reliability and ensure adequate generation capacity must therefore be found. The traditional efforts and practices directed at meeting new loads and maintain an acceptable level of system reliability can be seen in the addition of supply units in the generation-system side. Installing new conventional resources (e.g., oil, gas and coal) is not logically acceptable and conflicts with the idea of the use of PEV by transferring the emissions from the transportation sector to the electricity sector. Renewable energy sources (RES) have been pointed to as an alternative to supply the additional demand required for PEVs, and it seems a logical solution from an environmental perspective. A large and growing body of literature has thoroughly investigated the RES and quantified their positive and negative effects on system reliability [13]–[17]. The general consensus of these studies is that the contribution of the RES to improving system reliability is far less than that of conventional generation, because the RES is highly dependent on a source that is uncertain and variable and unavailable most of the time. Accordingly, increasing the share of RES is not yet a cost-effective solution to enhance system reliability bearing in mind the technical issues, inherit uncertainty, and challenges they produce.

Recently, there has been a growing trend towards investigating solutions at the demand side and exploiting the existing flexibility to help improve reliability [18], [19]. This trend has, in fact, been reinforced and facilitated by the smart grid concept, which emphasizes the maximization of resource utilization through 1) appropriate infrastructure that enables information-sharing and communication between system service providers and end-user customers, 2) expanded intelligent communication and control technologies for facilitating the development and incorporation of demand response (DR) programs, and 3) the provision of timely information and control options to consumers so that they can participate and adapt their energy consumption accordingly.

DR is defined by the Federal Energy Regulatory Commission [20] as “Changes in electricity use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market price or when system reliability is jeopardized.” Common types of DR programs include time-of-use (TOU) pricing, real time pricing (RTP), and critical peak pricing

(CPP). These programs are acknowledged as useful for maintaining a fairly uniform load level, thereby avoiding or deferring the costs of new supply resources, reducing wholesale market prices, and operating the grid reliably and efficiently [21]. The benefits of DR programs are also extended to participating customers, and these benefits fall into two categories. First, financial benefits can be recognized throughout the bill savings and/or incentives payments received by participating customers who adjust their electricity demand in response to system critical events. Second, a proper DR program helps in reducing the likelihood and consequences of electricity disturbances that might decrease customer comfort and satisfaction [19], [21].

Different DR programs have already been implemented by many North American utilities, and TOU programs have been in use for several years [22], [23]. To date, no previous studies have investigated the association between PEV owner response to TOU pricing and its effect on system reliability. and the following research questions require answers: 1) Are existing TOU rates designed for residential loads capable and efficient with regard to new PEV charging loads? 2) Does TOU-based billing help adjust consumer charging behaviour and mitigate adverse effects of uncontrolled PEV charging loads on system reliability? A primary goal of the research presented here was to develop a model that would address these questions. In addition, to the best of the author's knowledge, no study has reported the application of dynamic DR programs (e.g., CPP) for use with PEV charging loads from a reliability perspective. Filling this gap is a core contribution of the work presented in this thesis.

1.2 Research Objectives

Motivated by what has been discussed in the previous section, this thesis proposes an innovative reliability framework for the integration of different PEV charging load models. The development of the proposed framework is based on clear descriptions of relevant factors, careful collection of necessary data, and special treatment and innovative models for ensuring an accurate determination of the impact on reliability. The following are the distinctive features and main contributions of the proposed work:

1) For the first time, collections of probability distribution functions (PDFs) have been evaluated statistically in order to establish which models best reflect the main variables associated with

driver behaviour (e.g., arrival and departure times and daily mileage). Using theoretical PDFs offers several advantages [24] include:

a) They provide a physically realistic description of the behaviour of the variable of interest and ultimately produce satisfactorily accurate quantiles, performance indices, and risk estimates.

b) The mathematical formulas are a compact, easy, ready-to-use way of directly describing data relevant to driver behaviour variables. They save time and effort for planners, researchers, or others who wish to estimate realistic PEV charging load profiles.

c) They can be used to extend the range of sample data to include generated values that might actually occur but were missed in the sample, permitting estimates of extreme events beyond the sample range.

2) Novel stochastic PEV charging load simulations have been developed for use with uncontrolled and TOU-based strategies. To handle inherent uncertainties and generate multiple scenarios, the models are based on a Monte Carlo simulation (MCS) combined with fitted PDFs. A proposed decision tree model is coupled with the uncontrolled charging model to enable consideration of driver response to TOU pricing. For an accurate determination of the impact on reliability, both models are based on realistic estimates of factors affecting charging and explicitly take into account any underlying uncertainties associated with random variables.

3) The effect of PEV charging characteristics on the reliability and performance of generation systems has been thoroughly investigated through a comprehensive study of reliability assessment. Also provided are a detailed discussion of and important insights into the behaviour of reliability indices with respect to PEV charging characteristics: driver behaviour, penetration levels, charging levels, battery capacities, and customer response to TOU pricing.

4) A reliability framework is proposed for incorporating PEV charging loads with dynamic critical events programs. The framework involves two models: the first determines the time and demand for critical system events, when system supply facilities are unable to meet PEV loads, and the second assesses the feasibility of PEV owner response to critical events.

5) A novel reliability based framework is proposed for designing a TOU schedule well-adapted to the PEV charging loads. The proposed framework involves the accomplishment of three

main stages. The first stage is targeted at developing different stochastic simulation models that can generate a large number of time series data and properly consider the random components failures, the stochastic nature of wind generation, and the inherent randomness in driving patterns and other uncertainties of PEV characteristics. In the second stage, special data treatments, statistical tools, expert criteria are used to arrive at a range of possible scenarios of TOU schedules which are then examined exclusively in the third stage to determine the best schedule.

1.3 Thesis Outline

The remainder of the thesis is organized as follows:

Chapter 2 presents background information pertaining to power system reliability and its relevant aspects. This chapter also reviews the related concepts and available techniques for generating system adequacy assessment, and surveys the previously developed models with regard to PEV load and wind generation in particular.

Chapter 3 presents statistical analysis for evaluating groups of PDFs in order to determine the models that best reflect the main characteristics of driver behaviour.

Chapter 4 introduces the methodology of the proposed reliability assessment framework for establishing the effect of PEV charging loads under uncontrolled and TOU-based strategies.

Chapter 5 explains the methodology for applying a dynamic DR program with PEV charging loads and shows the effectiveness of the proposed framework with respect to improving system reliability using several case studies**.**

Chapter 6 introduces the methodology of the proposed reliability framework for designing efficient TOU schedules for PEV charging load.

Chapter 7 presents the thesis summary, conclusion and suggested future work.

Chapter 2
Background and Literature Review

2.1 Introduction

In Chapter 1, the motivations and research objectives of the presented work have been discussed, whereas this chapter is dedicated to reviewing the related concepts and the available techniques of generating system adequacy assessment in general, and surveys the previously developed models with regard to plug-in electric vehicle (PEV) charging load and wind generation in particular. This chapter is divided into four main parts. The first part reviews the general aspects of power system reliability, covering its scientific definitions as well as main types and categories. The second part summarizes the basic concepts and the related aspects of the generating system adequacy assessment, including the adequacy problem statement, and detailed descriptions of the elements involved and the most common probabilistic techniques. The third part discusses the issues imposed with the inclusion of PEV loads into the adequacy assessment of generating systems. This part of the chapter also reviews the methods proposed in the literature to incorporate PEV loads into reliability assessment. The final part provides an examination of the generation adequacy problem when wind generation is integrated.

2.2 Power System Reliability Evolution

One of the main objectives of modern electrical power system utilities is to provide their customers with reliable electrical energy at an acceptable cost. Achieving this goal is a significant concern for all parties associated with modern power systems: generation, transmission and distribution companies, individual operators, and end users. With respect to power systems, reliability is the term used for denoting the measure of the overall system ability to meet customers' electrical energy needs [25]. According to the North American Electric Reliability Corporation (NERC), power system reliability can be defined as "the ability to meet the electricity needs of end-use customers, even when unexpected equipment failures or other conditions reduce the amount of available power supply" [26].

Power system reliability is typically viewed as having two aspects: system adequacy and system security [27], [28]. System adequacy can be defined as the existence of sufficient facilities within a power system to meet the load requirements without the violation of steady-state limits. System adequacy refers to static conditions rather than dynamic or transient system disturbances, and is normally associated with the reliability assessment of system planning over the long term, which can range from a year to several years. System security, however, signifies the ability of the system to withstand sudden disturbances, such as voltage instability situations or the unanticipated sudden loss of system elements. System security is therefore associated with dynamic or operational measures over a short-term timeframe of a few minutes to an hour.

Because modern power systems are very large, complex, highly integrated networks, evaluating the reliability of an entire power system is difficult, if not impossible [27]. For this reason, experts in the field of power system reliability have traditionally divided a power system into three functional zones (generation, transmission, and distribution) in order to provide a succinct means of identifying which part of the power system is under analysis. These three functional zones can be organized into three hierarchical levels, as shown in Figure 2.1.

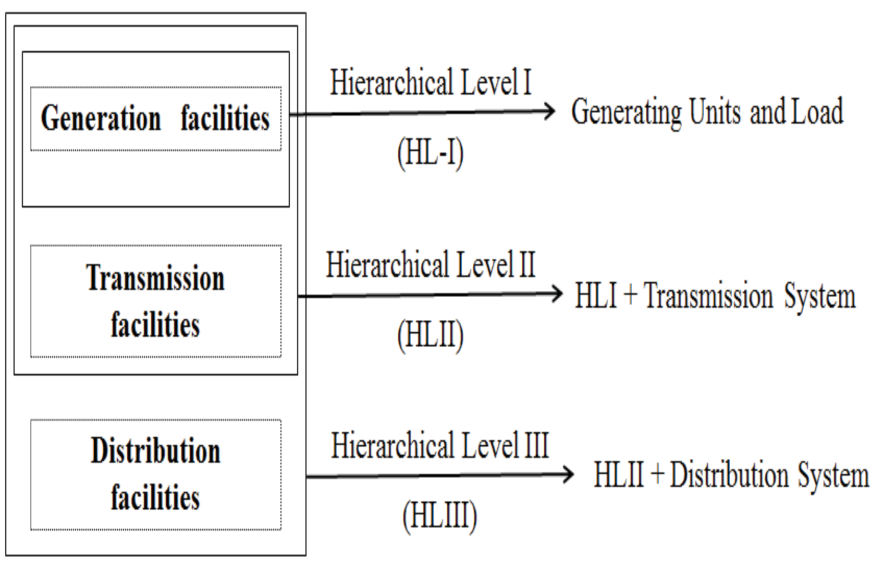


Figure 2.1 Reliability assessment hierarchical levels [27]

At hierarchical level I (HL-I), reliability evaluation usually pertains to the adequacy of generating capacity, with the only concern being an examination of the ability of the system to meet the aggregated system load. At this level, transmission and distribution systems are disregarded from the reliability study; these systems are assumed to have 100% reliability. Adequacy evaluation at hierarchical level II (HL-II) includes both generation and transmission facilities and normally pertains to the evaluation of the reliability of the composite system, or bulk power system. At this level, adequacy evaluation becomes an assessment of the integrated ability of the generation and transmission systems to deliver energy to the load points. The last level indicates an overall assessment that includes consideration of all three functional segments and is identified as hierarchical level III (HL-III). Adequacy evaluation at HL-III, which includes all three functional zones simultaneously, is quite difficult to conduct in a practical system due to the computational complexity and large-scale modeling involved. Reliability analysis at this level is therefore usually performed separately in the distribution functional zone, using the results of HL-II as input.

The presented research work is devoted to the aspect of adequacy assessment of power generating systems (HL-I) incorporating PEV and wind energy recourses.

2.3 Generation Adequacy Assessment HL-I

Generation adequacy assessment is an important aspect in the power system planning and design to make sure that sufficient resources are available to meet the expected demand plus required reserves. The main purpose of the adequacy assessment is to provide useful information to the system planners and the authorities to decide on and advice for new investment plans. With the expected rapidly increase in power demand in addition to the stochastic nature inherent in power systems (variability and uncertainty of renewable energy sources, components failures, and load variations), it becomes extremely important to evaluate the existing facilities and ensure the required degree of system reliability and continuity of service.

The adequacy of the generating capacity can be assessed with the use of either deterministic or probabilistic approaches [29], [30]. Deterministic techniques were used early on practical applications, and some power system utilities are still dependent on these techniques. With deterministic techniques, the estimation of the reserve required for maintaining an acceptable level of system reliability is dependent on the past experience and the expert judgment. These techniques seek the best installed supply capacity considering a fixed percentage reserve such as affixed reserve equal to the largest generating unit, a fixed percentage of the total installed capacity or the peak load, or a mix of these.

These techniques thus fail to take into account the stochastic nature of the behaviour of power systems that result from component failures or variations in demand. In the past, a number of factors, such as lack of reliability data and computational resources, created a preference for the use of deterministic techniques [25]. However, with the availability of applicable reliability data and advancements in computational technologies, these factors no longer apply, and logic now dictates the use of probabilistic techniques, which can include consideration of the stochastic nature inherent in renewable energy resources, component failures, and load variations and result in accurate estimations of risk reliability [29] .

Most probabilistic techniques developed for the evaluation of generating capacity can be categorized into two general types: analytical and Monte Carlo Simulation (MCS) [29], [31]. An analytical technique relies on basic mathematical models as representations of system elements and then produces system reliability indices using direct numerical solutions. MCS methods, on the other hand, estimate reliability indices using simulations of the actual process and random behaviour of the system. MCS techniques are further classified into two types: non-sequential and sequential. In non-sequential techniques, the system states for all components are sampled, and each time point is considered independently without the chronological time being taken into account. In contrast, as a means of creating the complete system operating cycle, sequential techniques include consideration of chronology so that the operating cycles of all components can be simulated and combined.

Each method has advantages and disadvantages, so the appropriate method is determined based primarily on the type of evaluation desired as well as the nature of the problem. The main procedures in the development of a model for assessing generating capacity adequacy, with reference to three of the most common probabilistic techniques, are presented in [30]. Also presented in [30] is a comparison of these techniques from different perspectives based on their application in two well-known test systems. In general, all of these methods are effective and efficient for evaluating the adequacy of conventional generating capacity. However, the following important points should be noted:

1- The analytical technique is very efficient since it requires a much shorter computational time than the MCS techniques; especially for the cases when conventional units are represented by only 2-states and when the system is relatively small.
2- The analytical method, however, is inappropriate for a complicated or large system, usually represented by multistate units, where variable energy sources such as wind and solar generation are included, necessitating further approximations.
3- Unlike the analytical method, MCS methods are unlikely to provide exact results because of their dependence on a random number generator.
4- In MCS methods, a small number of samples cannot guarantee accurate results, and the number of samples should therefore be well defined, a factor usually controlled by stopping criteria.
5- Compared to those of other techniques, the procedures involved in the non-sequential MCS method are very simple and straightforward.
6- The non-sequential MCS method offers no notable benefits over the analytical method, since it requires relatively lengthy computational time.
7- The non-sequential MCS method and the analytical method are characterized by the same weakness: failure to include consideration of the chronology in the representation of the nature of the generation and load, which means that neither the frequency and the duration indices nor the interruption indices can be computed.
8- The sequential MCS method includes recognition of the chronology of events and the stochastic behaviour of the system elements, so it provides additional data about the behaviour of a system, such as time-based indices (frequency and duration indices) and their probability distributions.
9- The features offered by sequential MCS method are essential for evaluating a power system that includes non-conventional resources such as wind, solar, and PEV, which are time-dependent and correlated.
10- The only disadvantage of the sequential MCS method is the need for longer computational time than with other methods.

However, rapid advancements in computer technologies have, to a large extent, eliminated this drawback and made the use of sequential MCS method practical and viable. In addition, since generation adequacy assessment problem is a long term planning problem (e.g. off-line problem) that is usually performed several years ahead, an accurate model is much desired while the computational time is less significant. Therefore, the sequential MCS technique has been employed in this research work owing to its remarkable features.

2.4 Background Information about PEV Load Characteristics

Currently, there are two main types of PEVs available in the market [32], as follows:

- Plug-in hybrid electric vehicles (PHEV): These vehicles are known bi-fuel vehicles that have the same characteristics as conventional (i.e., powered by internal combustion) cars, with the addition of battery storage systems that can be recharged from an external electricity supply.
- All-electric or battery electric vehicles (BEV): These vehicles run solely by using battery storage systems to supply an electrical motor, without the use of an internal combustion engine.

With respect to the estimated PEV charging load and its impact on different power applications, a variety of criteria and techniques have recently been showcased in numerous publications [4], [33]. Developing realistic PEV load profiles requires reliable estimates of a number of key factors, namely: the amount, place, and time of charge. Estimating these factors, however, is challenging, since none of the available data is precise, and therefore cannot be relied on. These factors and related aspects are summarized in Figure 2.2 and discussed in detail in the following subsections.

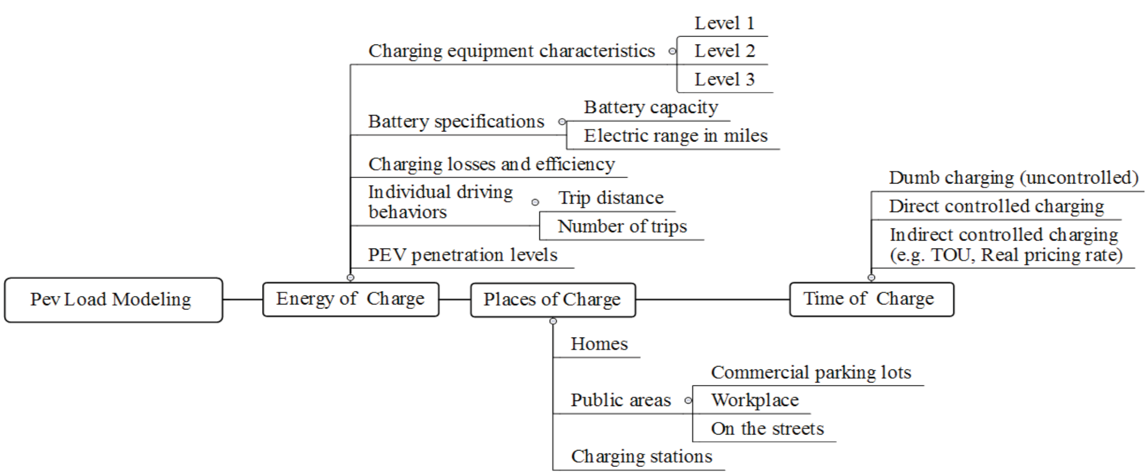


Figure 2.2 Factors involved in developing the PEV charging load

2.4.1 The Amount of Consumed Energy

The energy required by a PEV is highly dependent on a number of key considerations, including charging equipment characteristics, battery specifications, and driving patterns. Charging equipment denotes the rate of electric power at which PEV batteries are charged. For example, the Society of Automotive Engineers (SAE) in North America has proposed a set of charging standards for PEV, known as the J1772 standard. Table 2.1 provides an overview of the types of PEV chargers according to the J1772 standard.

Table 2.1 Charging levels based on the SAE J1772 standard [32]

Type	Voltage V	Current A	Power kW	Possible Use
Level 1	120	12/16	1.3/1.9	Residential and workplace charging
Level 2	208/240	30/80	6.24/19.2	Residential, workplace, and other public charging facilities (e.g., shopping centers, city parking lots, airports, hotels, etc.)
Level 3	Up to 600	Up to 200	50/150	Fast charging stations

The energy consumed by PEVs differs from one type to another according to their battery capacities and electric range in miles. Various models of PEVs offered by different brands are currently available in the market today, and they are different in terms of size, design, price, and powertrains in order to satisfy various consumer preferences.

Driving behaviours (e.g., daily travel mileages for each vehicle) differ from one driver to another. It is illogical to assume that all PEV travel the same daily distance and hence that they consume the same energy. Transportation survey data for the USA [34] offers very useful information about individual driving patterns. This kind of information helps in capturing real-life scenarios and provides a more realistic estimation for PEV charging profiles.

2.4.2 The Place of Charge

PEV charging infrastructure is an important aspect that determine the allocation of PEV demand for a given day. From the practical point of view, home is the most dominant place for charging, although some governments have been attempting to install a number of public charging facilities. The PEV owners' survey results reported in [35] reveal that more than 80% of PEV owners charge their vehicles at home. Where people prefer to charge their PEV is a question that has been answered by a large number of drivers (PEV owners and not owners) in several surveys in different countries [36]. The majority of respondents preferred to charge at home over public charging locations such as charging stations, work parking lots, or shopping parking lots. There are several possible explanations for this. One is that homes are considered the main place where people's vehicles are available and parked most of the time. So, the easy accessibility and convenience of home charging carries a strong appeal for PEV owners. Second is that a lack of awareness of public charging infrastructure due to its limited availability.

It is still to be determined which charging infrastructure is the best to support PEV deployment in a beneficial way for all associated parties. However, home charging infrastructure, compared with other public charging infrastructure, appears to be more consistent with the preference of most PEV drivers, suggesting that PEV policies should prioritize home charging access over public charging deployment. Nevertheless, improving the accessibility and viability of public charging facilities is crucially important, since some drivers might not have access to home charging or have short battery ranges that also require charging when away from home.

2.4.3 The Time of Charge

Time of charging is one of the essential elements in the determination of PEV charging profiles. In the literature, the time of charge is usually determined upon the charging schemes, which are mainly categorized into three types [37], [38]: uncontrolled, indirect controlled, and direct controlled. Further details of these types are discussed in the following:

Uncontrolled charging (UC): This is when decisions about charging are completely up to the PEV owners, and hence they can, without any restrictions, charge their PEVs at any time they choose. Studies are widely available in the literature that involve modeling UC using deterministic recharging schedules in which all PEVs are charged at predefined times (usually overnight) and left until fully charged. However, these models do not reflect the real world, where charging can occur at any time during the day, depending on the driver behaviour. Alternatively, other studies have used the arrival times at parking locations from transportation data in order to estimate the UC. Due to the lack of real data pertaining to the driving patterns of PEV, the transportation survey data for conventional vehicles are acknowledged as a good source to obtain useful information in regard to driving patterns, such as arrival and departure times, number and length of trips, and parking locations.

Indirect controlled charging (ICC): This scenario is similar to the previous one in that PEV owners can charge their vehicles as they choose. However, the incentives for indirect demand-side management activities may create a certain level of control over time of charging, prompting PEV owners to adjust their charging behaviour accordingly. With respect to the responses of PEV owners to time-of-use (TOU) electricity pricing, for example, it is assumed that PEV users arriving at on-peak and mid-peak hours will wait until the start time of an off-peak period. The idea of these management polices is to encourage consumers to shift their loads toward off-peak periods, where the cost is lower.

Controlled charging (CC): This scenario envisions an active management system in which PEV charging loads are solely controlled and managed by the service providers or an aggregator entity. Therefore, the time of charge is determined by the aggregator entity in a way that benefits and satisfies all associated parties taking into account the PEV owners' needs and the system's requirements. The PEV charging load will likely take place during the "valley hours" in order to avoid system overload, excessive voltage drops, and the huge investment required for system reinforcements or expansions. This context is extended to what is called "smart charging", which relies on a two-way communication infrastructure in a smart grid paradigm. The smart charging strategy enables bidirectional power flow between the PEV and the power grid (i.e., the V2G concept), where PEV can be discharged to provide ancillary services to the grid.

2.5 Inclusion of PEV Models into the Evaluation of Generation Adequacy

With respect to the estimated electric vehicle charging load and its impact on different power applications, a variety of criteria and techniques have recently been showcased in numerous publications [4]–[12]. For example, a large and growing body of literature was focused on exploring the impact of PEVs on distribution systems with regard to short- and long-term planning problems [5]–[8]; dynamic performance of a power system [5]–[8]; economic and financial analyses [10]; and electricity market polices and opportunities [11], [12]. However, the literature contains insufficient research related to assessing the impact of PEVs on power system reliability in general and on generating system adequacy in particular. Although some recent studies have produced very useful findings, most have involved gauging the impact at the power system distribution level. For example, the reliability performance of residential distribution systems that incorporate PEVs was discussed in [39], and the work presented in [40] evaluated the reliability of an urban distribution system in China, where a PEV charging load is considered interruptible. In [41], [42], reliability assessment at the distribution level was extended to include varied operation modes: vehicle-to-home (V2H) and vehicle-to-grid (V2G). An analytical approach was used in [43] for examining the reliability of distribution systems when an electric vehicle (EV) charging load is modeled to include consideration of the battery exchange mode. The authors of [39]–[43] focused on the assessment of a PEV load in a distribution system as a separate entity and assumed that the main supply facilities have unlimited capacity, or 100 % reliability. The focus has therefore not been on evaluating the supply-demand balance of a system, but rather on assessing distribution system facilities with respect to distributing the energy received from the bulk system to end users while maintaining acceptable levels of service continuity.

Few studies have been targeted at an equally important and related problem: assessing and determining whether existed generation facilities are sufficient for reliably accommodating PEV charging loads, with their different characteristics and associated uncertainties. Often called generation adequacy assessment, this problem represents an important component of power system planning and design. This crucial assessment provides system planners and authorities with the information they need in order to decide on new investment plans, system reserve margins, maintenance scheduling, and competitive markets [28], [44]. In line with the scope of this thesis, special attention has been paid to reviewing the literature pertaining to the adequacy assessment of generating systems that incorporate PEV charging loads. The authors of [45] investigated the potential impact of PEVs on the U.S. electricity supply. However, in the development of their PEV model, they relied on unrealistic assumptions and ignored important factors; for example, they assumed that all PEVs were driven 20 miles/day, consumed all of the energy in the batteries, and were charged simultaneously at an arbitrary start time. The study reported in [46] involved an investigation of PEV enhancement of power system reliability when wind energy resources were incorporated. In [47], a bidirectional charging power control model was introduced; it was developed to manage the power balance between generation and load, thereby reducing or eliminating generation shortages. The studies presented in [45]–[47] failed to include consideration of key factors that significantly influence PEV charging profiles: random variables pertinent to driver behaviour, such as daily mileage and arrival and departure times, the diversity of battery specifications, PEV market shares, and the uncertainties associated with these factors. The study presented in [48] was focused on estimating the EV impact on reliability when charging stations are operated based on battery swapping. The concept of battery swapping has received less attention in the U.S. and Europe than the plug-in mode due to its technical and economic limitations.

The authors of [49] developed a PEV charging load model as a means of evaluating the reliability of the U.S. Northwest Power Pool area for a variety of PEV penetration levels, and then, in [50], reported their estimate of the extension of generation facilities required. The work published in [51] described an analytical approach for assessing the reliability of a power system integrated with PEVs under different charging scenarios. Compared to previous research, the studies presented in [49]–[51] provided important findings because they involved the use of sample data from transportation sectors in order to incorporate varied daily mileages and arrival times as random variables and to develop PEV charging load accordingly. Even these approaches, however, were based on oversimplified assumptions and have limitations in common with previous studies; for example, small batteries with a fixed electric range are assumed for all PEVs and are considered to be charged to full capacity regardless of the randomness of driver stay-at-home habits. In addition to the lack of adequate representation of relevant PEV charging features, the manner of modeling uncontrolled PEV charging in a reliability analysis also involves oversimplifications and tends to be deterministic: only one charging scenario is developed, which is assumed to be constant over the reliability assessment time horizon (typically one year). This treatment of the problem is unrealistic, since current PEV load characteristics are highly uncertain because of the inherent variations in driving patterns and the randomness of PEV profiles (penetration levels, market shares, battery specifications, charging levels, etc.).

Based on the above discussion, it can be observed that, in previous models, several important aspects of PEV charging loads were either largely ignored or represented in an excessively simplified manner. In reliability analysis, the compound effects of ignoring these factors and their related uncertainty and variability are non-trivial. They can significantly affect the accuracy and validity of results, leading to inaccurate determinations of the actual PEV impact. For these reasons, there is crucial need for robust stochastic techniques that include effective consideration of the input variables associated with PEV charging characteristics and that explicitly take into account the underlying uncertainties connected with these variables.

When PEV charging loads become a significant factor in power systems and PEV charging times are uncontrolled, they represent a severe risk to generation reliability, especially at higher PEV penetration and charging levels. Solutions that maintain an acceptable level of system reliability and ensure adequate generation capacity must therefore be found. The traditional option for maintaining an acceptable level of system reliability is to expand power supply facilities to meet the required load, with some critical circumstances requiring power utilities to enact load curtailment. Modern electric utilities have recently directed increased attention at exploiting the flexibility in existing system demand by promoting load side management programs so that energy consumption management benefits and satisfies all associated parties [18], [19]. These tend, in fact, have been reinforced and facilitated by the notion of the smart grid, which has been envisioned to meet a wide range of objectives that include: 1) maximizing asset utilization and automating control actions to deliver high quality electricity service and enhanced system reliability; 2) activating customer participation by developing intelligent communication and control technologies and deploying varied demand response (DR) programs. Achieving these objective rests on overcoming a number of the special challenges and difficulties these changes produce in power systems. Therefore, addressing these challenges represents a major area of interest for academic and industrial researches.

The basic idea of DR programs is to encourage and incentivize the end users to reduce their consumptions when the system is stressed or when system reliability is threatened. Many DR programs have therefore already been implemented by several utilities around the world, and some are under pilot study. Common types of DR programs include time-of-use (TOU) pricing, real time pricing (RTP), and critical peak pricing (CPP). These programs are acknowledged as useful for maintaining a fairly uniform load level, thereby avoiding or deferring the costs of new supply resources, reducing wholesale market prices, and operating the grid reliably and efficiently. The benefits of DR programs are also extended to participating customers, and these benefits fall into two categories. First, financial benefits can be recognized throughout the bill savings and/or incentives payments received by participating customers who adjust their electricity demand in response to system critical events. Second, a proper DR program helps in reducing the likelihood and consequences of electricity disturbances that might decrease customer comfort and satisfaction [19], [21].

Different DR programs have already been implemented by many North American utilities, and TOU programs have been in use for several years. For example, in Canada's most populous province, the Ontario Energy Board launched static TOU rates in 2006, and now most residential and small business charges are based on these rates [22]. The basic TOU concept is to divide the day into annual static time periods (usually 3 periods for summer and winter weekdays) and to provide customers with the rate for each period months in advance (usually one or two annual announcements). To date, no previous studies have investigated the association between PEV owner response to TOU pricing and its effect on system reliability, and the following research questions require answers: 1) Are existing TOU rates designed for residential loads capable and efficient with regard to new PEV charging loads? 2) Does TOU-based billing help adjust consumer charging behaviour and mitigate adverse effects of uncontrolled PEV charging loads on system reliability? A primary goal of the research presented here was to develop a model that would address these questions.

Recent notable innovative dynamic DR programs include 1) CPP, whereby participating customers pay much higher prices during critical hours (e.g., in cases of severe stress on the grid or high market prices) and pay regular rates during other hours, and 2) peak time repeat (PTR) programs, whereby participating customers are paid for load reductions during critical events that occur for a limited number of hours or days per year (usually not exceeding 100 h/year, or 1 % of the year), and about which they receive only short notice [21]. A few studies have focused on the application of these DR programs. For example, in 2006, the authors of [52] studied the automated critical peak test field in California with the goal of evaluating how CPP automation could increase participation rates and load-saving efficiency. The study presented in [53] investigated the optimal scheduling of CPP events with the integration of wind energy sales into the day-ahead market. To the best of the author’s knowledge, no study has reported the application of dynamic DR programs for use with PEV charging loads from a reliability perspective. Filling this gap is a core contribution of the work presented in this thesis.

2.6 Inclusion of Wind Generation Models into the Evaluation of Generation Adequacy

Recent decades have seen a dramatic increase in the utilization of renewable energy resources by power utilities around the world. Of these resources, wind energy is a proven source of power generation with positive global, social, economic, and environmental benefits. Today, wind energy has become a mature, abundant, and emission-free power generation technology, with a significant percentage of electrical power demand being supplied by wind farms. However, wind generation is dependent on wind speed, which is difficult to predict with a high degree of accuracy. The intermittent nature of wind generation makes its operation and planning a complex problem. One impediment to the increased use of wind generation is linked to reliability assessment: a recognized ongoing need to study the contribution of wind generation to overall system reliability and to ensure the adequacy of generation capacity.

With respect to the evaluation of the reliability of power systems that incorporate wind energy, a variety of criteria and techniques have been developed over almost thirty years [14]–[16], [54]. A survey of the literature reveals that, with respect to reliability assessment, probabilistic techniques (analytical and simulation) are the most commonly acknowledged means of modeling wind generation. Most models developed for including wind generation capacity in adequacy assessment analysis can usually be classified based on two types of representation: 1) multi-state models or 2) time series models. In the former, a wind farm is treated as a conventional unit with multiple states (either fully rated or failed, or potential derated states), and is integrated with conventional units using an analytical technique or a non-sequential Monte Carlo simulation (MCS) technique [55]–[57]. However, these models and techniques are characterized by two main disadvantages. First, the chronological characteristics of wind speed cannot be taken into account, which means that some time-based indices (frequency and duration) cannot be accurately evaluated. Second, the inaccuracy and complexity associated with the discretization process make developing an accurate wind farm model very difficult. Instead, time series models are acknowledged as more useful for representing wind generation because of their essential feature of preserving the chronological variability associated with wind, which facilitates the integration of wind generation into the sequential MCS process used for conventional generation [13], [17]. This type of model in fact reinforces the major advantages of a sequential MCS method, which can comprehensively evaluate power system reliability and provide a wider range of indices than do analytical or non-sequential MCS approaches. However, it also requires significantly greater computing time and effort and involves more complex procedures. Recent rapid advancements in computer technology have somewhat dispelled this drawback and have made the use of simulation methods both practical and viable.

To accurately capture the stochastic nature and random behaviour of wind at a particular site, modeling wind generation for reliability assessment requires extensive historical wind speed/power measurements. However, in the face of the unavailability of sufficient data, reliable stochastic wind simulation techniques are called for. In recent years, owing to their ability to represent the chronological variability and stochastic nature of the wind, considerable research has been directed at time series wind speed/power simulation models. The literature describes two categories of proposed stochastic wind simulation models: stochastic wind speed models and stochastic wind power models [58]. The former are based on wind speed measurements, while the latter are developed from wind power measurements, as outlined in Figure 2.3.

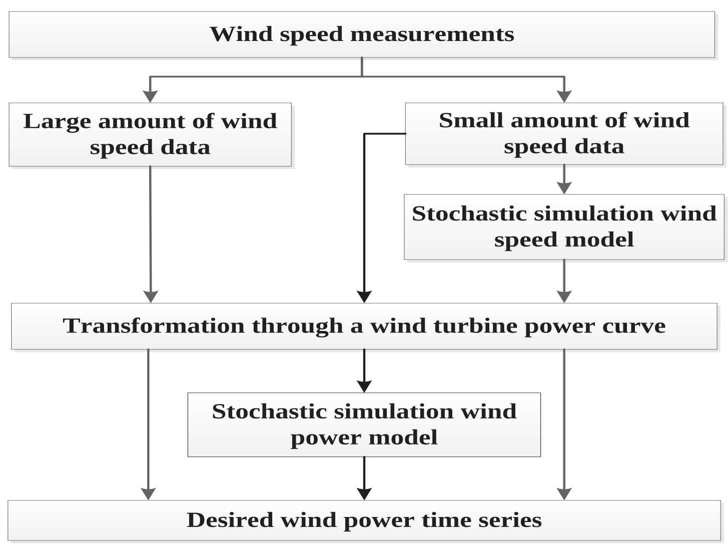


Figure 2.3 Classifications of stochastic wind simulation models

Considerable work has been conducted on the development of wind speed models, including autoregressive moving average (ARMA) models [58], [59] and Markov chain Monte Carlo (MCMC) models [60]–[65]. When the wind speed is between the cut-in and rated values, any error in wind speed modeling is increased by a cubic factor for the corresponding wind power. This drawback can be addressed if the measured wind speed data are first transformed to wind power data.

A reliability research group at the University of Saskatchewan developed a time series model for the evaluation of wind power reliability based on the ARMA model [59]. They considered different orders of the ARMA model in order to determine the optimal fit between the simulated wind speed time series and the measured wind data. The ARMA model is further enhanced incorporating the hourly mean and standard deviation of wind data over a long period of time (a 37 years database). They concluded that the wind speed data simulated by their developed ARMA time series model satisfied basic statistical tests, such as those related to hourly autocorrelation, seasonal characteristics, and diurnal distribution of wind speed, and that it thus could be used as a suitable time series model for integrating wind into the reliability evaluation of generating systems. In fact, this model is now used extensively for incorporating wind generation into the adequacy assessment of generating systems. In [17], the authors compared adequacy indices of generating capacity using five wind speed models: Mean Observed, ARMA, Moving Average, Normal Distribution, and Markov. The results show that the ARMA model can provide a more comprehensive representation of the actual wind regime than the other wind speed models and that it is the most suitable for use in a sequential simulation process. However, ARMA models cannot guarantee an optimal fit for the probability distribution function (PDF) of the simulated time series, as discussed in [61]. The process for obtaining the proper ARMA model involves high complexity for estimating coefficients, order and parameters, and should be done carefully for each wind site [55].The work reported in [58] also revealed that the direct application of ARMA models for building stochastic wind power models is infeasible, since the nature of wind power generation is non-stationary, non-Gaussian, and random.

Alternatively, Considerable work in the literature has widely studied the application of MCMC in developing a stochastic time series using either wind speed or wind power data. A Markov chain represents a system of elements that move from one state to another over time. In a Markov chain process, the probability of a given state at a given instant can be deduced from information about the preceding state [61]. The transition matrices in a Markov chain mimic the pattern of the hourly changes in historical wind data so that the simulated wind data track that pattern.

Early models based on MCMC were subject to practical shortcomings, such as the imperfect preservation of autocorrelation characteristics as well as the inaccuracy and complexity associated with the discretization process. However, a number of published studies have been undertaken in order to eliminate these drawbacks and improve the efficiency of MCMC models. The study presented in [60] used the first-order and second-order schemes of a Markov chain model as a means of simulating synthetic wind speed data; the authors concluded that a higher-order Markov chain scheme can provide slightly enhanced results. The effect of the choice of Markov chain states was also examined in [62]. The results revealed that increasing the dimensions of the Markov model provides more accurate results. In [61], synthetic wind speed was compared with synthetic wind power using an MCMC model. The results show that the development of a synthetic wind power model from data measured directly in the power domain is more accurate and provides an excellent fit for both probability distribution and chronological correlation.

To further improve the MCMC model, the authors of [63] suggested enhancing probability distribution and chronological correlation by representing monthly variations through the use of a transition Markov chain matrix for each month. The study presented in [64] investigates the application of a seasonal simulation for the synthetic generation of wind speed data using MCMC technique with only one month of data from each season. The authors of [64] conclude that only one month of data was sufficient to reproduce most of the general statistical characteristics for the related season implying that MCMC model can be efficient for completing missing data. In [65], two improvements on traditional MCMC method are introduced. The first one is a new state discretization process while the second improvement based on the empirical distribution of each state. A comparison result reveals that the improved method overperforms the traditional method.

Although MCMC models are widely used to generate wind speed/power time series, the application of MCMC models for use with a wind power time series in the assessment of the adequacy of generating capacity is very limited. This is might be due to the fact that MCMC models still have some shortcomings that would significantly affect time-based applications, which depend greatly on the accuracy of the simulated wind time series. The main shortcomings are the imperfect preservation of correlation characteristics with system load as well as the inaccuracy and complexity associated with the discretization process. In this thesis, these shortcomings are addressed when incorporating wind farm modeling into the conventional evaluation of generation adequacy.

2.7 Summary

This chapter first provided a review of the reliability assessment of power systems, including the standard definitions and different hierarchical levels. As a focus of the thesis, the related models, and commonly used techniques for generation adequacy assessment HL-I are discussed. This chapter also presented background information about PEV types, PEV load characteristics, and associated uncertainties. This was followed by a discussion on the existing work with regard to the reliability assessment of power generation systems that include PEV load. The last part of the chapter discussed the generation adequacy problem when wind generation is integrated, and also surveyed the models most-used in the literature to assess the reliability of wind generation capacity.

Chapter 3
Statistical Models for the Variables of the PEV Driver Behaviour Using Goodness of Fit Analysis

3.1 Introduction

Preceding chapter provided an overview of power system reliability in general, and emphasized the essential concepts of generating system adequacy assessment for HL-I. In addition, it reviewed the general information on plug-in electric vehicles (PEVs) and highlighted the existing work with regard to the adequacy assessment problem that include PEV load and wind generation. This chapter focuses on an innovative feature of the proposed work for modelling PEV charging load for use in many power system applications: the use of statistical analysis for evaluating groups of probability distribution functions PDFs in order to determine the model that best reflects the main characteristics of driver behaviour (e.g., home arrival and departure times and daily mileage).

Developing PEV charging load profiles for use in many power system applications requires reliable estimates of a number of random variables that characterize the charging process. Among these variables are the variables relevant to the driver behaviour. Determining reliable estimates of these variables is challenging, since no currently available sufficient real data that can be relied upon for precise descriptions of these variables. With respect to this topic, the literature are classified into three categories. Earlier studies that model PEV charging load for different power system problems either largely ignored the random variables pertinent to driver behaviour or else represented them in an excessively simplified manner [45], [46], [66]. For example, the study presented in [66] was based on the assumption that all PEVs were driven 30 mi/d, consumed all of the energy in the batteries, and were charged simultaneously at an arbitrary start time. Implementing these assumptions for modelling the PEV load will produce considerable errors in determining the actual PEV impact. Some other studies [4], [49], [50] involved the use of sample data extracted from the available transportation mobility data in order to incorporate varied daily mileages and arrival and departure times as random variables and to develop PEV charging load accordingly. The use of the sample data has two main limitations: 1) the accuracy of these studies is primarily based on the availability of large sample sizes which may not be accessible, and 2) the direct use of the sample data is implicitly based on the assumption that no values beyond the sample data can occur, which is unreasonable for many real-life situations. Alternatively, some recent studies [51], [67] fitted a theoretical PDFs to the sample data to describe the intrinsic randomness of driver behaviour variables and then generate the desired synthetic data from the fitted PDFs. The authors in [51] assumed Normal PDF for the arrival time and Lognormal PDF for daily travel mileage, while the authors in [67] assumed Chi-square PDF for the arrival and departure times and truncated power law PDF for daily travel mileage. There are, however, two main observations in many previous studies that use the theoretical PDFs. First, having no general consensus about certain PDF to be used for representing a certain variable can ultimately lead to contradictory findings. Second, most of these studies were built based on assumed PDFs (without providing statistical validation for this assumption); thus, the assumed PDFs may not accurately describe the behaviour of the variable of interest and ultimately not produce accurate quantiles, performance indices, and risk estimates [24].

Based on the above discussion, there is a crucial need for conducting a statistical evaluation study among a wide range of available theoretical PDFs in order to find the best model to reflect the random characteristics of each driver behaviour variable. Addressing this need is a core contribution of the work presented in this chapter. The presented work appears to be the first study to compare the performance of different statistical PDFs for preserving different variables of driver behaviour.

3.2 Proposed Methodology

Figure 3.1 shows the general procedures for the conducted statistical evaluation study. The details of the proposed procedures are discussed next.

3.2.1 Data Collection and Preprocessing

The U.S. National Household Travel Survey (NHTS) is used, since it is considered the most comprehensive reference for transportation data [34]. The NHTS offers highly useful information about individual driving patterns (e.g., arrival and departure times, number and length of trips, and parking locations). This survey encompassed 1,048,576 usable households and 309,164 vehicles. The data were filtered to include only four classes of vehicles: passenger cars (light, compact, medium, heavy); sport utility vehicles; pickup trucks; and vans. Hence, the resulting data group comprises approximately 350,000 usable households and 150,000 vehicles. The data pertaining to home arrival time, home departure time, and daily travel mileage of the selected classes were processed for the statistical evaluation study.

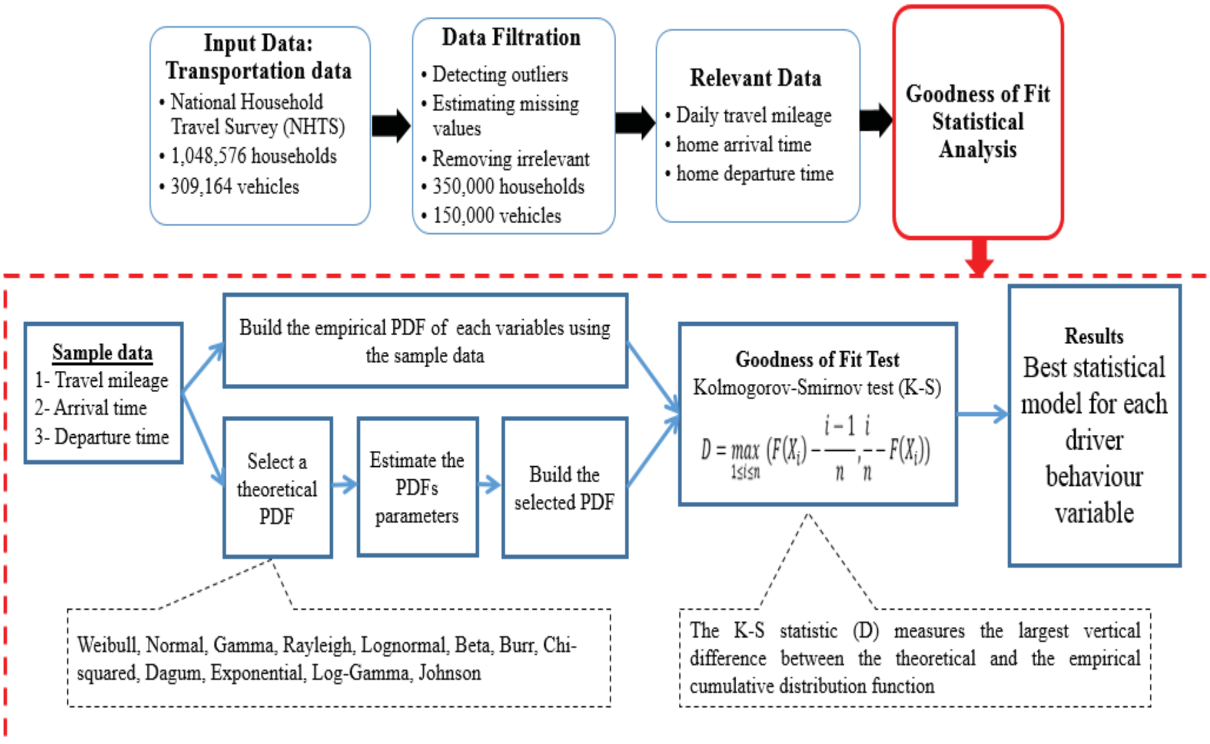


Figure 3.1 Layout for the statistical evaluation study

Figure 3.2 shows the important features need to be extracted from the NHTS, and explains the way of treating these features to obtain samples pertinent to the involved diver behaviour variables.

3.2.1 Theoretical Distribution Types

In this research, a selection of twelve different PDFs is used to examine their goodness of fit with the observed samples of different driver behaviour variables. Some of these PDFs have been used in previous studies for modelling driver behaviour characteristics (i.e., normal, lognormal, and chi-square), and others which are commonly used in different fields may have the potential to become the underlying distribution models for the variables of driver behaviour. Table 3.1 presents the PDFs of the selected distributions along with their equations and parameters. Further details are discussed in [68], [69].

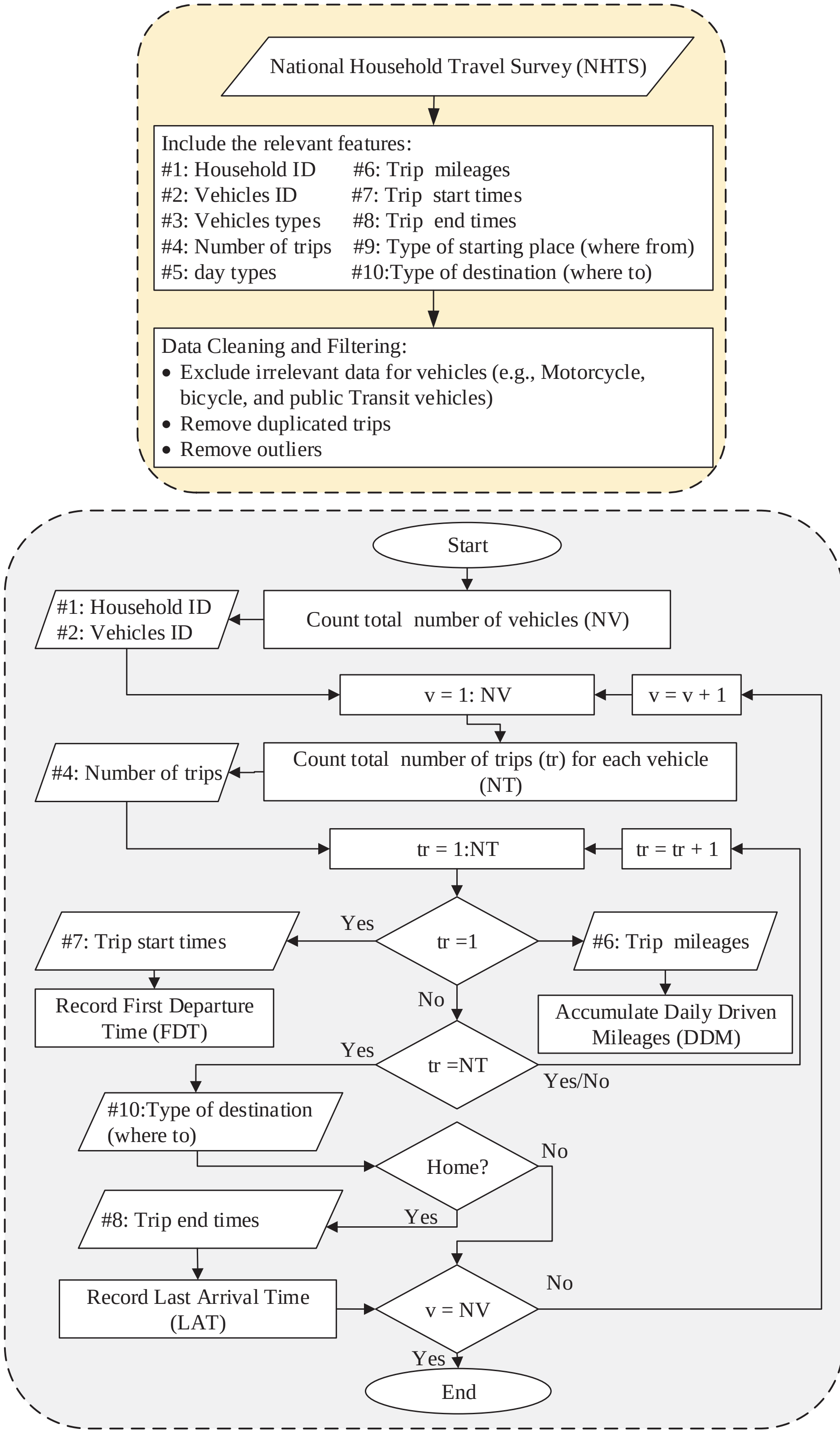


Figure 3.2 General procedures data collection and preprocessing

Table 3.1 Probability distribution functions (PDFs), related symbol, PDF equations, and parameters

Distribution	Symbol	$f(x)$	Parameters			
			Scale	**Shape**	**Location**	**Others**
Beta	BE	$\frac{(x-a)^{\alpha1-1}(b-x)^{\alpha2-1}}{\frac{\Gamma(\alpha1)\Gamma(\alpha2)}{\Gamma(\alpha1+\alpha2)}\ (b-a)^{\alpha1-\alpha2-1}}$	NA	$\alpha1, \alpha2$	NA	a , b - continuous boundary parameters
Burr	BU	$\frac{\alpha k(\frac{x-\gamma}{\beta})^{\alpha-1}}{\beta(1+(\frac{x-\gamma}{\beta})^{\alpha})^{k+1}}$	β	k, α	γ	NA
Chi-Squared	CS	$\frac{(x-\gamma)^{\nu/2-1}\ e^{-(x-\gamma)/2}}{2^{\nu/2}\ \Gamma(\nu/2)}$	NA	NA	γ	ν - degrees of freedom (positive
Dagum	DA	$\frac{\alpha k(\frac{x-\gamma}{\beta})^{\alpha k-1}}{\beta(1+(\frac{x-\gamma}{\beta})^{\alpha})^{k+1}}$	β	k, α	γ	NA
Exponential	EX	$\lambda\ e^{(-\lambda\ (x-\gamma))}$	λ	NA	γ	NA
Gamma	GA	$\frac{(x-\gamma)^{\alpha-1}\ \ e^{-(x-\gamma)/\beta}}{\beta^{\alpha}\Gamma(\alpha)}$	β	α	γ	NA
Johnson S unbounded	JSU	$\frac{\delta}{\lambda\sqrt{2\pi}\ \sqrt{z^2+1}} e^{\left(-\frac{1}{2}\left(\gamma+\delta\ln(z+\sqrt{z^2+1}\right)^2\right)}$, $z=\frac{x-\xi}{\lambda}$	λ	δ, γ	ξ	NA
Johnson S bounded	JSB	$\frac{\delta}{\lambda\lambda\sqrt{2\pi}\ z(1-z)} e^{\left(-\frac{1}{2}\left(\gamma+\delta\ln(\frac{z}{1-z}\right)^2\right)}$, $z=\frac{x-\xi}{\lambda}$	λ	δ, γ	ξ	NA
Log-Gamma	LGG	$\frac{(\ln x)^{\alpha-1}\ \ e^{-(\ln x)/\beta}}{x\ \beta^{\alpha}\Gamma(\alpha)}$	β	α	NA	NA
Lognormal	LGN	$\frac{e^{(-\frac{1}{2}\left(\frac{\ln(x-\gamma)-\mu}{\sigma}\right)^2)}}{(x-\gamma)\ \sigma\ \sqrt{2\pi}}$	σ	NA	μ, γ	NA
Normal	NO	$\frac{e^{(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2)}}{\sigma\ \sqrt{2\pi}}$	σ	NA	μ	NA
Rayleigh	RA	$\frac{(x-\gamma)\ e^{(-\frac{1}{2}\left(\frac{((x-\gamma)}{\sigma}\right)^2)}}{\sigma^2}$	σ	NA	γ	NA
Weibull	WE	$\frac{\sigma}{\beta}\ \frac{(x-\gamma)}{\beta}^{\sigma-1}\ \ e^{(-\left(\frac{((x-\gamma)}{\beta}\right)^{\sigma})}$	β	α	γ	NA

3.2.2 Goodness of Fit Tests

With respect to the goodness of fit tests, a variety of criteria and techniques has been showcased in numerous publications. The basic idea of these tests is to measure how well the selected theoretical PDFs fit a set of observations [70]. In this presented work, the Kolmogorov-Smirnov (K-S) test is used since it is an efficient goodness-of-fit test commonly employed in different applications. The K-S test is used to test the difference between theoretical and empirical (actual) PDFs. Equation (3.1) presents the K-S statistic (D) which is based on the largest vertical difference between the theoretical and empirical cumulative distribution function [70]:

$$D = \max_{1 \le i \le n} \left(F(X_i) - \frac{i-1}{n}, \frac{i}{n} - F(X_i) \right) \tag{3.1}$$

where X_i is the value of the i^{th} sample of the total number of samples (n), and F is the fitted cumulative distribution function (CDF).

The K-S test is based on the definition of the following hypotheses:

- H_0: the data follow the specified theoretical PDF;
- H_A: the data do not follow the specified theoretical PDF.

The null hypothesis (H_0) regarding a theoretical PDF is rejected if the K-S test statistic (D) is greater than the critical statistic obtained from the standard table at a selected significance confidence level (α). A value of significance confidence level is typically set to be 5% in many applications.

3.3 Results and Analysis

3.3.1 Case 1: Home Arrival Time

In this case, the selected PDFs are fitted to the home arrival time data. In Table 3.2, the PDFs are ranked based on the lowest statistics obtained from the K-S test. Figure 3.3 shows the three best-fitted PDFs along with the three worst-fitted PDFs. As stated earlier, the K-S test measures the difference between theoretical and empirical (actual) PDFs; thus, the PDF with the lowest statistic is the distribution that best fits the actual data. At a significant confidence level of 5%, if the K-S test statistic for a PDF is greater than the critical statistic obtained from the standard table (shown in the first row in Table 3.2), then this PDF is significantly different from the real data and cannot guarantee an excellent fit. From the table and chart, the most obvious findings to emerge are as follows:

1- The statistics of the selected PDFs, with the exceptions of Log-Gamma, Exponential, and Rayleigh, are less than the critical statistic. This indicates the ability of these PDFs to capture the variable characteristics of the driver's behaviour regarding arrival times.

2- Degum, Burr, and Johnson-SU PDFs are shown to be the three best-fitted PDFs with the lowest statistics. These PDFs are very flexible because of their additional shape parameters that enable them to be fitted with a wide range of real-life data.

3- Log-Gamma, Exponential, and Rayleigh are shown to be the three worst-fitted PDFs, revealing a significant difference from the real data. Figure 3.3 shows how significantly these PDFs are different from the sample data of home arrival time.

Table 3.2 Goodness of fit results for different PDFs for home arrival time

Critical Statistic is 0.2690			
Rank	**PDF**	**Statistics**	**Parameters**
1	DA	0.0834	$k=0.4958$ $\alpha=3.1271E+7$ $\beta=4.365E+7$ $\gamma=4.365E+7$
2	BU	0.0894	$k=3.9332$ $\alpha=280.31$ $\beta=721.0$ $\gamma=-699.44$
3	JSU	0.0920	$\gamma=1.6677$ $\delta=2.3166$ $\lambda=5.776$ $\xi=21.885$
4	BE	0.0942	$\alpha_1=4.0788E+6$ $\alpha_2=8.265$ $a=-5.0128E+6$ $b=27.07$
5	WE	0.0950	$\alpha=5.6649$ $\beta=18.236$ $\gamma=0$
6	NO	0.1140	$\sigma=3.5483$ $\mu=16.916$
7	LGN	0.1144	$\sigma=0.00271$ $\mu=7.1793$ $\gamma=-1295.1$
8	GA	0.1159	$\alpha=17680.0$ $\beta=0.02684$ $\gamma=-457.57$
9	CS	0.1910	$\nu=18$ $\gamma=-0.84555$
10	LGG	0.2032	$\alpha=79.793$ $\beta=0.03502$
11	RA	0.2625	$\sigma=13.497$ $\gamma=0$
12	EX	0.4287	$\lambda=0.06283$ $\gamma=1.0$

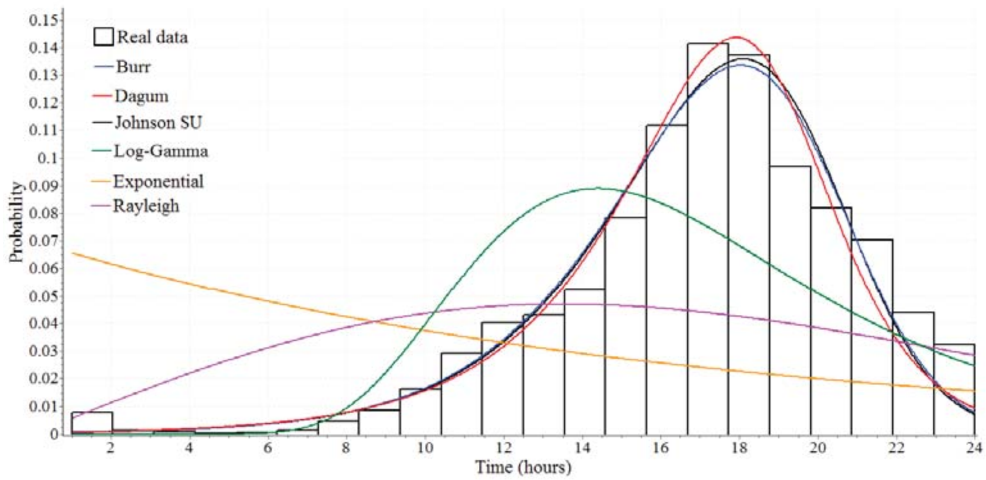


Figure 3.3 The three best and three worst PDFs plotted against a histogram of home arrival time data

3.3.2 Case 2: Home Departure Time

This case is conducted to examine how well the selected theoretical PDFs fit the data pertaining to the home departure time. The PDFs are ranked based on the statistical values obtained from K-S test, as listed in Table 3.3. As is evident from the table, Degum, Burr, and Johnson-SB PDFs represent the best-fitted PDFs, revealing an evident agreement with the results of Case 1. As shown in Figure 3.4, these PDFs almost comply with the pattern of the real data. It is apparent from this figure that Normal, Exponential, and Rayleigh PDFs are the worst-fitted PDFs; thus, the use of these PDFs to model the variable of home departure time might significantly affect the accuracy and validity of the intended results.

Table 3.3 Goodness of fit results for different PDFs for home departure time

Critical Statistic is 0.2693			
Rank	**PDF**	**Statistics**	**Parameters**
1	BU	0.1062	k=0.19202 α=4.014E+8 β=2.463E+8 γ=2.4632E+8
2	DA	0.1166	k=2.6209 α=4.529 β=6.7842 γ=0
3	JSB	0.1242	γ=1.5186 δ=0.97264 λ=20.809 ξ=5.1345
4	LGG	0.1250	α=49.45 β=0.04469
5	LGN	0.1359	σ=0.33655 μ=2.1395 γ=0.58916

6	GA	0.1369	α=8.7439 β=1.0973 γ=0
7	BE	0.1411	α_1=6.7948 α_2=7.1668E+6 a=0.96097 b=9.2119E+6
8	CS	0.1546	ν=9 γ=0.98751
9	WE	0.1592	α=2.7566 β=9.6709 γ=0.98989
10	NO	0.1803	σ=3.2447 μ=9.5945
11	RA	0.2350	σ=7.6553 γ=0
12	EX	0.4094	λ=0.11635 γ=1.0

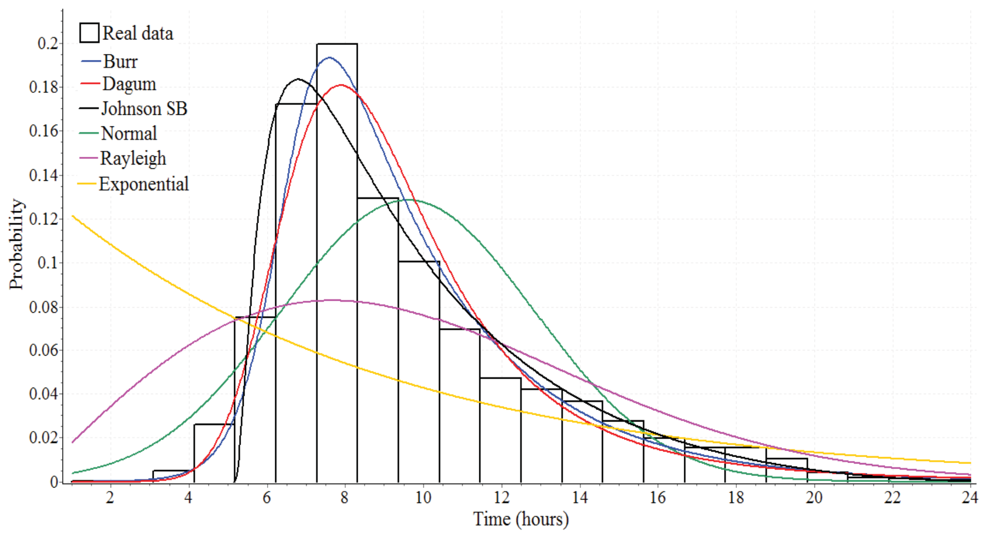


Figure 3.4 The three best and worst PDFs plotted against a histogram of home departure time data

3.3.3 Case 3: Daily Travel Mileage

In this case, the selected PDFs are fitted to the daily travel mileage data. In Table 3.4, The PDFs based on the K-S test are ranked from best- to worst-fit. Figure 3.5 shows different fitted PDFs plotted in conjunction with the histogram of daily travel mileage data. It is clear that the Lognormal, Burr, and Johnson-SB are the closest PDFs to the observed data and hence are the best fit, an outcome which is also confirmed from the test results presented in Table 3.4.

In contrast, Chi-square, Normal, and Rayleigh are the worst-fitted PDFs, which indicates their deficiency of considering the stochastic nature of this variable of driver behaviour.

Table 3.4 Goodness of fit results for different PDFs for daily travel mileage data

Critical Statistic is 0.2010			
Rank	**PDF**	**Statistics**	**Parameters**
1	LGN	0.0781	σ=0.90619 μ=3.1741 γ=0.90546
2	BU	0.0792	k=1.7716 α=1.7068 β=40.922 γ=0
3	JSB	0.0796	γ=2.1464 δ=0.89427 λ=271.73 ξ=2.7744
4	WE	0.094	α=1.2449 β=38.588 γ=0
5	DA	0.095	k=0.88553 α=2.0913 β=28.107 γ=0
6	EX	0.114	λ=0.03252 γ=5.0
7	GA	0.114	α=1.2861 β=27.795 γ=0
8	LGG	0.115	α=14.129 β=0.2285
9	BE	0.191	α_1=0.64335 α_2=3.4433 a=5.0 b=200.26
10	CS	0.223	ν=421 γ=-385.83
11	NO	0.262	σ=31.521 μ=35.747
12	RE	0.328	σ=40.128 γ=-11.443

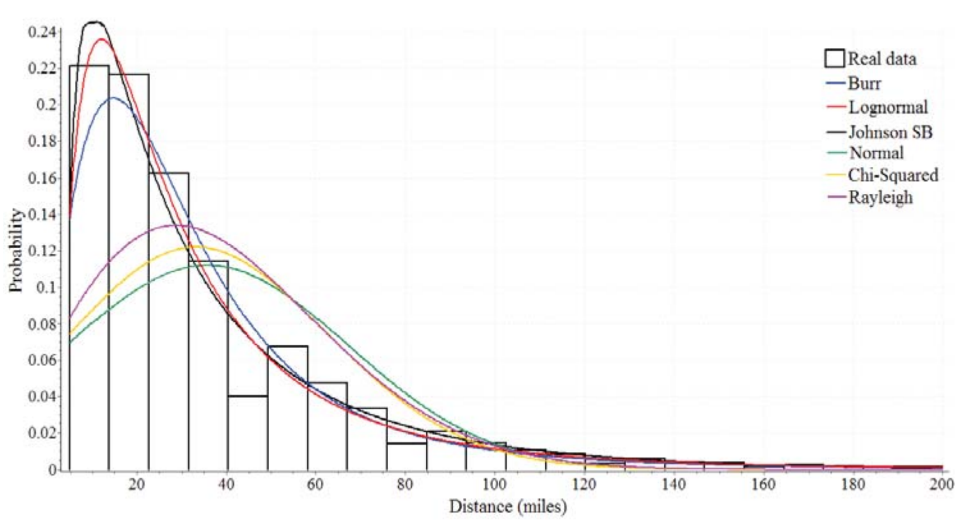


Figure 3.5 The three best and worst PDFs plotted against a histogram of daily travel mileage data

3.4 Summary

The aim of the presented research was to examine and validate the use of different statistical models for preserving the random characteristics of different driver behaviour variables. Overall, the results show that Dagum, Burr, and Johnson are among the best-fitted PDFs for all random driver behaviour variables. Their additional shape parameters enable them to be very flexible and fitted with a wide range of real-life data. In addition, these results indicate that the Lognormal is the best-fitted PDF to describe the daily mileage.

We believe that the study presented in this chapter makes contribution to the current literature tackling the PEV charging modeling. This study provides a realistic description models for the behaviour of the variable of interest and ultimately produces accurate quantiles, performance indices, and risk estimates. Planners, researchers, or anyone endeavoring to estimate a realistic PEV charging load profile can directly use these PDFs, thus saving time and effort.

Next chapter presents a real application for the best fitted PDFs in conjunction with MCS simulation in order to develop a wide range of possible PEV charging profiles. The generated profiles thereafter convolve with the conventional adequacy models to assess the imposed impacts of different PEV charging characteristics on adequacy indices.

Chapter 4

Generation Adequacy assessment Framework for the Impact of Uncontrolled PEV Charging load

4.1 Introduction

In the previous chapter, a goodness-of-fit statistical study is conducted to determine proper probability distribution functions (PDFs) models that best reflect the main characteristics of driver behaviour. This chapter presents a comprehensive reliability framework for incorporating different plug-in electric vehicle (PEV) charging load models into the evaluation of generation adequacy. Addressing the drawbacks of previous studies reviewed in details in Chapter 2, the proposed framework comprises special treatments and innovative models to achieve an accurate determination of the impact of PEV load models on reliability. The main research objectives and expected contributions of this work are as follows:

1) Development of a probabilistic model for PEV charging loads that includes realistic estimates of the elements characterizing the charging process and explicitly takes into account the underlying uncertainties of the random variables. The activities carried out in developing realistic load profiles for PEV are:
   i. Use of high-quality data: The research data in this thesis are drawn and analyzed from four main sources: 1) Vehicle mobility data, to precisely capture driver behaviours that are essential in characterizing the charging process (e.g., mileage driven, arrival times, and departure times); 2) market sales data to extract information pertinent to PEV types and their market share percentages; 3) manufacturers' data to obtain data pertinent to battery technologies in terms of capacities and PEV ranges; and 4) SAE J1772 standards to obtain data pertinent to charging levels.
   ii. Development of a reliable stochastic model: MCS is deployed to simulate the input variables needed to assess PEV charging loads in view of the underlying uncertainty of the random variables. Hence, a multitude of scenarios for PEV charging loads are generated and assessed.
2) Development of a comprehensive reliability evaluation model to investigate the effect of different PEV charging load characteristics on the reliability and performance of generation systems. This model is applied to a well-known test system (IEEE-RTS), and the behaviour of

different reliability indices, including basic system indices and frequency and duration indices, are thoroughly studied. Within this study, special attention is paid to investigating the influence of each PEV load parameter on system reliability, including the effect of different penetration levels, different charging levels, and different PEV types with different battery specifications.

3) Assessment for the effectiveness of the application of the current TOU tariff in controlling consumers' charging behaviour and investigate whether or not TOU efficiently mitigate the effect of uncontrolled charging on generation adequacy.

4.2 Reliability Assessment Framework for the Effect of PEV Load Characteristics

This section describes the methodology for the proposed framework for assessing the effect of uncontrolled and TOU-based strategies on the reliability performance of generation systems.

4.2.1 Input Data Required for PEV Charging Models

To develop realistic PEV load profiles, a reliable estimate of the elements characterizing the charging process must be obtained: penetration levels, charging equipment characteristics, battery specifications, and driving patterns. This task is challenging, however, since no currently available data can be relied on for precise definitions of these elements. To estimate PEV loads as accurately as possible, this work was based on a number of key considerations:

1) The U.S. National Household Travel Survey (NHTS) [34] is used to extract information about individual driving patterns, and helps capture real-life scenarios that can provide a more realistic estimate of PEV charging profiles. As previous chapter discussed, the data pertaining to the home arrival time (HAT), home departure time (HDT), and daily travel mileage (DTM) of the selected classes were used for producing the PDFs employed in the MCS to generate random samples for each parameter. As is evident from the statistical analysis conducted in Chapter 3, the Burr distribution represents the best-fit PDF for weekend HAT and weekday HDT, while the Dagum distribution represents the best-fit PDF for weekday HAT and weekend HDT. Equations (4.1) and (4.2) are the formulae for Burr and Dagum PDFs, respectively. For both weekday and weekend DTM, the best-fit PDF is the lognormal distribution, as given by (4.3).

$$f(x) = \frac{\alpha k (\frac{x-\gamma}{\beta})^{\alpha-1}}{\beta(1+(\frac{x-\gamma}{\beta})^{\alpha})^{k+1}} \tag{4.1}$$

$$f(x) = \frac{\alpha k (\frac{x-\gamma}{\beta})^{\alpha k-1}}{\beta(1+(\frac{x-\gamma}{\beta})^{\alpha})^{k+1}} \tag{4.2}$$

$$f(x) = \frac{\exp(-\frac{1}{2}\left(\frac{lnx-\mu}{\sigma}\right)^2)}{2\sigma\sqrt{2\pi}} \tag{4.3}$$

where k and α are the shape parameters, β is the scale parameter, γ is the location parameter for the Burr and Dagum distributions, μ is the location parameter, and σ is the scale parameter for the lognormal distribution. Table 4.1 presents the values for the parameters of the best-fit PDFs obtained for each driver behaviour variable.

Table 4.1 Parameters of the fitted PDFs for each driver behaviour variable

	Fitted Distribution	**Parameters**			
HAT-WD	Dagum	$k = 0.495$	$\alpha = 1.01E+5$	$\beta = 1.41E+5$	γ =-1.4E+5
HAT-WE	Burr	$k = 77.82$	$\alpha = 10.92$	$\beta = 55.56$	$\gamma = -18.55$
HDT-WD	Burr	$k = 0.455$	$\alpha = 8.2221$	$\beta = 7.4766$	$\gamma = 0$
HDT-WE	Dagum	$k = 9.222$	$\alpha = 30.124$	$\beta = 68.559$	$\gamma = -64.29$
DTM-WD	Lognormal	$\mu = 3.228$		$\sigma = 0.8589$	
DTM-WE	Lognormal	$\mu = 3.125$		$\sigma = 0.9153$	

2) U.S. PEV market sales [71] were analyzed, and four of the most popular types were chosen. Two are hybrid EVs (Chevrolet Volt (CV) and Toyota Prius (TP)), and the other two are battery EVs (Nissan LEAF (NL) and Tesla S (TS)). Table 4.2 lists their market share percentages, battery capacities, and electric ranges.
3) In this study, for consistency with the available finalized SAE J1772 standards for residential use [32], two charging levels were used, as indicated in Table 4.3.

Table 4.2 Data for the PEVs used in this research

PEV Type	Battery capacity (KWh)	Range (Miles)	Specific energy (kWh/mile)	Market share (%)
CV	16	35	0.457	32
NL	24	73	0.327	32.5
TP	4.4	11	0.400	16.5
TS	85	265	0.320	19

Table 4.3 Charging levels based on the SAE J1772 standard

Type	Voltage V	Current A	Power kW
Level 1	120	12	1.44
Level 2	240	30	7.2

4) For the case studies presented in this thesis, it was assumed that PEV charging occurs at home. This assumption is based on the results of several surveys [35], [36] that revealed that the majority of respondents tend to charge their PEVs at home rather than at public charging stations. This preference has several possible explanations: homes are considered the primary place where vehicles are parked most often, and most daily mileage is less than the available electric range of most PEVs. The easy accessibility and convenience of home charging has strong appeal for PEV owners.
5) An important preliminary step in developing the PEV charging load models was to determine the number of PEVs in a system. For this purpose, the following equation was used for establishing the number of PEVs in a system at different penetration levels:

$$N_{PEV} = X_p \times N_h \times n_C \tag{4.4}$$

where N_{PEV} is the number of PEVs, X_p is the percentage of PEVs with respect to the total number of vehicles, N_h is the number of houses in a given system, and n_C is the estimated average number of vehicles per household according to the 2009 NHTS: 1.9 vehicles. N_h is calculated by dividing the total residential load (P_r) by the average load of each house in a given system (P_h), where P_r was estimated by the IEEE committee in [72] to be 35 % of the system peak, and P_h was estimated to be 2.08 kW.

To illustrate the use of (4.4), consider a system with a peak load of 1000 MW. As mentioned above, the percentage share of residential loads is about 35 % (i.e., 350 MW), and therefore the number of houses in this system can be calculated by dividing the residential load by the average load of a typical house (350 MW/2.08 kW = 168,000 houses). Now, a PEV 10 % share can be estimated as $X_p \times N_h \times n_C = 0.1 \times 168{,}000 \times 1.9$ ≈32,000vehicles.

6) Five PEV penetration levels are assessed, ranging from 10 % to 50 %, in 10 % increments. The maximum penetration level in this work is set to 50% as estimated in 2030 by the Electric Power Research Institute [2]. For each penetration level, the number of PEVs in the system is distributed based on the percentage of each vehicle class according to its market share [71].

4.2.2 Simulation Model of Uncontrolled PEV Charging Loads

The charging profile of each PEV is determined based on three factors: the energy required to charge the battery, the duration of the charge, and the time of the charge [4], [6], [73], [74]. The stochastic uncontrolled PEV charging simulation model is outlined in Figure 4.1 and in the following step-wise procedures.

Step 1: Read the customer behaviour data (i.e., the fitted HAT, HDT, and DTM PDFs) plus any additional PEV-related data (e.g., battery capacity, electric range, market share, charging level, charging efficiency, SoC limits, and PEV penetration level).

Step 2: Start with the simulation of the first day’s charging profile for the whole PEV fleet.

Step 3: Begin to simulate the charging profile for the first PEV in the fleet.

Step 4: Generate a uniform random number, interpreted as a probability, between 0 and 1.

Step 5: Equate the value of the random number with the inverse CDF of the DTM in order to estimate the DTM driven for each PEV.

Step 6: Determine the battery SoC for each PEV when it arrives home. The SoC can be estimated as in (4.5)[6], [74]:

$$SoC = \begin{cases} 20\% & \overset{if}{\Leftrightarrow} DTM \geq ERM \\ \left(\frac{ERM-DTM}{ERM}\right) \times 100\% & \overset{if}{\Leftrightarrow} DTM < ERM \end{cases} \tag{4.5}$$

where DTM is the daily travel mileages driven by each PEV in miles, and ERM is the electric range in miles that can be driven by each PEV in electric mode.

Step 7: With respect to battery life, a 70 % maximum allowable depth of charge is often assumed [6], [75]; i.e., the battery cannot be charged if the SoC ≥ 90 % and cannot be run down if the SoC ≤ 20 %. If this condition is satisfied, then continue to the next step. Otherwise, go to Step 3 to simulate the charging profile for the next vehicle.

Step 8: Calculate the daily charging energy (CE) required for each PEV using (4.6)[6], [74]:

$$CE = (0.9 - SoC) \times BC \tag{4.6}$$

where BC is the battery capacity in kWh.

Step 9: Calculate the charging duration (CD) required for a PEV, as expressed in (4.7), based on the CE, the charging levels (ch_L), and the efficiency (η_{ch}), where η_{ch} is the charging efficiency, which is often assumed to be 90 % [5].

$$CD = \frac{CE}{\eta_{ch} \times ch_L} \tag{4.7}$$

Step 10: Generate another two uniform random numbers between 0 and 1.

Step 11: Estimate the arrival and departure times for each PEV using the generated random numbers and the inverse CDFs of the HAT and HDT.

Step 12: Determine the stay duration (*SD*) by calculating the difference between the arrival and departure times. If the stay duration for a PEV at home is greater than the time needed for charging, then the PEV is charged at the charging level power rate starting from its arrival and ending once it is fully charged, as expressed in (4.8). Otherwise, it keeps charging until its departure time, as expressed in (4.9).

$$P_i(t) = ch_L \ \xrightarrow{where} \ t = (AT, \dots \dots, AT + CD - 1) \tag{4.8}$$

$$P_i(t) = ch_L \ \xrightarrow{where} t = (AT, \dots \dots, DT - 1) \tag{4.9}$$

Step 13: The same procedures (Step 3 to Step 12) are repeated sequentially in order to simulate the daily charging profile for each PEV.

Step 14: The simulated individual PEV charging profiles are then combined chronologically in order to determine the total charging profile for the entire fleet, as given in (4.10).

$$P_{PEV}(t) = \sum_{i=1}^{no.of\ PEV} P_i(t) \xrightarrow{where} t = (1, \dots \dots, 24) \tag{4.10}$$

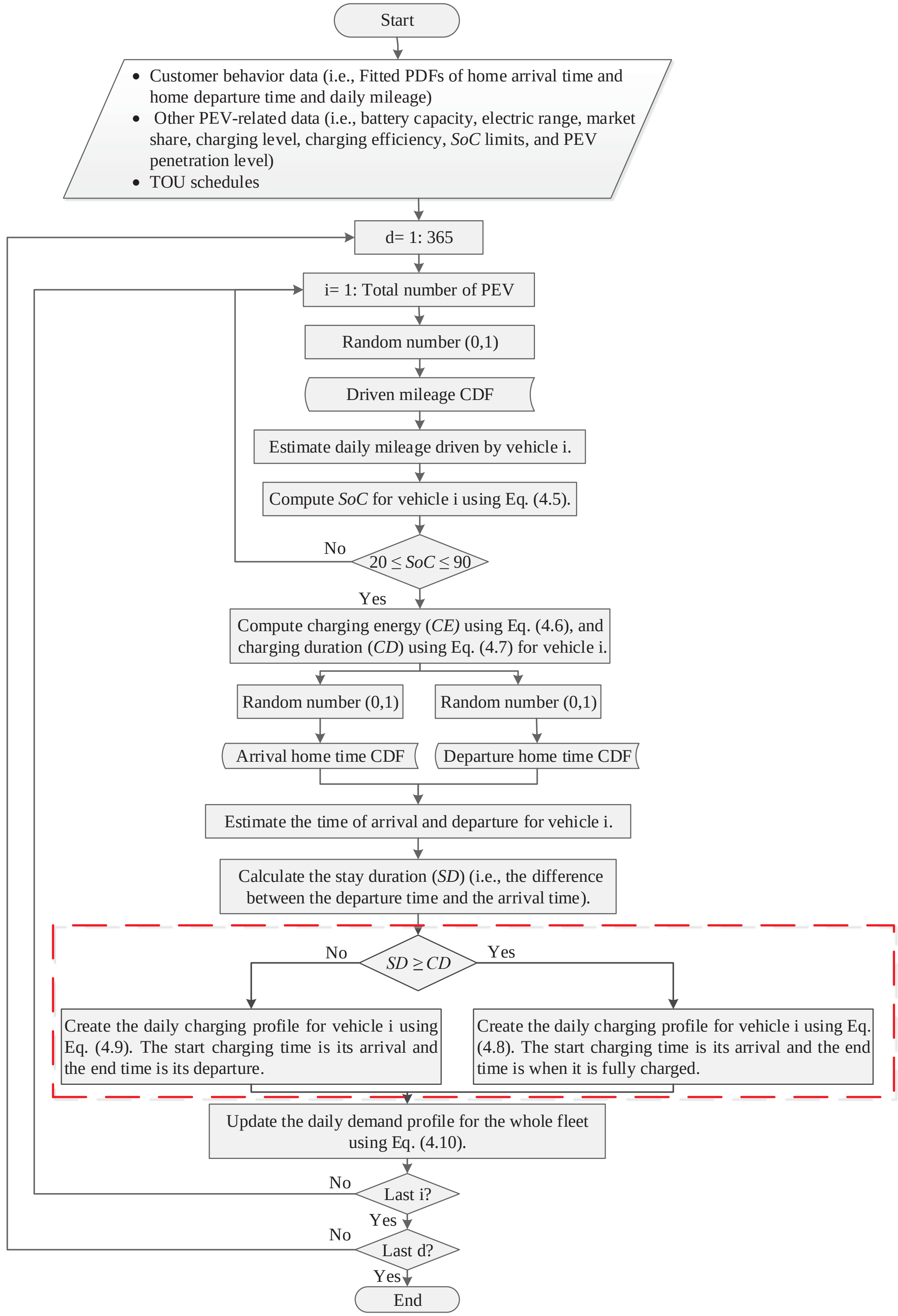


Figure 4.1 Main procedures for determining the uncontrolled PEV charging load.

4.2.3 Simulation Model of the PEV Charging Load Based on TOU pricing

The model described in the previous section concerned the development of the uncontrolled PEV charging load, with the PEV considered to be charged upon arrival at home. Without incentives for drivers, this charging strategy is more rational because it is based on the assumption that the PEV will be charged by the time the driver next needs it. However, TOU electricity pricing may create a level of control over PEV charging loads. Driver decisions to wait and charge during off-peak periods are based primarily on individual customer driving behaviour, including charging energy required, the charging duration required, and the duration of the home stay. Accordingly, a decision tree model is proposed for use with the uncontrolled charging model so that driver decisions in response to TOU pricing can be taken into account. Figure 4.2 simplifies the basic logistics for the development of PEV charging load with the response to the TOU rates, and further details are provided in the simulation steps below. For modeling driver response to TOU rates, the California TOU residential rates [23] were used in this work.

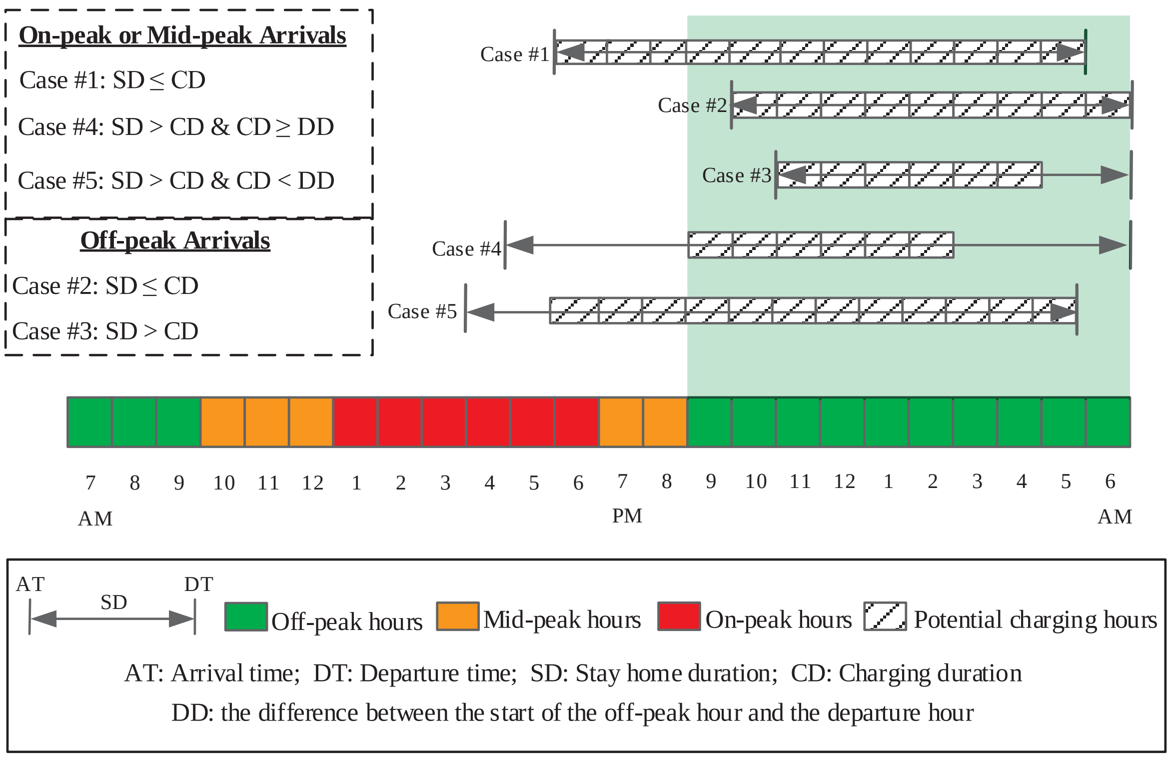


Figure 4.2 Basic logistics of the development of PEV charging load with the response to the TOU

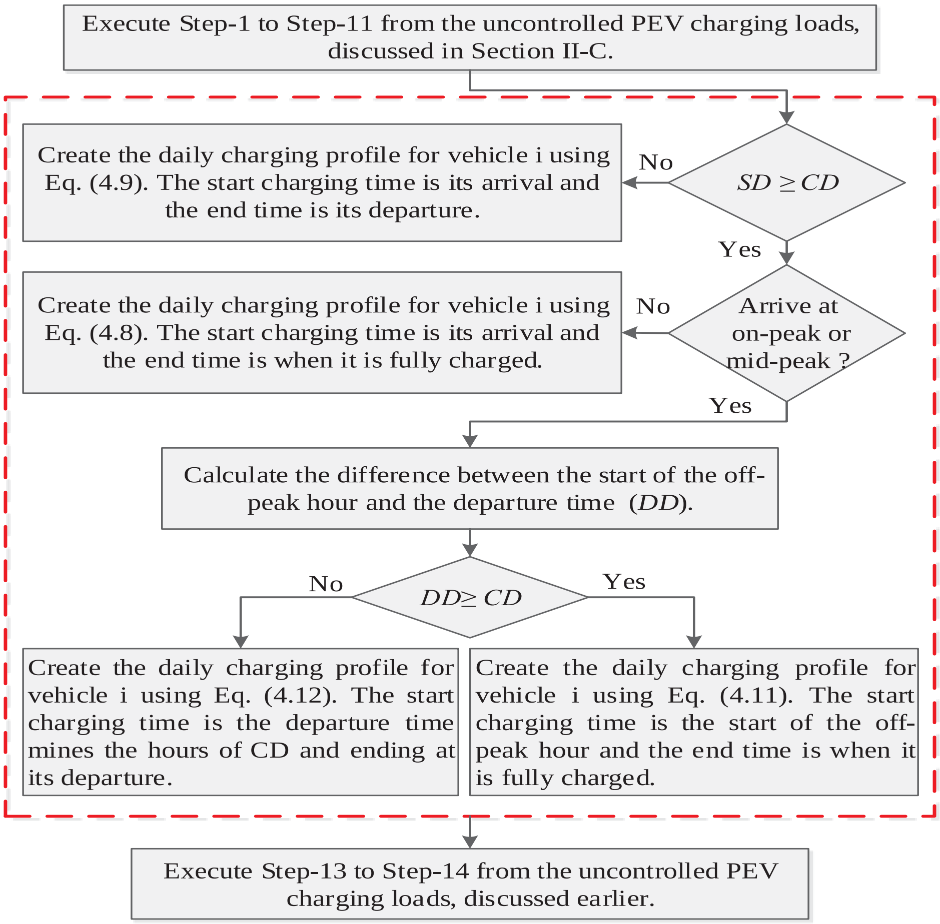


Figure 4.3 Main procedures for determining the PEV charging load considering the responses of PEV owners to TOU.

The core procedure in the driver decision tree model for establishing the TOU-based charging load is shown in Figure 4.3 Essentially, the steps within the dotted box in Figure 4.1 are replaced by those within the dotted box in Figure 4.3, and they are described in the following step-wise procedures.

Step 1: Execute Step 1 to Step 11 from the uncontrolled PEV charging model discussed earlier.

Step 2: Determine the stay duration (*SD*) by calculating the difference between the arrival and departure times. If the stay duration for a PEV at home is shorter than the charging duration (*CD*), then the PEV is charged beginning upon arrival and ending at its departure, as expressed in (4.9). Otherwise, continue to the next step.

Step 3: If the estimated arrival time is within an off-peak period, then the start time for charging is set to correspond to the arrival, as expressed in (4.8). If not, continue to the next step.

Step 4: Calculate the period from the off-peak time to the departure time.

Step 5: If the period calculated for on-peak or mid-peak arrivals is greater than the time needed for charging the vehicle, then the start time for charging is set to correspond to the start time of the off-peak period (ST^{OFF}), as expressed in (4.11). For those with a charging duration greater than the period from the off-peak time to the departure time, the start time for charging is set to correspond to the departure time mines the hours of *CD*, as expressed in (4.12).

$$P_i(t) = ch_L \xRightarrow{where} t = (ST^{OFF}, \dots, ST^{OFF} + CD - 1) \tag{4.11}$$

$$P_i(t) = ch_L \xRightarrow{where} t = (DT - CD, \dots \dots, DT - 1) \tag{4.12}$$

Step 6: Execute Step 13 and Step 14 from the uncontrolled PEV charging model discussed earlier.

4.2.4 Reliability Evaluation Including PEV Charging Models

In this research, a sequential MCS technique was employed owing to its remarkable features of including consideration of the chronology of events and the stochastic behaviour of system elements and its ability to provide a comprehensive evaluation of the reliability of power systems by offering a wider range of indices. The following is a brief description of the general simulation procedures for incorporating PEV charging load modeling into the evaluation of generation adequacy:

1) Develop hourly sequential PEV charging load profiles using the approaches discussed in the previous sections.
2) Construct a chronological conventional load profile using the IEEE Reliability Test System (IEEE-RTS) load data points [76] given on an hourly basis for a typical one-year period. The IEEE-RTS chronological hourly load profile is widely used in reliability studies and was applied in this work to represent conventional loads. The hourly IEEE-RTS load is given as a percentage of the annual system load peak so that daily, weekly, and seasonal patterns are included. Once the annual peak load (L^{peak}) is determined, the chronological hourly load model (8760 hours) can be developed using (4.13).

$$P_{CL}^{w,d,h} = L^{peak} \times P^w \times P^d \times P^h \xRightarrow{where} \begin{cases} w = (1,2, \dots \dots, 52) \\ d = (1,2, \dots \dots, 7) \\ h = (1,2, \dots \dots, 24) \end{cases} \tag{4.13}$$

where $P_{CL}(t)$ is the system load at each hour (i.e., $P_{CL}(t) = P_{CL}^{w,d,h}$) , P^w is the weekly peak load as a percentage of the annual peak load, P^d is the daily peak load as a percentage of the weekly peak load, and P^h is the hourly peak load as a percentage of the daily peak load. Equation (4.14) shows the total system load (P_{TL}).

$$P_{TL}(t) = P_{CL}(t) + P_{PEV}(t) \xRightarrow{where} t = (1, \ldots, 8760) \tag{4.14}$$

3) Construct the generation capacity model by simulating the sequential operating cycles for all generating units using the conventional MCS procedures for generation system reliability evaluation. These procedures are discussed in detail in [30], [31] and the essential concept is summarized as follows.

   Due to the intrinsic uncertainties associated with component failures, the unavailability of generation capacity has a major influence on the reserve margin of the system and on the supply/demand balance. In a reliability analysis, a two-state Markov model (up state and down state) is commonly used for modeling the operational cycles of a conventional generating unit. The up state signifies that a unit is operating at its fully rated capacity, while the down state indicates that the unit is out of order due to failure or maintenance. The duration of both the up state and the down state (i.e., the time to failure (TTF), and the time to repair (TTR)), is recognized as following an exponential distribution. In a sequential MCS approach, the time during which the component works or fails is simulated in a sequential order for each unit based on a random selection from their residence time distribution, as expressed in (4.15) and (4.16), respectively. The operating capacity cycles for each unit can then be simulated using (4.17). The simulated operating capacity cycles of all units are then combined chronologically in order to determine the overall available system capacity, as given in (4.18).

$$TTF = -(\frac{1}{\lambda}) \times ln\,\mathcal{R} \xRightarrow{where} \mathcal{R} \backsim U[0,1] \tag{4.15}$$

$$TTR = -(\frac{1}{\mu}) \times ln\,\mathcal{R} \xRightarrow{where} \mathcal{R} \backsim U[0,1] \tag{4.16}$$

$$P_c(t) = \begin{cases} P_c^{rated} & \overset{if}{\Leftrightarrow} \quad t \in TTF \\ 0 & \overset{if}{\Leftrightarrow} \quad t \in TTR \end{cases} \tag{4.17}$$

$$P_{TG}(t) = \sum_{c=1}^{no.\ of comp.} P_c(t) \xrightarrow{where} t = (1, \ldots, 8760) \tag{4.18}$$

where λ is the component failure rate, μ is the component repair rate, $P_{\boldsymbol{c}}(t)$ is the output power generated from each component (c) at each hour (t), P_c^{rated} is the rated power for each component, and P_{TG} is the total system generation capacity.

4) Superimpose the total available capacity of the generation system on the overall system load, and observe the system capacity reserve margin. A wide range of reliability indices can be calculated after the above procedures are repeated for a large number of sampling years. The simulation is terminated whenever it reaches 5 % as a coefficient of variation tolerance. As presented below in (4.19)-(4.22), these indices are viewed as two categories: annual system indices and interruption indice [31].

$$X(t) = \begin{cases} 1 & \overset{if}{\Leftrightarrow} \quad P_{TG}(t) < P_{TL}(t) \\ 0 & \overset{if}{\Leftrightarrow} \quad P_{TG}(t) \geq P_{TL}(t) \end{cases} \tag{4.19}$$

$$LOLE = \frac{\sum_{n=1}^{N} \sum_{t=1}^{8760} X(t)}{N} \tag{4.20}$$

$$LOEE = \frac{\sum_{n=1}^{N} \sum_{t=1}^{8760} X(t) \, \|P_{TG}(t) - P_{TL}(t)\|}{N} \tag{4.21}$$

$$LOLF = \frac{\sum_{n=1}^{N} \sum_{t=1}^{8760} X(t)}{N} \overset{if}{\Leftrightarrow} X(t+1) - X(t) = 1 \tag{4.22}$$

where $X(t)$ is the one-zero indicator variable for the system state at each hour, LOLE is the loss of load expectation (h/yr), LOEE is the loss of energy expectation (MWh/yr), and LOLF is the loss of load frequency (int/yr).

4.3 Cases under Study

The previously described models were applied on a well-known test system: the IEEE-RTS, which entails 32 conventional generators with capacities ranging from 12 MW to 400 MW, a total installed capacity of 3405 MW, and an annual peak load equal to 2850 MW. The relevant reliability data for IEEE-RTS generators are listed in Table 4.4. The relevant data for the load model are given in Appendix A. Figure 4.5 shows the single line diagrams of the IEEE-RTS.

Table 4.4 Generator data for the IEEE-RTS [76]

No. of Units	Unit Size (MW)	Unit Type	Forced Outage (%)	Failure Rate (λ)	Repair Rate (μ)
1-5	12	Oil/Steam	0.02	3.40E-04	1.67E-02
6-9	20	Oil/CT	0.1	2.22E-03	2.00E-02
10-15	50	Hydro	0.01	5.05E-04	5.00E-02
16-19	76	Coal/Steam	0.02	5.10E-04	2.50E-02
20-22	100	Oil/Steam	0.04	8.33E-04	2.00E-02
23-26	155	Coal/Steam	0.04	1.04E-03	2.50E-02
27-29	197	Oil/Steam	0.05	1.05E-03	2.00E-02
30	350	Coal/Steam	0.08	8.70E-04	1.00E-02
31-32	400	Nuclear	0.12	9.09E-04	6.67E-03

The primary focus of this study was to provide a comprehensive evaluation of the effect of different PEV charging models on the reliability performance of generation systems. To verify the success of this work in achieving this goal, five case studies were conducted, as set out in Table 4.5.

Table 4.5 Scenarios under study

<table>
<tr><th>Case Studies</th><th>Charging Scenarios</th><th>Charging Levels</th><th>PEV Types</th><th>Penetration Levels</th></tr>
<tr><td>Case 1.A</td><td rowspan="2">Uncontrolled (Arrive & Plug)</td><td>Level-1</td><td rowspan="4">Market share</td><td rowspan="5">0 % to 50 %</td></tr>
<tr><td>Case 1.B</td><td>Level-2</td></tr>
<tr><td>Case 2.A</td><td rowspan="2">Indirect controlled (Static TOU tariff)</td><td>Level-1</td></tr>
<tr><td>Case 2.B</td><td>Level-2</td></tr>
<tr><td>Case 3</td><td>Uncontrolled (Arrive & Plug)</td><td>Level-1</td><td>One-at-a time</td></tr>
</table>

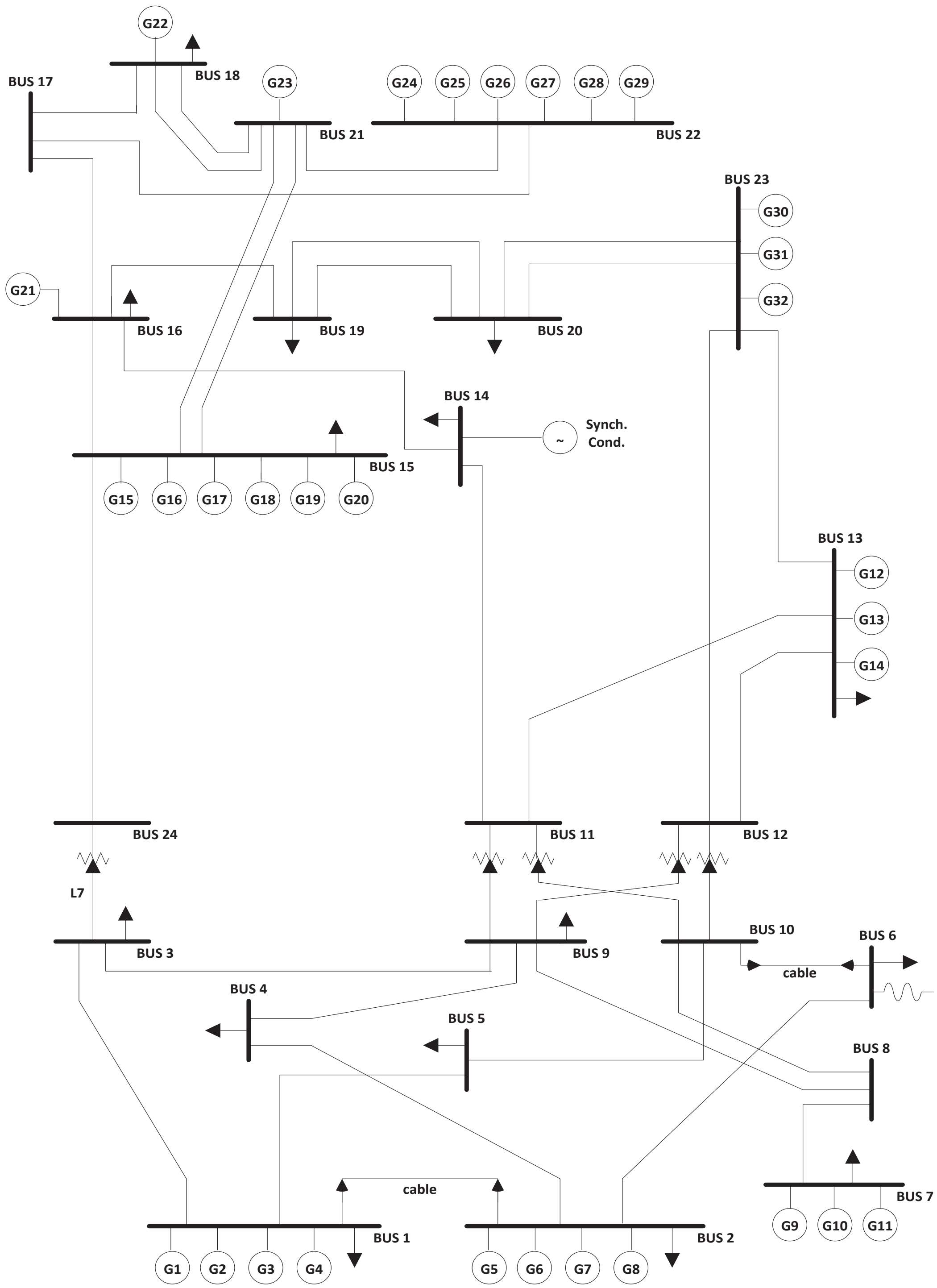


Figure 4.4 Single line diagram of the IEEE Reliability Test System (IEEE-RTS)

4.3.1 Case 1: Uncontrolled PEV Charging Load

In this case, the key considerations include different penetration levels (the distribution of each penetration level among the PEV types based on their market shares) and PEV charging upon arrival at home (designated "uncontrolled charging") at different charging levels. Figure 4.5 shows uncontrolled PEV charging profiles for different scenarios over one simulation trial. Figure 4.6 reveals that the addition of uncontrolled PEV charging loads on top of the conventional load does not significantly alter the shape of the conventional load except for scaling it up, which indicates a high degree of correlation between the PEV charging load and the conventional load profile.

Compared with the PEV charging profiles when charging level-1 is used, the PEV charging load at level-2 causes a significant increase in the peak system load. Although PEVs consume the same amount of energy at both charging levels, with level-2, they require a shorter charging time with a significantly higher magnitude of power, which tends to be concentrated and synchronized with the peak system hours. On the other hand, a PEV charged using level-1 requires a lower magnitude of power, which tends to be distributed over longer time periods, and also exploits off-peak hours.

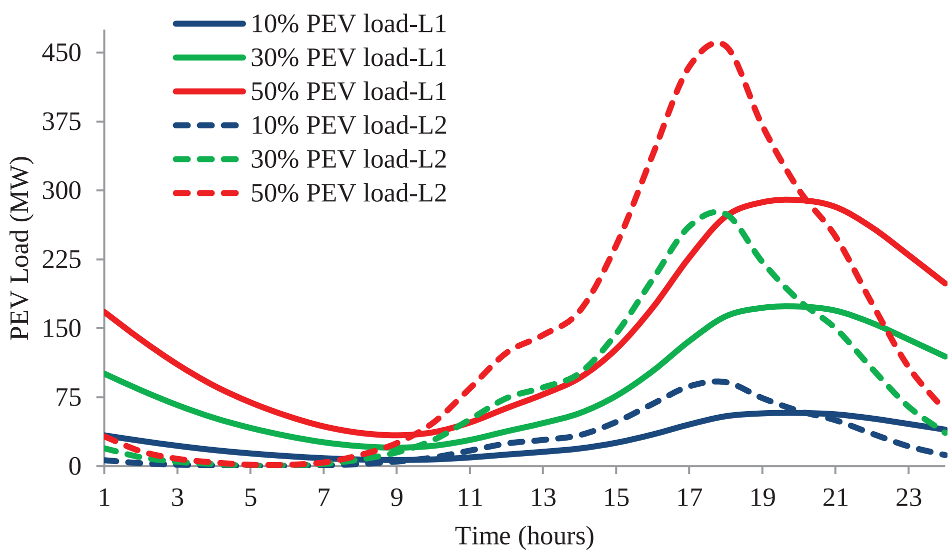


Figure 4.5 Expected peak-day uncontrolled PEV charging profiles.

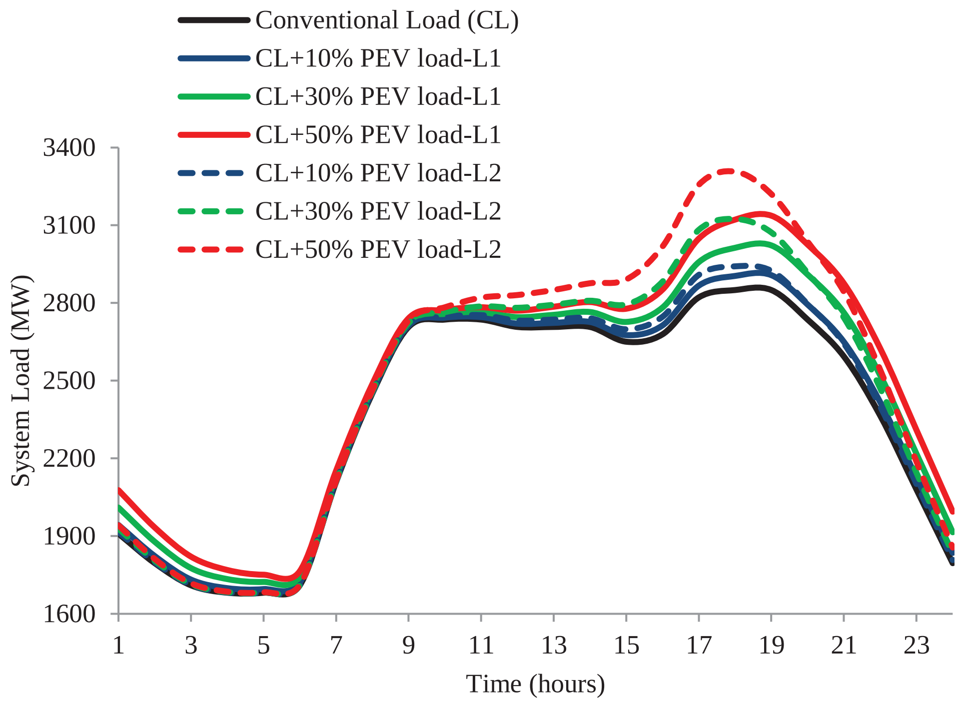


Figure 4.6 Expected peak-day system load profiles when uncontrolled PEV charging profiles are included.

A range of indices for different PEV penetration levels is listed in Table 4.6, which can be interpreted from a variety of perspectives. Overall, these results indicate that the addition of PEVs has a significant effect on reliability indices. The LOLE with charging level-1, for example, increases exponentially at a rate of 27 %: the LOLE increases by an approximate growth factor of 1.27 each time the PEV penetration is increased by 10 %. For the case when charging level-2 is used, the LOLE increases exponentially at an average rate of 38 %. From Table 4.6, it can be seen that with level-2 charging, the adequacy indices are much higher than those obtained in the case of level-1. Figures 4.6 and 4.7 show the percentage increase in the adequacy indices for charging level-1 and level-2, respectively. As the penetration level increases, the percentage increases become more significant. It can also be observed that the adequacy indices at a 50 % PEV penetration level using level-1 charging are relatively close to what they would be for a 30 % PEV penetration level using level-2 charging.

Table 4.6 Adequacy evaluation indices for case study 1

PEV Penetration %	Case 1.A Uncontrolled PEV charging load using level-1				Case 1.B Uncontrolled PEV charging load using level-2			
	Peak Load MW	**LOLE** (h/yr)	**LOEE** (MWh/yr)	**LOLF** (int/yr)	**Peak Load** MW	**LOLE** (h/yr)	**LOEE** (MWh/yr)	**LOLF** (int/yr)
0	2850	9.36	1193	1.96	2850	9.36	1193	1.96
10	2907	11.14	1400	2.42	2941	13.16	1699	2.86
20	2965	14.60	1927	3.18	3033	20.69	2861	4.67
30	3022	19.37	2568	4.42	3124	29.68	4411	7.10
40	3080	25.54	3540	5.96	3216	43.39	6627	11.30
50	3137	35.09	5060	8.08	3307	63.74	10478	17.30

Based on these results, it can be concluded that the PEV charging load is highly dependent on the charging level, thus clearly making it a major factor that strongly affects system adequacy. From a customer perspective, a higher charging level is preferable because a shorter time is required to charge the vehicle. Crucial steps must therefore be taken to prepare the system for expected increases in power demand, either by expanding existing facilities or by investigating appropriate demand-side management programs.

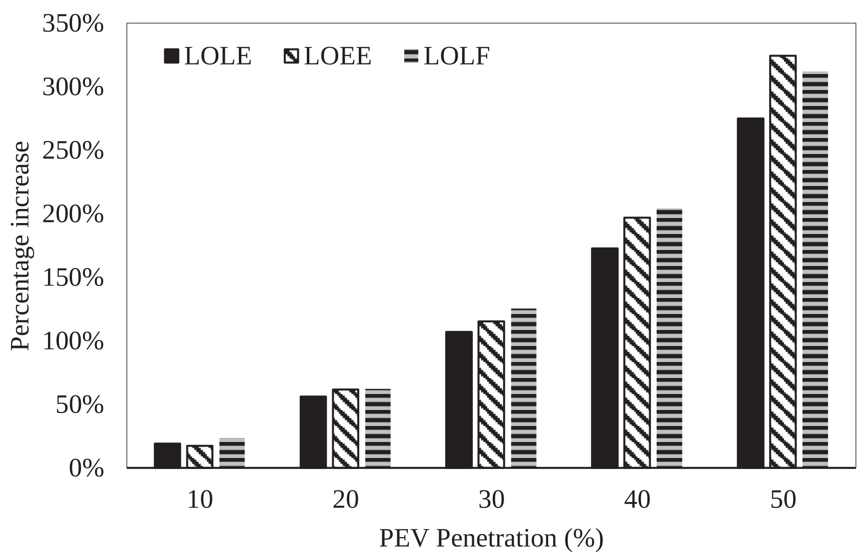


Figure 4.7 Percentage increase in the adequacy indices with charging level-1.

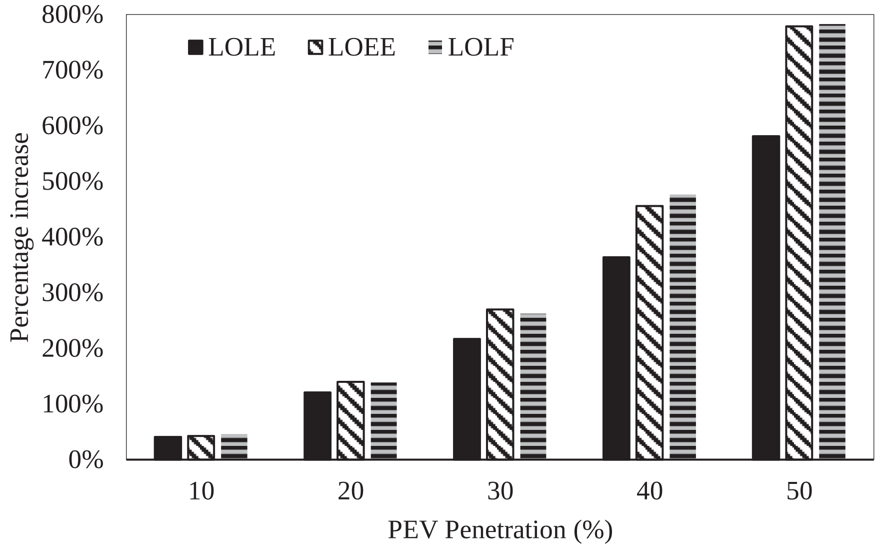


Figure 4.8 Percentage increase in the adequacy indices with charging level-2.

4.3.2 Case 2: PEV Charging Load with Response to TOU Tariffs

The previous case studies were concerned with evaluating the effect of PEV charging loads on system adequacy, with PEVs considered to be charged upon arrival at home using charging level-1 and -2. This assumption is more rational in the absence of any incentives for the driver. However, TOU pricing can create a degree of control over PEV charging loads so that PEV owners are encouraged to adjust their charging behaviour accordingly. This section discusses the impact of this charging strategy on generation system adequacy.

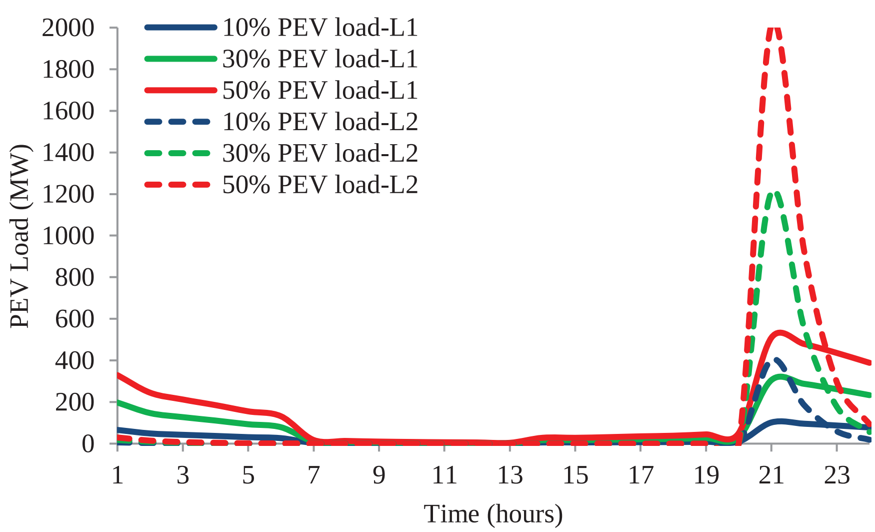


Figure 4.9 Peak-day PEV charging profiles in response to the TOU tariff.

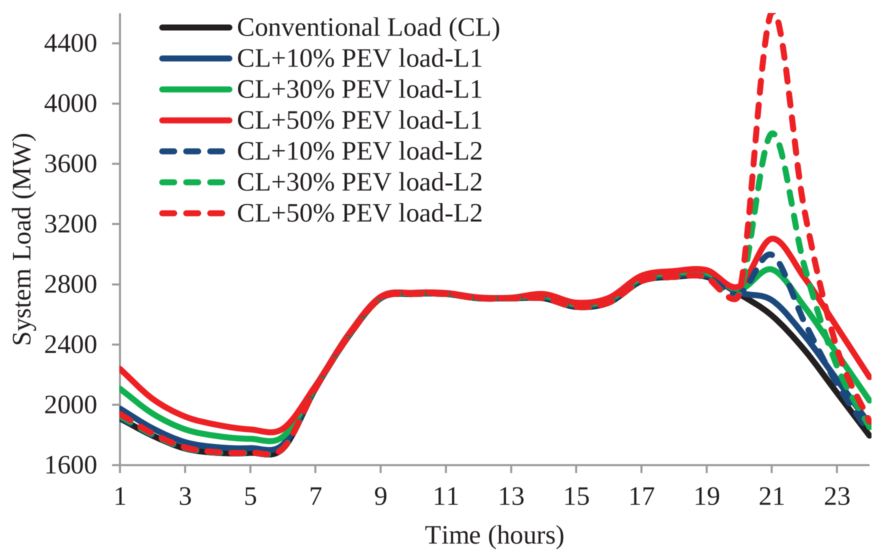


Figure 4.10 Expected peak-day system load profile with the inclusion of PEV charging profiles based on a TOU strategy.

Figure 4.9 shows different PEV charging profiles in response to TOU pricing over one simulation trial. A significant spike can be observed at hour 21, the start time of off-peak pricing. This finding indicates that a large proportion of PEV owners arriving during on-peak or mid-peak hours will wait and begin charging once the off-peak hours start. Figure 4.10 shows the changes in the conventional base load profile with the inclusion of TOU-based PEV charging profiles. A considerable change in the base load characteristics can be observed where the peak shifts from hour 19 to hour 21, especially at higher penetration and charging levels.

An interesting finding is that the system peaks with the addition of different PEV load penetration levels under the TOU strategy using level-1 charging are somewhat lower than the peaks when the PEV charging load is left uncontrolled. Compared with the indices obtained for the uncontrolled charging strategy (Case 1.A in Table 4.6), a reasonable reduction in the LOLE and LOEE is observed when using the TOU charging strategy (Case 2.A in Table 4.7). For example, at 50 % PEV penetration, the LOLE and LOEE are reduced by approximately 30 % compared to the arrive-and-plug charging strategy (Case 1.A). However, the behaviour of the LOLF index is quite different in this case: the LOLF is less than that for the case of the uncontrolled scenario for PEV penetration levels of 30 % or less. Nonetheless, compared to the case involving no TOU response (Case 1.A), the LOLF is worst when the penetration level exceeds 30 %. This effect is attributable to the characteristics of the PEV charging load and the way it varies from hour to hour, which is a contributing factor in the LOLF. Hence, a load profile with smooth changes does not cause as great a loss of load events as a load profile with high-amplitude spikes.

On the other hand, with level-2 charging, compared with the uncontrolled charging mode (i.e., Case 1.B vs. Case 2.B), the TOU charging strategy causes a significant increase in the system peaks for all penetration levels considered. As is evident from the results of Case 2.B listed in Table 4.7, the reliability indices are much higher than those obtained when PEV owners plug in their vehicles as soon as they arrive home (i.e., Case 1.B). This result can be attributed mainly to the finding extracted from the load profiles shown in Figure 4.10: a large proportion of PEV owners begin charging during the same hour, which creates a significant new system peak.

Table 4.7 Adequacy evaluation indices for case study 2

PEV Penetration %	**Case 2.A** PEV charging load based on TOU response using level-1				**Case 2.B** PEV charging load based on TOU response using level-2			
	Peak Load MW	**LOLE** (h/yr)	**LOEE** (MWh/yr)	**LOLF** (int/yr)	**Peak Load** MW	**LOLE** (h/yr)	**LOEE** (MWh/yr)	**LOLF** (int/yr)
0	2850	9.36	1193	1.96	2850	9.36	1193	1.96
10	2859	10.36	1343	2.13	2996	13.90	1796	6.07
20	2868	11.35	1409	2.65	3399	51.44	9122	42.01
30	2899	14.30	1836	4.07	3801	186.14	48763	171.98
40	3001	17.73	2326	6.38	4204	355.21	155047	327.36
50	3103	24.16	3321	10.58	4607	418.91	300716	365.34

These results indicate that the applicability of the TOU pricing rate at charging level-2 is no longer valid and creates a severe risk with respect to generation reliability. The findings underscore the need for practical solutions to address the new problems arising from PEV integration, such as appropriate DR incentives, two-way communication for smart charging, and/or facilities expansion.

4.3.3 Case 3: Uncontrolled PEV Charging Load, and Different PEV Types

In previous case studies, the number of PEV in the system is distributed based on the percentages of each vehicle class according to its market share. However, the considered factors in this case are the same as in Case 1.A except that the number of PEV in the system is represented by each

PEV type individually. Figure 4.11 shows the effect of each PEV type on the LOLE index. Overall, these results indicate that PEV type is a factor that strongly affects the system adequacy, and that developing a study based on PEV types with small battery capacities produces too optimistic results.

A comparison of these results reveals that the indices obtained using the TP are much lower than those obtained using CV, NL, and TS. This is because the TP has a smaller battery with a shorter range, which requires lower daily energy consumption than the other types. An interesting finding is that the contribution of TS to the increased adequacy indices is relatively similar to those of CV and NL, although TS has a much higher battery capacity and electric range. This result can be explained by the following two reasons. First, most of the vehicles drive 35 miles or less per day, according to the NHTS, and this range can be offered by all of these PEV (i.e., CV, NL, and TS). This means that these PEV consume approximately the same daily amount of energy. Second, the energy consumed per mile for a CV is relatively higher than for NL and TS. For example; 1 mile driven in electric mode by a CV consumes 0.45 kWh, while the consumption is about 0.32 kWh for NL and TS.

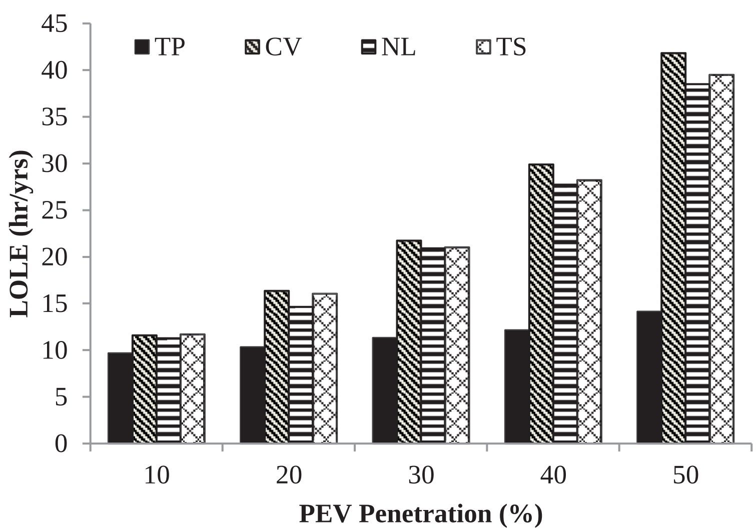


Figure 4.11 LOLE index for different PEV types over different penetration levels

4.4 Summary

The expected rapid increase in PEV integration and the unique challenges accompanying PEV loads motivated the research presented in this chapter. An innovative, comprehensive framework has been created for understanding and evaluating PEV charging behaviour characteristics and their effect on power system reliability. Models development were based on clear definitions of relevant factors, careful selection of necessary data, and simple and efficient algorithms for ensuring an accurate determination of any effect on reliability. A groundbreaking statistical analysis technique guided the evaluation of best-fit PDFs for use with MCS to devise novel stochastic simulations of PEV charging loads and their associated uncertainties, which were then applied with uncontrolled and TOU-based charging strategies. The proposed framework enables a thorough investigation of the impact on reliability of PEV charging characteristics: driver habits, vehicle type, charging level, penetration level, and TOU rates.

The important findings to emerge from this work are as follows. First, the deployment of PEV load under uncontrolled charging scenario is very likely to add considerable loading on electrical systems, severely threatening system reliability. The risk arises because large proportion of PEV owners will arrive and expect to charge during peak system hours. Solutions that maintain an acceptable level of system reliability are therefore required. Second, the application of current TOU rates with respect to PEV loads at charging level-1 somewhat reduces the system peak and helps in achieving a reasonable reduction in the reliability indices. When charging level-2 is used, however, the TOU rates is no longer valid, which creates a severe risk on the system reliability, worse than the case involving no response to TOU.

Chapter 5
Assessment Framework for Flexibility of Plug-in Electric Vehicles Charging Load to Respond to System Critical Events

5.1 Introduction

The previous chapter described the development of detailed and realistic PEV charging models under uncontrolled and TOU strategies for facilitating an accurate and comprehensive assessment of the impact of PEV on the system reliability. The uncontrolled PEV charging model represents a realistic scenario that can occur when electric utilities charge their customers based on flat rates: PEV owners will likely start charging upon arrival in order to ensure that the PEV will be charged by the time it is needed. The massive deployment of PEV under this charging scenario is very likely to add considerable loading on an electric system, severely threatening system reliability. This risk is attributable primarily to the finding based on arrival rates that a large proportion of PEV owners arrive and expect to charge during peak system hours.

For utilities who charge their customers based on static TOU tariff rates, it is anticipated that most PEV owners arriving at on-peak and mid-peak hours will wait until an off-peak period to take advantage of the off-peak price. This expectation is based mainly on the results from the NHTS of driver behaviour, which gives the average duration of vehicle at-home time as 16 hours, and the average time required for charging as about 7 hours using a level-1 charger and 2 hours using a level-2 charger. When a large number of PEVs begin charging simultaneously, a new system peak would be expected, thus exacerbating the negative effect on system reliability.

While the importance of developing accurate models for assessing the reliability impact of the above charging scenarios must be recognized, investigating potential solutions for mitigating the negative impact of these scenarios is also crucial. An apparent trend on the part of many modern electric utilities is to encourage and incentivize customers to reduce consumption when the system is stressed or during unbalanced supply-demand events. Before the implementing of any DR programs, electric grid regulators or planners must have confidence about two facts that are 1) the loads of end-users (targeted customers) should have the ability to be easily modified (i.e., inherit flexibility); 2) the existing flexibility should match the system needs (i.e., load can be shifted from peak hours to valley hours without breaking customer satisfactions).

This chapter presents a daily basis assessment framework for the application of a dynamic critical events call program for use with adequacy assessment in the presence of PEV charging loads. The framework involves the development of two models: The first model is targeted at determining the time of critical system events (day and hours), when system supply facilities are unable to meet the PEV load, as well as the PEV demand not supplied. The second model examines the feasibility of PEV owner response to the critical events. It worth mentioning that the proposed framework is in line with the recent trend of many modern electric utilities so that customers are encouraged and incentivized through a proper dynamic DR program to reduce consumption when the system is stressed or during unbalanced supply-demand events. The basic principle of these programs is based on customer response to limited critical events.

5.2 Proposed PEV Charging Model Based on a Dynamic Call DR Program

This section introduces a new reliability framework for the application of a dynamic critical events call program for use with adequacy assessment in the presence of PEV charging loads. The overall structure of the proposed framework comprises two main stages as shown in Figure 5.1 and 5.2 respectively, and detailed discussions of these stages are provided in the following subsections.

5.2.1 Stage 1: Critical Event Determination

New model is developed in this chapter to determine the time and duration of critical events as described in Figure 5.1 and in the following step-wise procedure:

Step 1: Using the approaches described in the previous chapter, develop the yearly generation capacity model, the conventional load model, and the uncontrolled model on an hourly basis.

A detailed discussion of these models provided in section 4.2 in the previous chapter, and an explanation of this step in the proposed framework is thus omitted.

Step 2: Assess the ability of the system generation capacity to meet the system demand on a day-to-day basis. At this point, the PEV charging load during normal days, when the system supply facility is adequate for meeting the system demand, will be left under uncontrolled mode. On days with a shortage of supply (critical events), the PEV charging load will be subject to further analyses, which entail the following new indices:

a. For the critical hours of critical days: PEV demand not supplied (DNS^{PEV}), as expressed in (5.1), is obtained. This index is then used for determining the number of PEVs required to participate in the DR program (N_{DR}^{PEV}), as expressed in (5.2).

$$DNS^{PEV}(t) = \begin{cases} P_{PEV}(t) + P_{CL}(t) - P_{TG}(t) & \overset{if}{\Leftrightarrow} \quad P_{CL}(t) < P_{TG}(t) < P_{PEV}(t) + P_{CL}(t) \\ P_{PEV}(t) & \overset{if}{\Leftrightarrow} \quad P_{TG}(t) \leq P_{CL}(t) \end{cases} \tag{5.1}$$

$$N_{DR}^{PEV}(t) = \frac{DNS^{PEV}(t)}{ch_L \times \eta_{ch}} \tag{5.2}$$

b. For the non-critical hours of critical days, the extra accommodation level (EAL) is determined, as expressed in (5.3), which indicates the additional number of PEVs that can be accommodated without threating the supply-demand balance. This index is very important because it provides information about the candidate hours and their accommodation levels, to be used for shifting the PEV load from critical hours.

$$EAL^{PEV}(t) = \frac{P_{TG}(t) - P_{CL}(t) - P_{PEV}(t)}{ch_L \times \eta_{ch}} \quad \overset{if}{\Leftrightarrow} \quad P_{TG}(t) > P_{CL}(t) + P_{PEV}(t) \tag{5.3}$$

Step 3: Along with other PEV charging parameters, these indices are set as input for adapting the uncontrolled PEV charging load to include consideration of the flexibility of driver behaviour in response to the critical events call.

Step 4: The PEV charging profile adapted for critical days then replaces the uncontrolled one and is used for evaluating the system reliability indices and determining the effectiveness of this program.

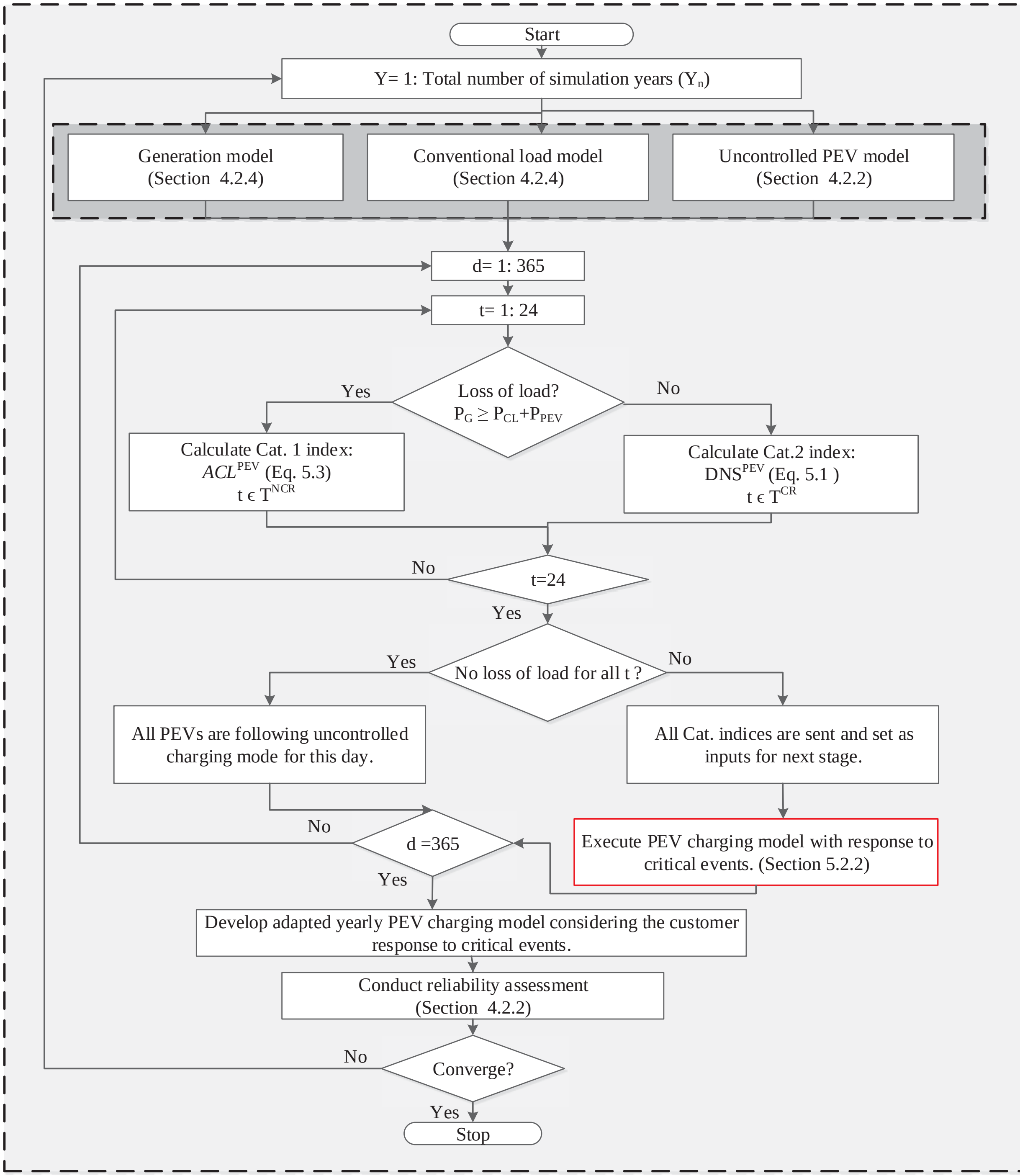


Figure 5.1 Stage 1 procedures for critical event determination

5.2.2 Stage 2: Development of the PEV Charging Load with Customer Response to Critical Events

In this stage, the PEV charging load is adapted by exploiting the customers' inherent flexibility in response to critical system events. To ensure the practicality of the application of this program, the decision to respond to critical system calls is based mainly on the customers' flexibility; i.e., it should be within customer behaviour boundaries and not cause inconvenience. PEV owners can participate in this program if both of the following conditions are applied: 1) the duration of the home stay is greater than the charging time required, and 2) the charging hours intended under the uncontrolled mode intersect with the critical hours. Figure 5.2 and the following steps outline the primary procedures for developing a PEV load response to a critical system event:

Step 1: Read the data pertaining to critical event calls (outcomes from Stage 1) and other PEV charging data (customer behaviour data, battery specifications, market share, charging levels, etc.) (discussed in section 4.2.1).

Step 2: As discussed in section 4.2.2, execute Step 1 to Step 12 in the uncontrolled PEV charging model to determine the following parameters: HAT, HDT, SoC, *CE*, and *CD*.

Step 3: Define the following time periods: T^{NCR} denotes non-critical hours during which the system can provide an extra level of PEV accommodation, T^{CR} defines critical hours during which the system must shift a specific level of demand, T^{UNC} defines hours during which a PEV was intended to be charged, and T^{SH} defines hours during which a PEV is at home. The example in Figure 5.3 illustrates the definitions of these time periods.

Step 4: When a PEV requires a charging time greater than or equal to its time at home (i.e., *CD* >= *SD*), the PEV owner cannot respond to critical events, and hence the PEV remains charging under uncontrolled mode according to (4.9). In other cases, (i.e., *CD* < *SD*), two further scenarios are investigated:

1) If the intended charging hours for a PEV under uncontrolled mode do not intersect with the critical hours (i.e., $T^{UNC} \cap T^{CR} = \emptyset$), the PEV owner is not a subject for participation in this program, and hence the PEV remains charging under uncontrolled mode using (4.8).

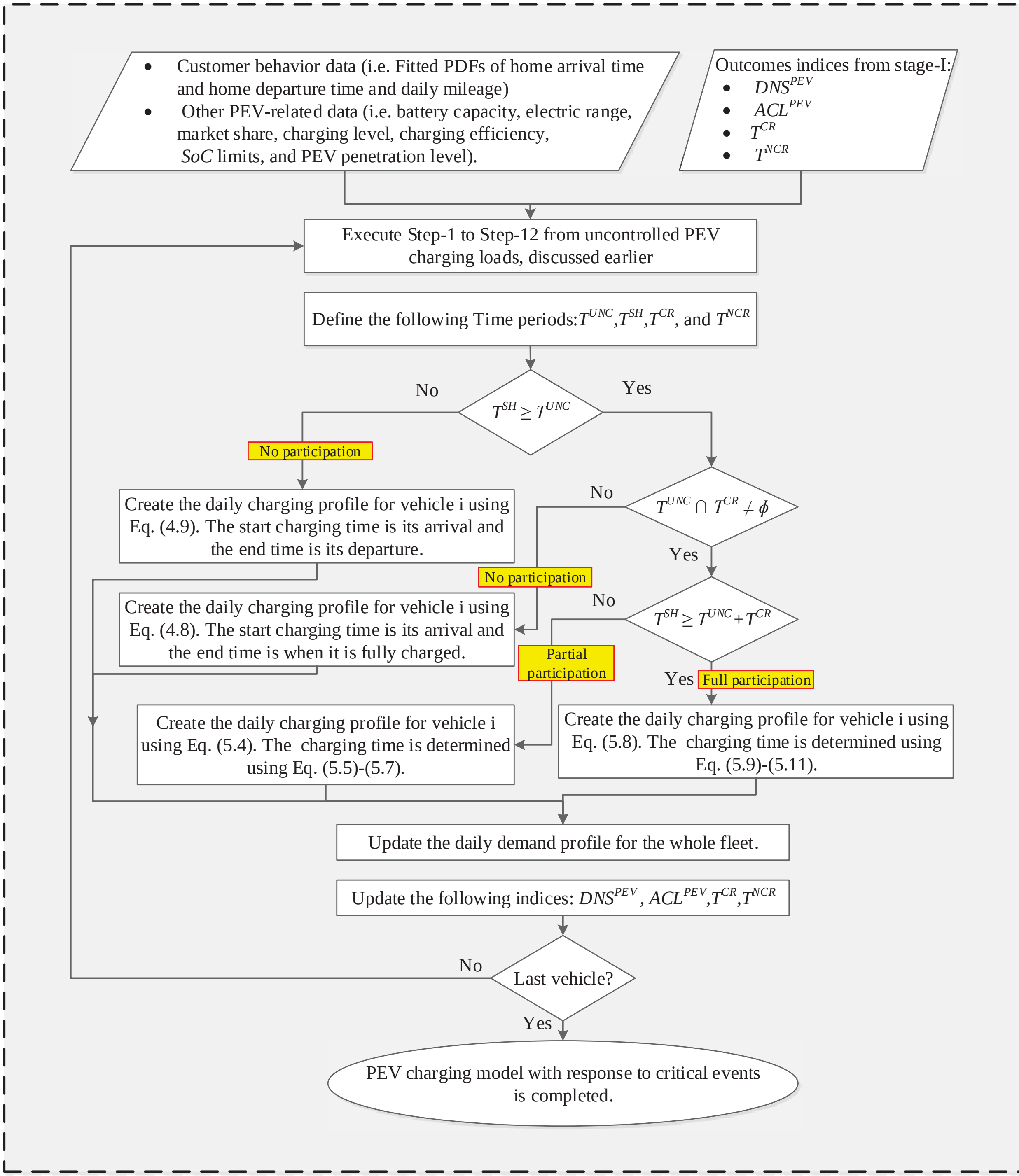


Figure 5.2 Development of PEV load model that are responsive to the system critical events

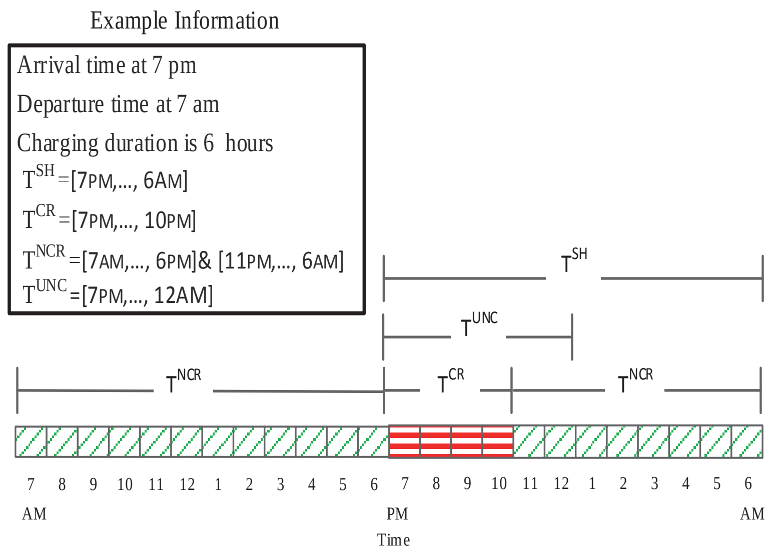


Figure 5.3 Example that illustrates the definitions of the time periods.

2) Otherwise, (i.e., $T^{UNC} \cap T^{CR} \neq \emptyset$), the PEV owner can then partially or fully participate in responding to critical hours based on the following scenarios:
   a) Partial participation: When the hours in which a PEV stays at home are less than the sum of the required charging hours and the critical hours (i.e., $(T^{SD}) < (T^{UNC} + T^{CR})$), the PEV owner can participate partially in the program and avoid charging during some critical hours. The participation is partial because the non-critical hours that coincide with the vehicle's stay hours are insufficient to charge the vehicle. In this scenario, the PEV is therefore charged during two periods, defined as follows: T^{X1} contains the non-critical hours that coincide with the vehicle's stay hours, and T^{X2} contains the critical hours that coincide with the vehicle's stay hours and that are arranged in ascending order based on DNS^{PEV}, as expressed in (5.4)-(5.7). It should be noted that the PEV is charged during some hours of the T^{X2} period, which are equal to the number of hours in T^{X1} minus the required charging hours.

$$P_i(t) = ch_L \quad \overset{where}{\Longrightarrow} t \in T^{X1} \ \& \ t \in T^{X2} \tag{5.4}$$

$$T^{X1} = T^{SH} \cap T^{NCR} \tag{5.5}$$

$$T^{Y} = T^{SH} \cap T^{CR} \tag{5.6}$$

$$T^{X2} = (T^{Y}|\text{ascending order } (DNS^{PEV})) \tag{5.7}$$

b) Full participation: When a PEV stays at home more than or equal to the required charging hours plus the critical hours, the PEV owner can participate by avoiding charging during all critical hours. In this scenario, the PEV is charged according to (5.8)-(5.11), in which T^{z1} contains the non-critical hours that coincide with the intended hours of charging under uncontrolled mode, and T^{Z2} contains the complementary hours of T^{Z1} that intersect with the vehicle's stay hours and are arranged in descending order based on ACL^{PEV}. It should be pointed out that the PEV is charged during some hours of the T^{Z2} period that are equal to the number of hours in T^{Z1} minus the required charging hours.

$$P_i(t) = ch_L \quad \xrightarrow{where} t \in T^{Z1} \ \& \ t \in T^{Z2} \tag{5.8}$$

$$T^{Z1} = T^{UNC} \cap T^{NCR} \tag{5.9}$$

$$T^{W} = T^{SH} \cap \overline{(T^{UNC} \cup T^{NCR})} \tag{5.10}$$

$$T^{Z2} = (T^{SH}|\text{descending order } (ACL^{PEV})) \tag{5.11}$$

Step 5: Update the charging profile of the entire fleet (P_{PEV}), DNS^{PEV}, and ACL^{PEV}.

Step 6: The same procedures (Step 1 to Step 5) are repeated sequentially until all critical events are responded to or the charging profiles are simulated for the entire fleet.

5.3 Cases under Study

The results presented in the previous chapter provide important insights about the need for solutions that maintain overall system reliability and ensure adequate generation capacity. Based on these considerations, the work in this chapter was extended to include an examination of a dynamic DR program based on utilizing the flexibility of driver behaviour in response to critical system events. The considered system and the key factors in this chapter are the same as the base case in the previous chapter.

This section presents the results of the application of a dynamic critical events call program for use with PEV charging loads. For both charging levels, Figure 5.4 shows a 50 % PEV charging load penetration level with/without response to the critical events program. It is clear that, during peak hours (15PM to 20 PM), the uncontrolled PEV charging load is shifted to less critical hours, thus largely reducing the system peak to the base profile, as shown in Figure 5.5. It should be pointed out that with level-2 charging, the system peak hours are reduced so that they are equal to the original base load (i.e., the case without PEV), while a slight increase in the peak hours load compared to the original base load cannot be avoided when using level-1 charging. This effect is due to the charging duration being highly dependent on the use of charging levels. A level-1 charger hence results in a longer charging time than a level-2 charger does.

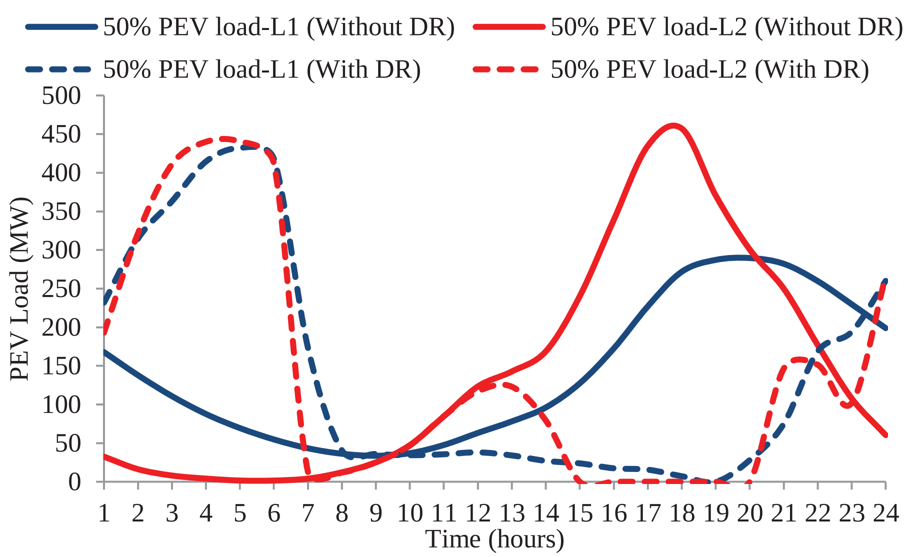


Figure 5.4 The 50 % PEV penetration charging load with/without response to the critical events program, for both charging levels.

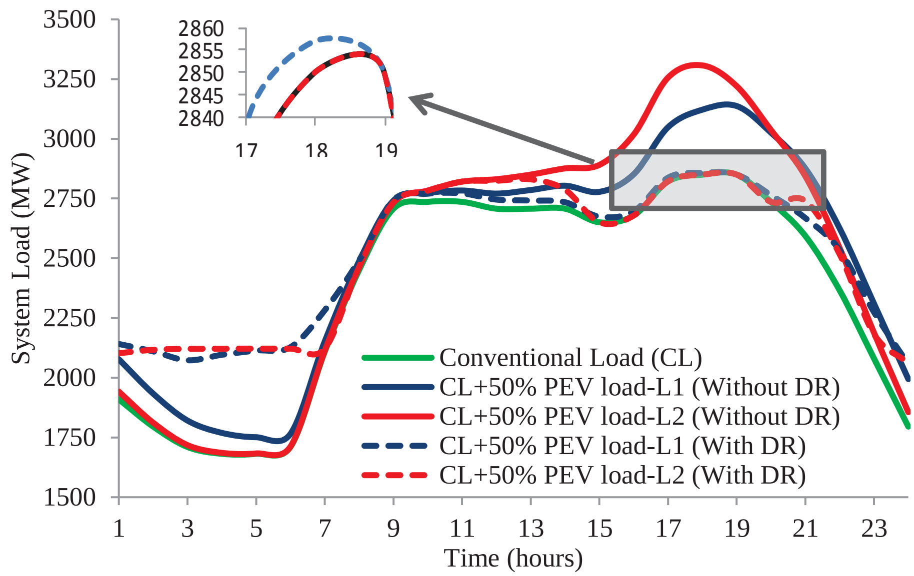


Figure 5.5 The system load profile that includes 50 % PEV penetration charging load with/without response to the critical events program, for both charging levels.

It is worth mentioning that the response to critical events calls is based mainly on the customers' flexibility; i.e., it should be within customer behaviour boundaries and not cause inconvenience. With these points in mind, the considerable reduction achieved in the system peak with the application of this DR program indicates that customers have enough flexibility and ability to respond to critical system events without violating their behavioural limits. As stated earlier, the PEV charging load with response to the dynamic DR is developed based on two stages: the first is targeted at determining critical system events and the amount of PEV demand not supplied. Figure 5.6 shows a sample of the outcome indices of the first stage at a 30 % PEV penetration level: PEV demand not supplied, number of critical days per year, and number of critical hours per year. These kinds of indices offer highly essential information about system behaviour that can be used for managing the PEV charging load.

This figure reveals that the critical system events caused by the addition of PEV loads over a large number of simulation years are limited to a relatively small number of days and hours per year. This is, in fact, the essential key to the practicality of this program for managing the PEV charging load. The second stage involves examining the feasibility of PEV owner response to critical events and then adapting the PEV load accordingly. To assess the contribution of the PEV charging load to system reliability when customers respond to the critical events program, Table 5.1 shows the results of different indices for both charging levels.

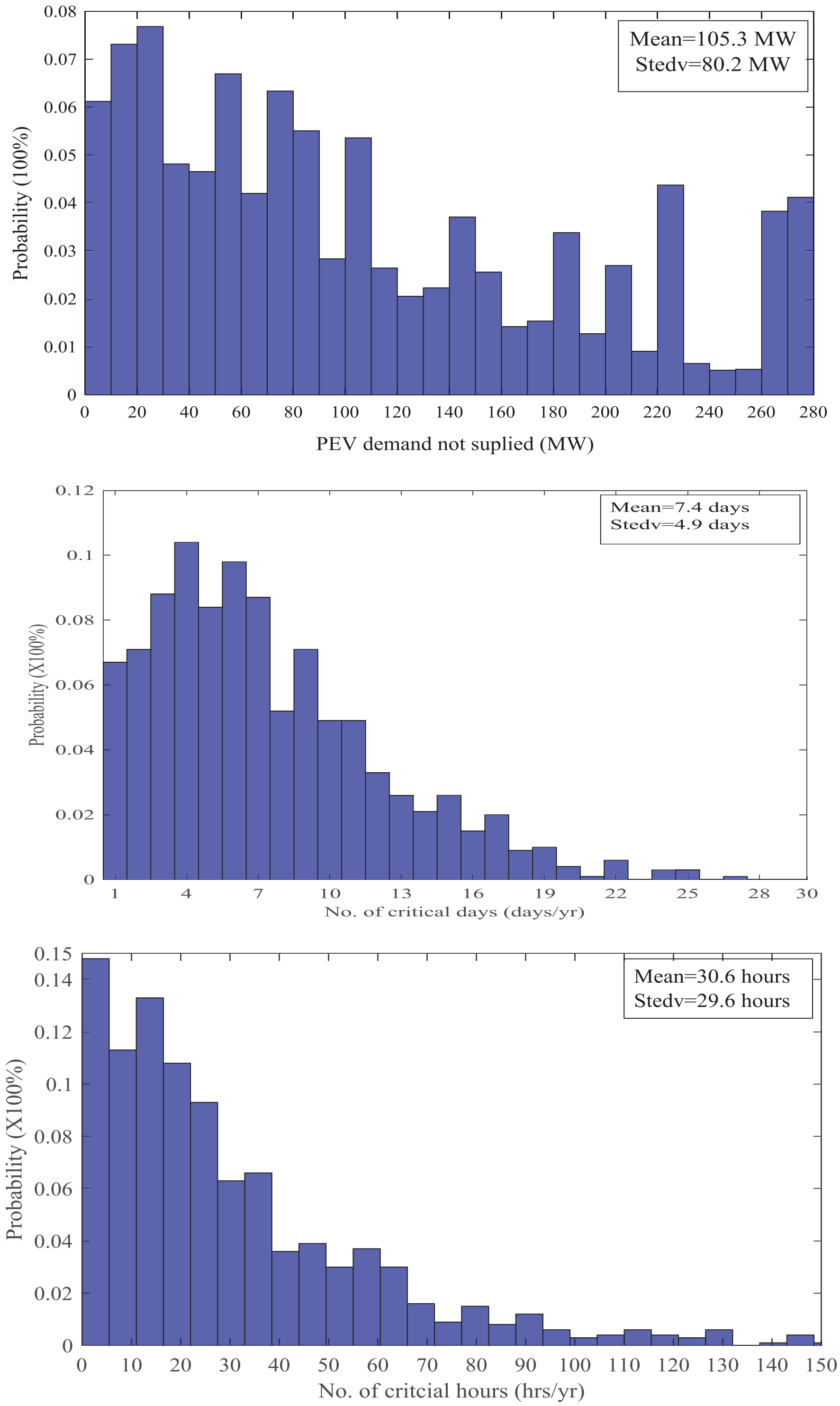


Figure 5.6 Sample of the first-stage outcome indices at a 30 % PEV penetration level using charging level-2.

These results demonstrate that adequacy indices at all penetration levels and for level-2 charging are significantly reduced so that they are equal to the case without PEV. Figure 5.6 and 5.7 shows the comparison of LOEE indices obtained using PEV load model with and without the DR program. At all penetration levels, for level-1 charging with the use of DR program, a significant reduction in all adequacy indices can be observed compared with uncontrolled charging strategy (Case 1.A in Table 4.6). Small differences from the results of the base case are to be expected for the reasons mentioned earlier in the Figure 5.5 discussion. With respect to system reliability, this reduction in the indices is considered significant and reveals that the critical event DR program is a very promising option that should be considered for the effective management of PEV charging loads.

Table 5.1 Adequacy evaluation indices for both charging levels

PEV Penetration %	**Case 1** PEV charging load based on dynamic DR using level-1				**Case 2** PEV charging load based on dynamic DR using level-2			
	Peak Load MW	**LOLE** (h/yr)	**LOEE** (MWh/yr)	**LOLF** (int/yr)	**Peak Load** MW	**LOLE** (h/yr)	**LOEE** (MWh/yr)	**LOLF** (int/yr)
0	2850	9.36	1193	1.96	2850	9.36	1193	1.96
10	2851	9.52	1196.44	1.96	2850	9.36	1193	1.96
20	2853	9.70	1202.51	1.97	2850	9.36	1193	1.96
30	2854	9.92	1214.60	1.98	2850	9.36	1193	1.96
40	2856	10.25	1240.33	2.02	2850	9.36	1193	1.96
50	2857	10.78	1293.39	2.08	2850	9.36	1193	1.96

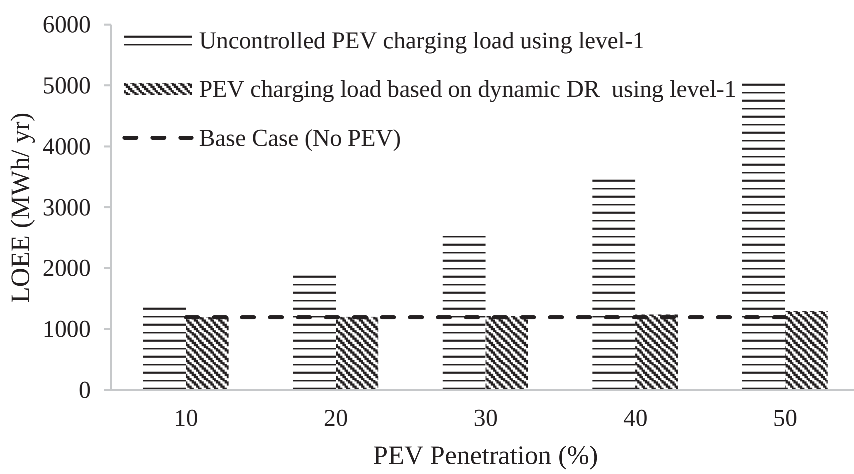


Figure 5.7 LOEE indices obtained for PEV load model with and without the DR program using levlel-1

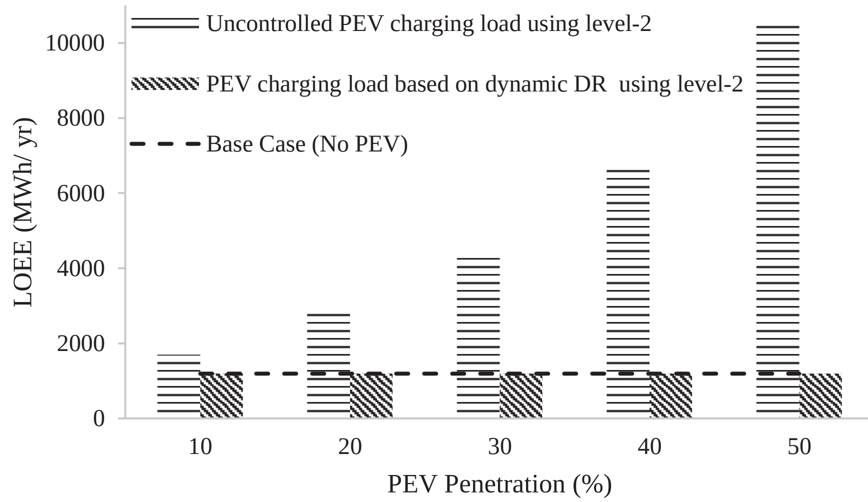


Figure 5.8 LOEE indices obtained for PEV load model with and without the DR program using levlel-2

5.4 Summary

To mitigate the impact on reliability that would be expected when PEVs are charged in uncontrolled mode, this chapter presented a methodology to investigate the level of compatibility between system critical events and PEV charging flexibility. Two integrated models were developed, the first of which determines the time and duration of critical system events as well as the amount of PEV demand not supplied. The second model uses the outcomes of the first model and examines the existing flexibility in PEV loads to respond to critical events. The important finding to emerge is that PEV charging loads offer a large degree of flexibility to avoid system critical events without violating customer behaviour boundaries and causing inconvenience. This finding supports the current trend that calls for an investigation into solutions on the demand side to help improve reliability. The finding also provides insights into the application of dynamic DR programs as promising solutions that may be considered for the effective management of PEV charging loads.

Chapter 6
Reliability-Based Framework for Designing Time-of-Use Schedules Well Adapted to PEV Charging Loads

6.1 Introduction

The previous chapter reported the investigation of compatibility between system-critical events and plug-in electric vehicle (PEV) charging flexibility. The important finding was that a PEV charging load has a substantial degree of flexibility with respect to avoiding system-critical events without violating customer behaviour boundaries and causing inconvenience. This conclusion supports the current trend of improving reliability by investigating solutions at the demand side. The results also provide insights related to the application of dynamic demand response (DR) programs as promising solutions for facilitating the effective management of PEV charging loads. However, major challenges are associated with the implementation of these programs [21], [51]: 1) they require robust infrastructure that enables information-sharing and communication between system service providers and the huge number of customers in residential sectors, and 2) without automating technologies, responding to and keeping track of hourly price changes is difficult for residential customers. For these reasons, dynamic DR programs have thus far been targeted at special customers, such as large industrial and commercial customers who have the manpower to negotiate with utilities and track dynamic changes in the hourly rates. In contrast, TOU programs are the ones most widely employed at residential and small business load levels. The basic concept of TOU rates is the setting of three rate blocks, each of which is predetermined and constant for a relatively lengthy time period (usually a season). The consistency of the tariff over a long time makes a TOU program easy to understand and follow and thus practicable enough for residential customers. However, significant difficulty is associated with establishing only one TOU tariff that is valid for an entire season and that at the same time reflects the realistic random behaviour of the system, including random component failure, the stochastic nature of non-dispatchable components, and load variability and uncertainty.

In light of the above discussion, the aim of the work presented in this chapter was to develop a reliability-based framework for designing a TOU schedule well adapted to PEV charging loads. The following are the primary contributions of the proposed framework:

1) Stochastic simulation models have been developed with the goal of quantifying the reliability performance of existing generation facilities that incorporate massive PEV deployment and increased shares of wind power generation. The models created generate a multitude of scenarios for each individual system component based on consideration of the uncertainties associated with random component failure, the stochastic nature of wind generation, and the inherent randomness of driving patterns and of other PEV characteristics.
2) A Markov chain Monte Carlo (MCMC) method is employed in a novel manner in conjunction with a k-means clustering technique as a means of taking into account the chronological correlation between two variables (system load and wind generation) and of reducing the number of variables in the simulation.
3) This thesis proposes innovative data treatment, a box-plot method, and expert rules in order to deal with the massive amount of data generated for each individual system component and to facilitate the simple and effective representation of the system reserve margin (SRM) at each hour.
4) The above models and output are incorporated into a novel proposed methodology for arriving at TOU schedules that are well adapted for PEV loads. The proposed methodology entails the following processes:
    a) Use the outcomes of the box-plot method and expert rules to determine an initial decision about the type of each hour (off-, mid-, or on-peak).
    b) From the initial decision, reduce all combinations of these hour types to a reasonable number of possible combinations, in this way facilitating the assessment of those scenarios.
    c) Develop PEV charging load profiles that are responsive to the predefined set of TOU schedule scenarios, and examine the improvement in reliability provided by each scenario.

6.2 Proposed Framework for designing a TOU Schedules for PEV Charging Loads.

This section introduces a new reliability-based framework for designing appropriate TOU schedules for PEV charging loads. Figure 6.1 provides an overall schematic of the proposed framework, which involves the completion of three main stages. The first is targeted at the development of a variety of stochastic simulation models that can generate large amounts of time series data and that include effective consideration of random component failure, the stochastic nature of wind generation, and the randomness inherent in driving patterns and other uncertainties associated with PEV characteristics. The outcomes of these models are fed into Stage II, which involves the application of special data treatment and statistical tools based on expert criteria in order to produce an initial decision with respect to the type of each hour (off-, mid-, or on-peak). The output from Stage I and Stage II is then employed in Stage III for the assessment of a range of possible TOU schedule scenarios in order to determine the optimal schedule.

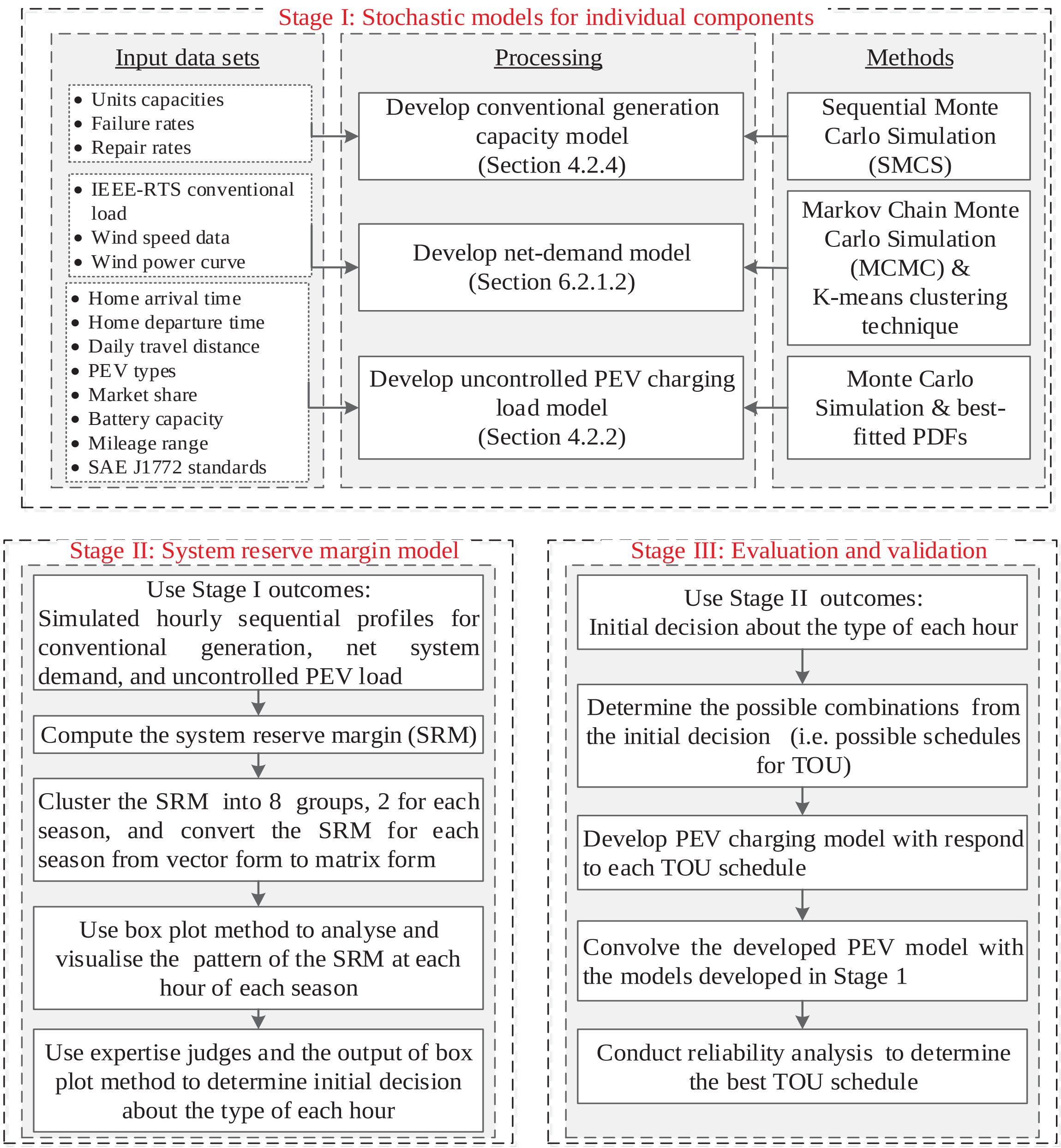


Figure 6.1 Overall structure of the proposed framework

6.2.1 Stage I: Stochastic Models for Individual System Components

6.2.1.1 Conventional Generation Capacity Model

The rated installed capacity of existing generation resources is not always available because the generating units are exposed to unplanned or planned outages (i.e., unexpected failures or scheduled maintenance). This deficiency underscores the need for probabilistic techniques that can address the intrinsic uncertainties associated with component failure and determine the generation capacity available at each instant. In the work described in this chapter, a sequential Monte Carlo simulation (MCS) approach was employed for simulating the chronological capacity available from all generating units using equations (4.15-4.18) in section 4.2.4. The detailed sequential MCS process is presented in section 4.2.4.

6.2.1.2 Wind generation and system demand models (Net demand model)

Modeling wind generation for use in different power system applications requires a large database of historical wind speeds so that the stochastic behaviour of the wind generation can be accurately analyzed. However, the lack of sufficient data calls for reliable stochastic wind simulation techniques. Such wind power/speed models should preserve the main characteristics of the historical measurement data (e.g., distributional and temporal variations of the wind speed) and generate the desired wind speed/power time series. Most of the available time series models described in the literature can be classified into two categories: autoregressive moving average (ARMA) models and Monte Carlo Markov Chain (MCMC) models. These models are acknowledged as being useful for wind generation because of their essential feature of preserving the special and chronological variability of the wind, which facilitates the integration of wind generation into various time-based applications. The models based on MCMC offer basic advantages compared with the ARMA models, discussed in details in section 2.6. Although the MCMC models are widely used to generate wind speed/power time series, they still have some downsides, such as the imperfect preservation of correlation characteristics with system load as well as the inaccuracy and complexity associated with the discretization process. To address these issues and further improve the efficiency of this approach, we propose a novel way of deploying the MCMC model. First, the development of simulation procedures is based on data measured directly from the net system demand (the residual amount of system demand after wind generation is deduced from the total demand). Combining these variables (i.e., wind generation and system load) in this way has the advantages of 1) considering the inclusion of the chronological correlation between these variables; 2) reducing the number of variables so that the simulation estimates one random variable instead of dealing with two variables independently. The letter feature helps in reducing the states of the Markov chain and, complexity and computational time consequently. The second improvement to the existing MCMC model is the application of the k-means clustering technique to identify a proper number of system states needed to build the Markov chain transition matrices. The basic idea of the k-means technique is to cluster a big and scattered data into a finite number of centroids with aim minimizing the error between the data points and the centroids. In this way, the accuracy associated with the discretization process will be to, large extent, enhanced.

The main procedures of the stochastic simulation model can be summarized as in Figure 6.2 and are discussed in detail in the following subsection.

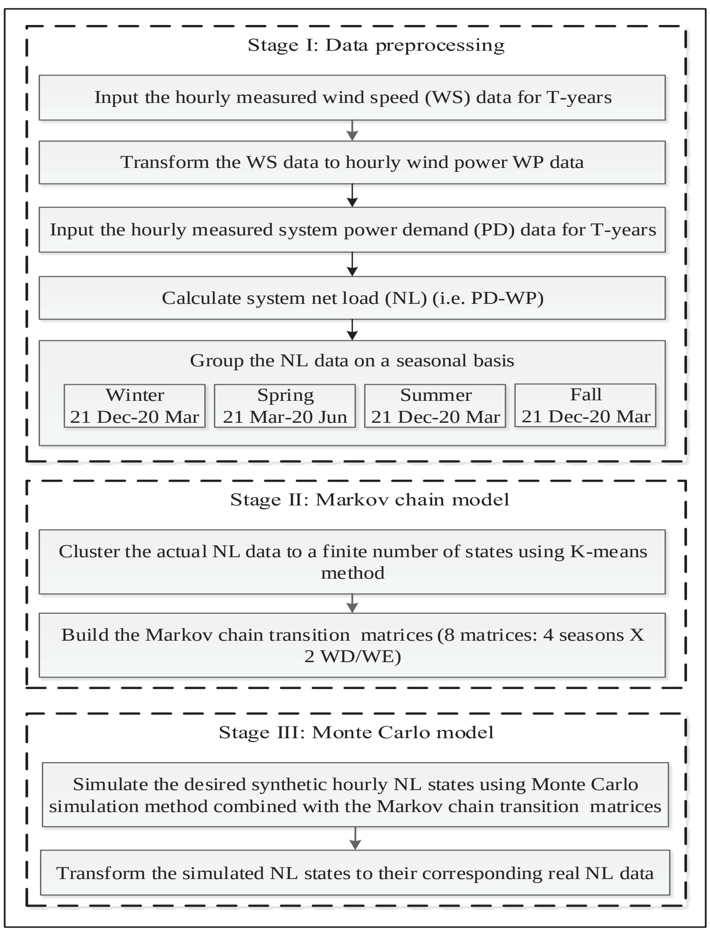


Figure 6.2 Main procedures of the MCMC model

6.2.1.2.1 Data collection and preprocessing

The hourly wind speed data observed over three years for the Bonavista site located in Newfoundland, Canada, were collected from Environment Canada [77] and used in this study. These data were applied to the power curve of the wind turbine generator, as expressed in (6.1), to transform the data from the wind speed domain to the wind power domain. Doing so helps reduce the number of Markov transition states, because the data of all wind speed states that lie outside the cut-in or the cut-out zones of the wind turbine power curve are represented by only one power state (i.e., zero), and the wind speed states that are within the rated power of the wind turbine are represented by only one power state (i.e., rated).

$$P(\omega) = \begin{cases} 0 & 0 \le \omega \le \omega_1 \\ (a_1 + a_2\omega + a_3\omega^2)P_{rated} & \omega_1 < \omega < \omega_r \\ P_{rated} & \omega_r \le \omega \le \omega_{cut-out} \\ 0 & \omega > \omega_{cut-out} \end{cases} \tag{6.1}$$

The constant terms a_1, a_2, and a_3 can be expressed in terms of the cut-in speed (ω_1) and the rated wind speed (ω_r) [78].

For the system demand data, the IEEE-RTS chronological hourly load model [76] is extensively used as a benchmark system to represent conventional loads in different power system applications. The IEEE-RTS load is given as a percentage of the annual system load peak so that daily, weekly, and seasonal patterns are included. Once the annual peak load (L^{peak}) is determined, the chronological hourly load model (8760 hours) can be developed using (6.2).

$$P_{CL}(t) = L^{peak} \times \; P^{w} \times P^{d} \times P^{h} \xRightarrow{where} t(1, \ldots, 8760) \tag{6.2}$$

where $P_{CL}(t)$ is the system load at each hour, (P^{w}) is the weekly peak load as a percentage of the annual peak load, (P^{d}) is the daily peak load as a percentage of the weekly peak load, and (P^{h}) is the hourly peak load as a percentage of the daily peak load.

Then, the net system demand $P_{NL}(t)$ at each observed instance can be calculated by subtracting the wind power generation $P_W(t)$ from the system load $P_{CL}(t)$, as expressed in (6.3). Prior to commencing the MCMC process, the hourly historical net load data are clustered into 8 groups, two group (weekdays, and weekends) for each of the four season. Each group contains a series of data points equal to 24 hours multiplied by the number of days in each season multiplied by the number of available years.

$$P_{NL}(t) = P_W(t) - P_{CL}(t) \tag{6.3}$$

6.2.1.2.2 Markov chain model

The Markov chain model has frequently been used to mimic the sequence behaviour of stochastic systems by modeling the transitions probabilities between a system's states, as illustrated in Figure 6.3. The basic idea of deploying the Markov chain model in time series applications is to preserve the system-transition characteristics and sort them in a matrix form with a dimension of $n * n$ (number of system states). This matrix can be then used to generate a large number of possible sequential data that are maintaining the main characteristics of the measured data.

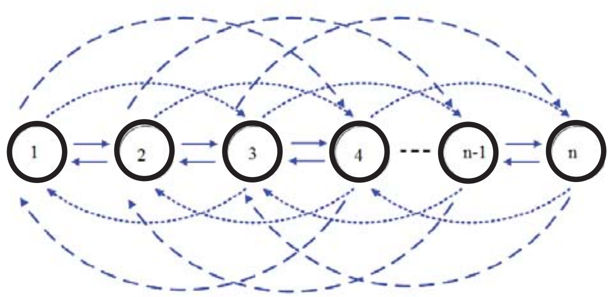


Figure 6.3 Illustrative example for some states transitions of Markov chain

For a system with the state space S= [1, 2,….., n], the system at each time instant can reside in any state, and there will be $n * n$ possible numbers of transitions between two successive time instances. Defining these transitions from the measured data facilitates the formation of Markov discrete transition matrix (p_{dtm}), as shown in (6.4). Each row of the matrix relates to the current state, while each column relates to a possible next state. Each element of the matrix represents the transition probability (p_{ij}) between any two system states.

$$D^{mat} = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,n-1} & p_{1,n} \\ & \vdots & \cdots & \vdots & \\ & \vdots & \cdots & \vdots & \\ p_{1,n} & p_{2,n} & \cdots & p_{n,n-1} & p_{1,n} \end{bmatrix} \tag{6.4}$$

As expressed in (6.5), the state probabilities can be calculated from the relative frequencies of the possible states where n_{ij} is the number of transitions from state *i* to state *j* for successive times in the measured data set. As each row relates to the probabilities of transition from one state, the summation of theses probabilities should equal one ($\sum_{j=1} p_{ij} = 1$).

$$p_{ij} = \frac{n_{ij}}{\sum_j n_{ij}} \tag{6.5}$$

After the discrete transition matrix is constructed, the cumulative probability transition matrix (p_{ctm}) can be created. The element of the p_{dtm} can be computed as follows:

$$P_{ij} = \sum_{k=1}^{j} p_{ij} \tag{6.6}$$

An essential step before creating the transition matrices is to cluster the measured net load data into a finite number of states. Determining the number of states is crucial but represents a trade-off between the accuracy of the results and the complexity of the process. To address this issue, some researchers have used clustering techniques that are dedicated to determining the minimum number of states that guarantee less complexity and reasonable accuracy. For this purpose, a clustering technique called K-means is used because of its simplicity and the reasonable accuracy it provides. The K-means clustering technique is discussed in detail in [79], [80], and its procedures can be summarized as follows:

1- Select the initial cluster means (centroids) M_k of the clusters, where k is the number of clusters. Eleven centroids (i.e., k = 11) were initially selected for this study, as determined by dividing the states of P_{NL} equally into 0.2 steps (i.e., k = 0, 0.2,..., 2).

2- Calculate the distance D_{ki} from each net load value P_{NL_i} to each centroid M_k, as given in (6.7).

$$D_{ki} = \left|M_k - P_{NL_i}\right| \tag{6.7}$$

3- Assign all of the wind power data to the nearest centroid.

4- Calculate new cluster means or centroids using (6.8), where the average of the wind power data in cluster *k* is divided by the total number of data points in the same cluster N_k.

$$M_k = \frac{\sum_{P_{NL_i} \epsilon N_k} P_{NL_i}}{N_k} \tag{6.8}$$

5- Repeat steps 2 to 4 until the centroids remain unchanged after a number of iterations.

6.2.1.2.3 MCMC for the Simulated Wind Power Time Series

Using the MCMC transition matrices, the number of sequences desired for the hourly P_{NL} samples are simulated for each season. The initial state is selected randomly, and a random value between 0 and 1 is then produced by a uniform random number generator. To determine the next state in the Markov process, the value of the random number is compared with the elements of the i_{th} row of the cumulative probability transition matrix. If the value of the random number is greater than the cumulative probability of the preceding state but less than or equal to the cumulative probability of the succeeding state, the succeeding state is chosen to represent the next state.

The same procedures are repeated sequentially in order to simulate the required hourly P_{NL} data for each season. Based on these calculations, the hourly P_{NL_i} time series can be obtained for a year (1, 2, 3…8760). The loop is repeated for the desired or prespecified number of years.

6.2.1.3 Uncontrolled PEV Charging Model

In Chapter 4, a comprehensive uncontrolled PEV load model is presented based on the use of an MCS in conjunction with fitted probability distribution functions (PDFs). Because the uncontrolled PEV load model is an essential part of the proposed framework, the same model presented in section 4.2.2 is used in the work presented in this chapter. A discussion of this model is therefore not repeated in this chapter, and an explanation of this step in the proposed design framework is thus omitted.

6.2.2 Stage II: System Reserve Margin Assessment

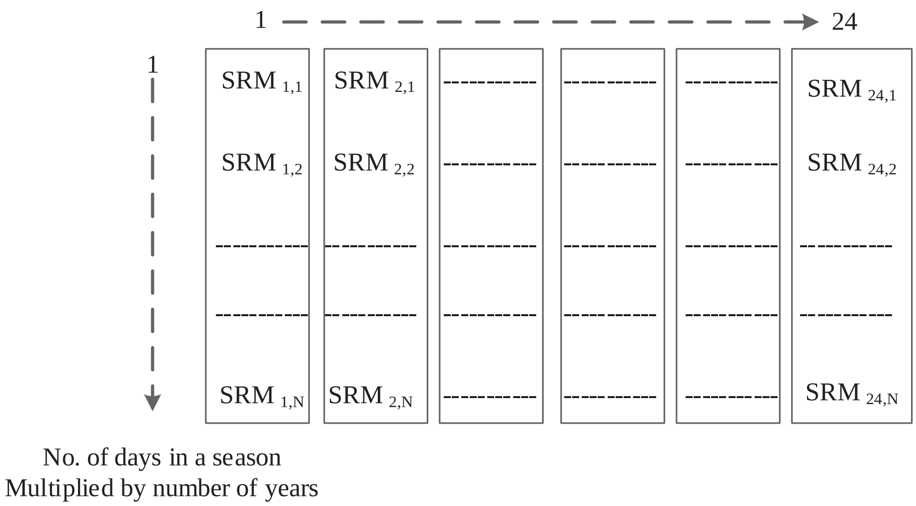
Different stochastic approaches to modelling and representing the diverse components of power systems have already been discussed. These approaches enable the generation of a desired number of synthetic data that preserve the spatial and chronological characteristics of the original samples while addressing the inherent natural variability and randomness associated with component failure. This section explains how to treat the massive number of generated scenarios obtained from each model and, hence, evaluate the SRM at each hour of each season throughout all of the simulated years. The SRM provides an indication of the level of system accumulation at each hour and determines whether the system is operating under critical or normal conditions. The key question is how to deal with the massive amount of data for each hour of each season, all of which have different characteristics. These data must be presented in a simple but adequate manner in order to facilitate decisions about the type of each hour (off-, mid-, or on-peak). A primary goal of the research presented in this section was to develop an effective approach that would address this challenge. To achieve this goal, a methodology based on four main steps is proposed. For illustration purposes, the following steps explain how the methodology is applied to a winter weekday; however, the same analysis is carried out for the other seasons as well.

1- Seasonal synthetic time series data are generated for all variables using the approaches discussed for the first stage. For each data point in each season, the SRM is calculated based on (6.9):

$$SRM(t) = P_{CG}(t) - P_{NL}(t) \tag{6.9}$$

A vector (one row matrix) of the SRM sequential data for each type of day in each season is obtained. The length of each vector is equal to the total number of hours in each season multiplied by the number of years simulated (e.g., for a winter weekday, 24 h/d * 22 d/mo * 3 mo/season = 1584 h/simulated yr).

2- The data vectors are reshaped from one-row matrices to a matrix of 24 columns * N rows, where N is equal to the total number of days in each season multiplied by the number of simulated years. The matrix takes the form of (6.10), where each row represents one chronological daily profile (24 h) while each column represents the possible SRM scenarios for each hour. This data arrangement preserves the main characteristics of each hour and simplifies the assessment analysis and decision process for determining the hour type. With this treatment, eight matrices are created: two matrices (weekdays and weekends) for each season.



(6.10)

3- The matrices developed are then set as input that enables the statistical analysis tool to provide a visualization and analysis of the SRM behaviour at each hour before and after the inclusion of an uncontrolled PEV load. From a wide range of statistical tools, a box-plot technique was chosen because it offers a standardized method for the display and visualization of the quantitative data pattern for easier and more effective decision-making. In an elegant miniature package, a box plot enables a comparison of datasets for each hour and displays the degree of data dispersion (from min to max), the likely range of variation (the interquartile range (IQR)), a typical value (the median), and outliers [81]. As shown in Figure 6.4, a box-plot provides a clear visual format of the variability or spread in the data sets, along with five summary measures: first quartile, median, third quartile, and lower and upper fences.

4- The box-plot measures are applied to the expert techniques, which represent the usual practices employed by many utilities for determining the SRM; here the method is used to help set up the initial decision about hour type. The following are the most common expert techniques [28], [82]:

i. Percentage Margin: A required reserve margin should be equal to a fixed percentage value of the predicted demand (usually 10 %).
ii. Loss of the Largest Unit plus Percentage Margin: A required reserve margin should be equal to the capacity of the largest generator unit plus a fixed percentage value of the predicted demand.

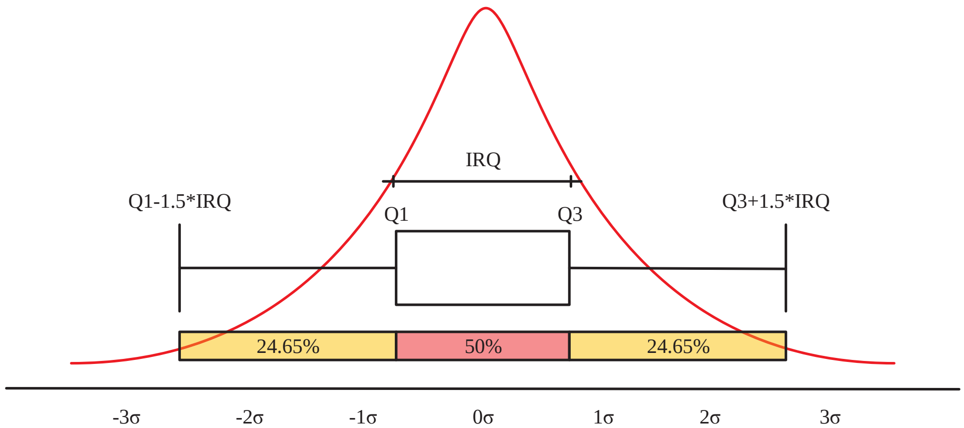


Figure 6.4 Box plot with five important distribution measures

For this research, these techniques were used as thresholds that are mapped against the box-plot measures in order to distinguish the level of risk, as illustrated in Figure 6.5.

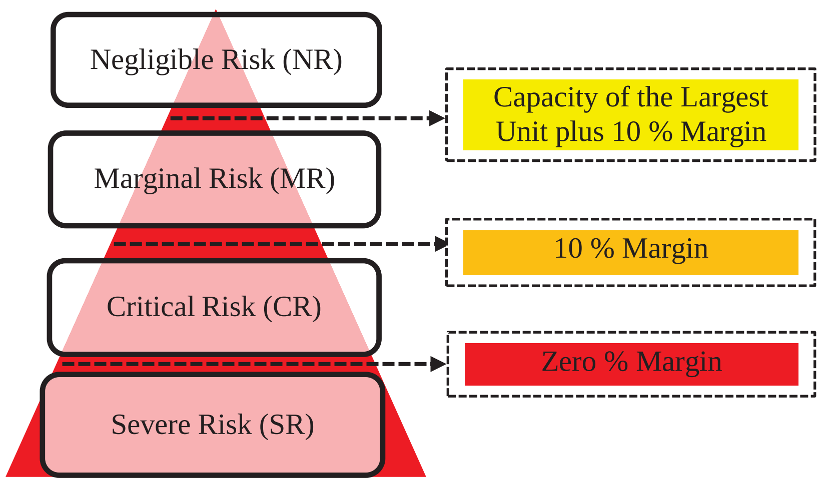


Figure 6.5 Expert techniques mapped against the box-plot measures

The following set of rules are used for arriving at an initial decision about the type of each hour (off-, mid-, or on-peak):

a) If at least 75 % of the SRM is greater than the marginal risk (MR) threshold (i.e., Loss of the Largest Unit and Percentage Margin) and the remaining percentage of the SRM is greater than the severe risk (SR) threshold, then the hour examined is set to be off-peak.

b) If at least 75 % of the SRM is greater than the critical risk (CR) threshold (i.e., Percentage Margin) and the remaining percentage of the SRM is greater than the SR threshold <u>or</u> less than the SR threshold but the addition of the PEV load does not significantly worsen the SRM, then the hour examined is set to be either off- or mid-peak.

c) For conditions different from those considered in (a) and (b), the hour examined is set to be either mid- or on-peak.

It is worth emphasizing that the first off-peak hour just after the mid- or on-peak period is set to be either off- or mid-peak even if it meets the conditions set out in (a). This provision is applied in order to check whether this hour can accommodate the energy shifted from the mid- or on-peak hours. Figure 6.6 shows the hourly SRM pattern for a winter weekday before and after the inclusion of a PEV charging load. Applying the proposed procedures for the SRM enables the initial decision about the type of each hour to be determined, which significantly helps reduce the possible combinations: from ($3^{24} = 2.8 \times 10^{11}$) to ($2^6 = 64$) (Figure 6.7). The outcome of Stage II is a range of possible TOU schedule scenarios, which are then fully examined during Stage III in order to determine the optimal schedule for improving system reliability.

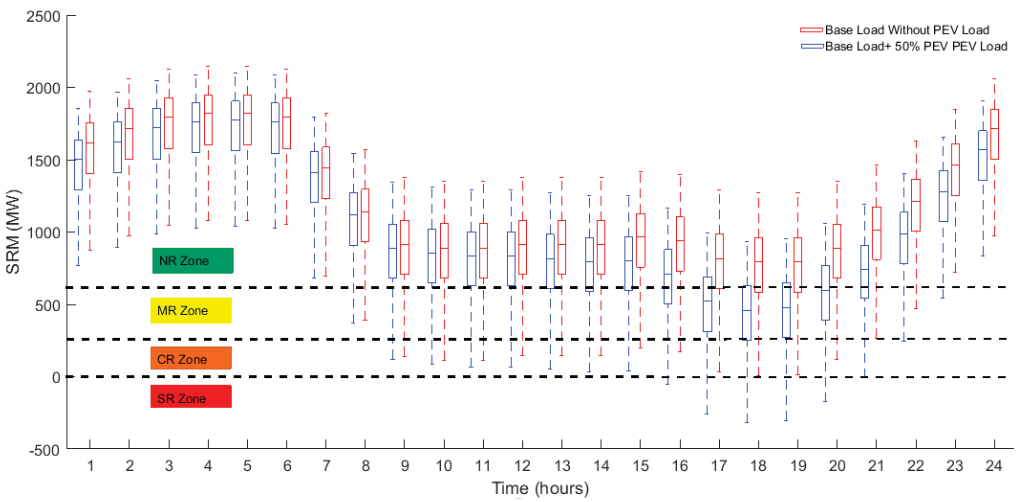


Figure 6.6 SRM for a winter weekday before and after inclusion of the PEV charging load

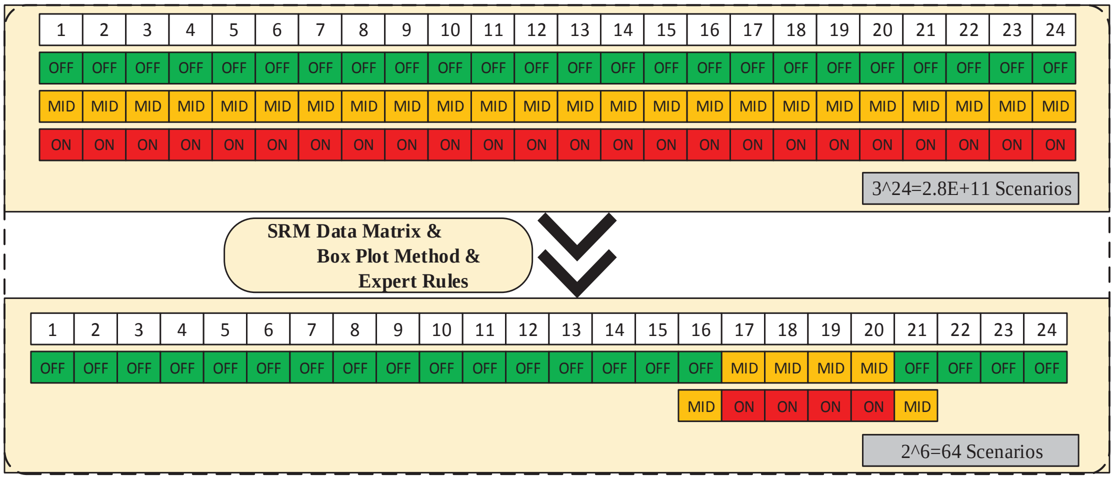


Figure 6.7 Illustrative example of the initial decision about the type of each hour and possible combinations

6.2.3 Stage III: Evaluation and Validation Model

During this stage, possible TOU schedule scenarios are examined with respect to reliability measures (e.g., loss of load expectation (LOLE) and loss of energy expectation (LOEE)). To evaluate the performance of these scenarios, a model is developed of the PEV charging load, taking into account individual customer driving behaviour and the hour type in each TOU schedule. The developed PEV charging model is then convolved with the other system models (generation and conventional load) in order to assess the reliability indices. The following is the step-wise procedure executed by the proposed PEV model, as outlined in Figure 6.8:

Step 1: Read the data pertaining to the possible TOU schedules (Stage II outcomes) and other PEV charging data (i.e., driver behaviour data, battery specifications, market share, charging levels, etc.), as discussed in section 4.2.1.

Step 2: Start with the simulation of the PEV charging load for the first TOU schedule.

Step 3: Execute Step 1 to Step 12 in the uncontrolled PEV charging model, as discussed in section 4.2.2, in order to determine the following parameters: HAT, HDT, SoC, *CE*, and *CD*.

Step 4: Define the time period T^{SH}, which identifies the hours during which a PEV is at home.

Step 5: When a PEV requires a charging time greater than or equal to its time at home (i.e., *CD* >= *SD*), the PEV owner cannot respond to the TOU rates, and the PEV hence remains charging under uncontrolled mode according to (4.10). For other cases, (i.e., *CD* < *SD*), the following scenarios are investigated:

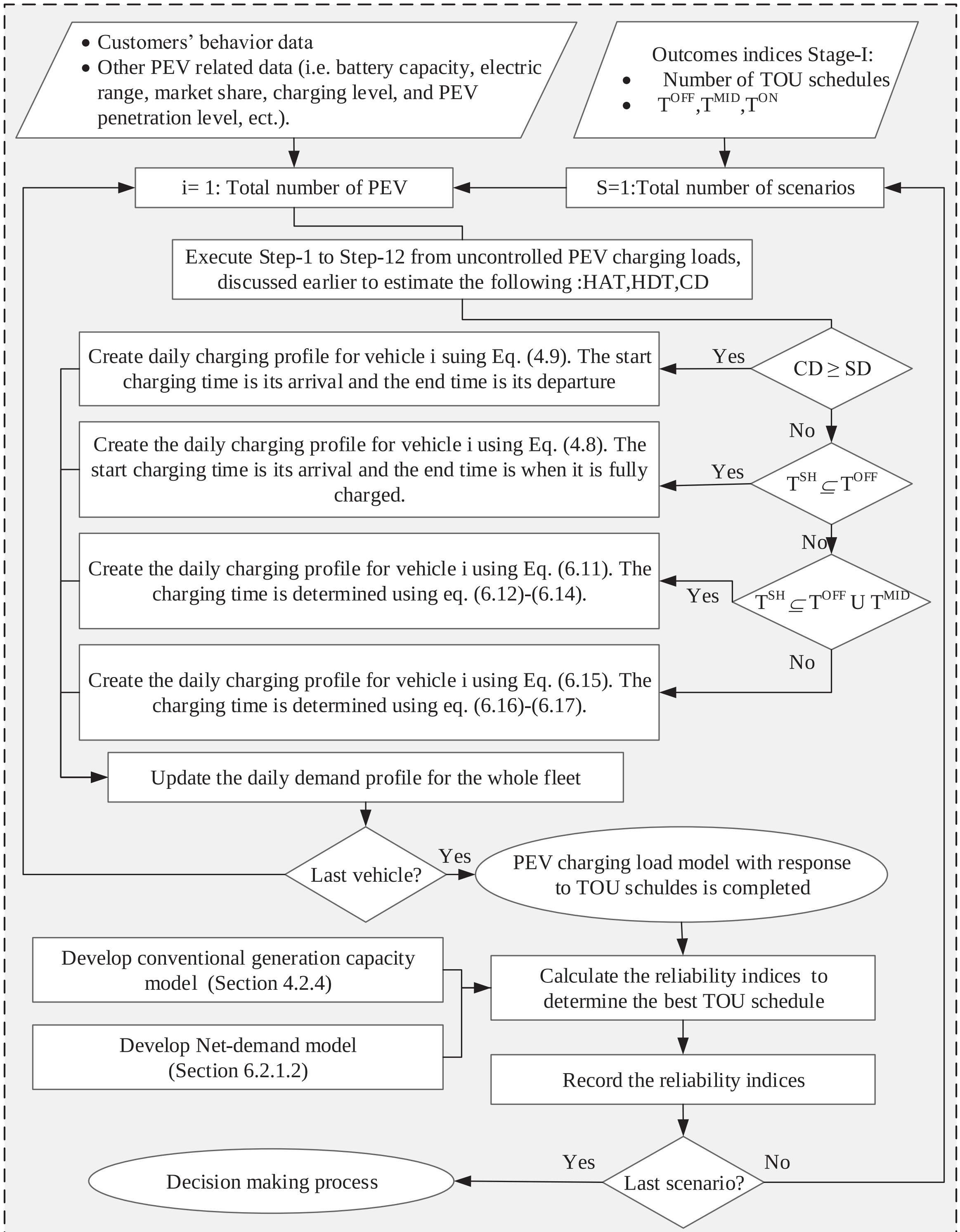


Figure 6.8 Development of PEV load model profiles that are responsive to the predefined set of TOU schedule scenarios

a) When the set of hours during which a PEV stays at home (T^{SH}) is a subset of the off-peak hours (T^{OFF}), the PEV is charged at the charging level power rate starting from its arrival and ending once it is fully charged, which is mathematically expressed in (4.11). If not, the next two further cases are examined.

b) If the T^{SH} is a subset of the union of the off-peak and mid-peak hours ($T^{OFF} \cup T^{MID}$), the PEV is then charged during the periods defined as T^{X1} and T^{X2}, as expressed in (6.11). T^{X1} and T^{X2} contain the off-peak and mid-peak hours that coincide with the vehicle stay-at-home hours, as expressed in (6.12) and (6.13), respectively. The charging time is set to correspond to all elements (hours) of T^{X1} and some hours of T^{X2} that are equal to the required charging duration (*CD*) minus the total hours of T^{X1} (n), as expressed in (6.14).

$$P_i(t) = ch_L \quad \xRightarrow{where} \begin{cases} t = (T_1^{X1}, \dots \dots ., T_n^{X1}) \\ t = (T_1^{X2}, \dots \dots ., T_k^{X2}) \end{cases} \tag{6.11}$$

$$T^{X1} = T^{SH} \cap \, T^{OFF} \tag{6.12}$$

$$T^{X2} = T^{SH} \cap \, T^{MID} \tag{6.13}$$

$$k = CD - n \tag{6.14}$$

c) If cases (a) and (b) do not apply, it means that T^{SH} is a subset of the union of all block tariff periods ($T^{OFF} \cup \, T^{MID} \, \cup \, T^{ON}$). In this scenario, the PEV is charged during the periods defined as T^{Y1} and T^{Y2}, as expressed in (6.15). T^{Y1} contains the union of the off-peak and mid-peak periods that coincides with the vehicle's stay-at-home hours, as expressed in (6.16), while T^{Y2} contains the on-peak period that coincides with the vehicle's stay-at-home hours, as expressed in (6.17) .

$$P_i(t) = ch_L \quad \xRightarrow{where} \begin{cases} t = (T_1^{Y1}, \dots \dots ., T_n^{Y1}) \\ t = (T_1^{Y2}, \dots \dots ., T_k^{Y2}) \end{cases} \tag{6.15}$$

$$T^{Y1} = T^{SH} \cap \, (T^{OFF} \cup \, T^{MID}) \tag{6.16}$$

$$T^{Y2} = T^{SH} \cap \, T^{ON} \tag{6.17}$$

Step 7: Repeat the procedures set out in Step 3 to Step 6 sequentially until the charging profiles are simulated for the entire fleet.

Step 8: Convolve the PEV charging profile that has been adapted for the TOU schedule with the other system profiles (i.e., generation and other load) in order to evaluate the system reliability indices using the models described in section 4.2.4.

Step 8: Record the indices and repeat the same procedures (Step 2 to Step 8) until all possible TOU schedules have been examined.

Step 9: Analyze the reliability indices obtained for each scenario and determine the optimal TOU schedule.

6.3 Cases under Study

The primary focus of this chapter is the design of an appropriate TOU schedule that is adapted to the PEV charging demand in a way that mitigates its impact on system adequacy. To this end, the proposed framework was tested on the IEEE Reliability Test System (RTS) [76]. Two main case studies were considered: 50 % PEV penetration level with and without wind generation.

The vehicles considered are makes commonly found in the US market that were sold from 2009 to 2016 [71]. Details about the vehicles, including their market share percentage, are provided in Table 4.1. The 2009 National Household Travel Survey (NHTS) data [34] have been employed for simulating driver behaviour. Two different charging levels were used in this study: Level-1 (1.44 kW) and Level-2 (7.2 kW), with shares of 65 % and 35 %, respectively [83]. The charging efficiency is assumed to be 90 % [5], and the penetration level is assumed to be 50 %, as estimated for 2030 by the Electric Power Research Institute [2]. In the first case study, the generation model is developed using the data pertaining to conventional IEEE-RTS generators, as given in Table 4.4 (section 4.3): a total installed capacity of 3,405 MW and an annual peak load equal to 2,850 MW. For case 2, a 1000 MW wind farm consisting of 500 identical 2 MW wind turbine generators (WTGs) was added to replace one 400 MW conventional nuclear unit.

6.3.1 Case 1: Conventional Generation and 50 % PEV Penetration

This subsection reports and analyzes the results of applying the proposed methods to the conventional-generation IEEE-RTS model with a 50 % PEV penetration level. The proposed approaches explained for Stage I (section 6.2.2) are used for determining the initial hour-type decision, which helps reduce the enormous number of combinations of TOU schedules to a reasonable number for assessment. These combinations are examined using the proposed Stage II model described in section 6.2.2 (based on system reserve margin assessment) in order to arrive at the optimal TOU schedule.

Figure 6.9 shows the outcomes of these stages for the seasons that are affected by the addition of the PEV charging load. The proposed methodology is used for extracting an initial decision about the type of each hour so that the total number of TOU schedule scenarios can be reduced to 64 for the winter season, for example. Corresponding to these schedules, 64 PEV charging load profiles are developed and assessed using the reliability measures, as indicated in Figure 6.10. The difference between the summer and winter seasons in terms of the number of scenarios (possible combinations) and the hourly decisions is attributable primarily to the different load profile characteristics for those seasons. It can also be observed that the final decision regarding the mid- and on-peak hours is strongly correlated with the hours during which a large proportion of PEV owners arrive and expect to charge during peak system hours. These results validate the effectiveness of the proposed framework with respect to designing an appropriate TOU that takes into account driver behaviour as well as other system component characteristics.

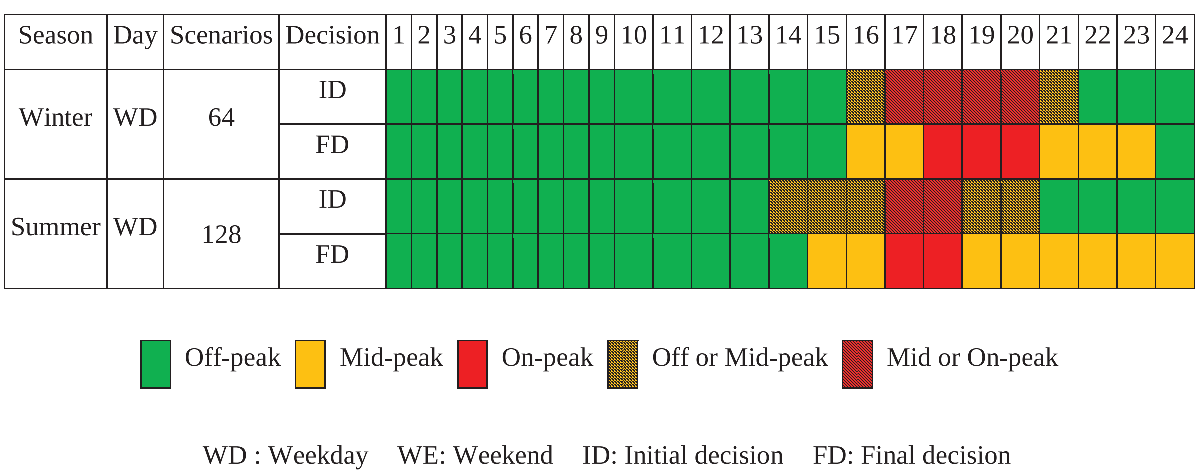


Figure 6.9 Initial and final TOU schedule decisions for the affected seasons by the addition of the PEV charging load

The results shown in Figure 6.9 reveal that the hours 22 pm and 23 pm were initially selected as off-peak hours and then subsequently changed to mid-peak hours. As mentioned earlier in this chapter, the start hour of the off-peak period is subjected to further analysis in order to check whether it can accommodate the energy shifted from the mid- and on-peak hours. This step is implemented in order to avoid the significant spike in the system load that might occur when a large proportion of PEV owners arrive during on-peak or mid-peak hours to begin charging as soon as the off-peak period begins. Figure 6.11 displays the system LOLE for different off-peak start times. These indices represent the optimal scenario for each start time. Based on the results, starting the peak period at hour 24 am is clearly the best scenario for the winter season. These results also indicate that if the off-peak start time is set after hour 24 am, then the indices will start to deteriorate because the duration of the off-peak hours might be insufficient for charging the vehicles, which means that some PEV owners will be forced to charge their vehicles during mid- or on-peak hours.

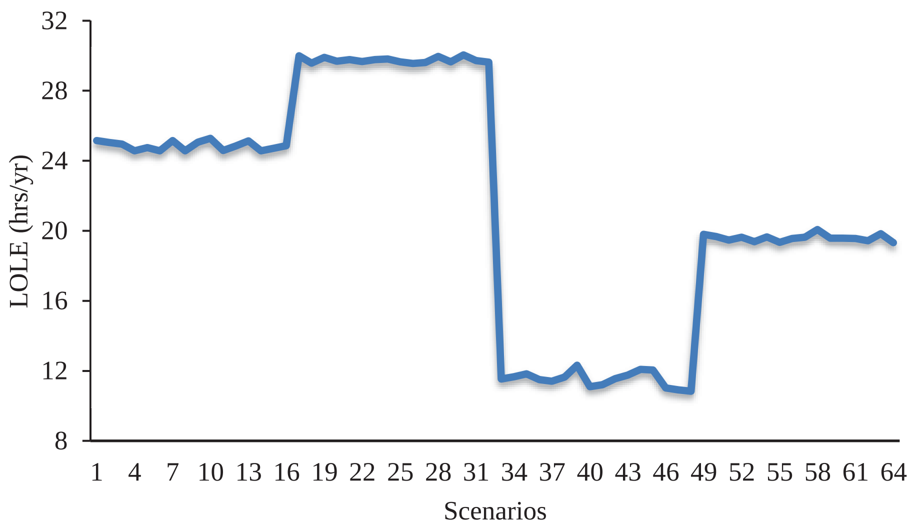


Figure 6.10 LOLE indices for the 64 winter TOU schedules

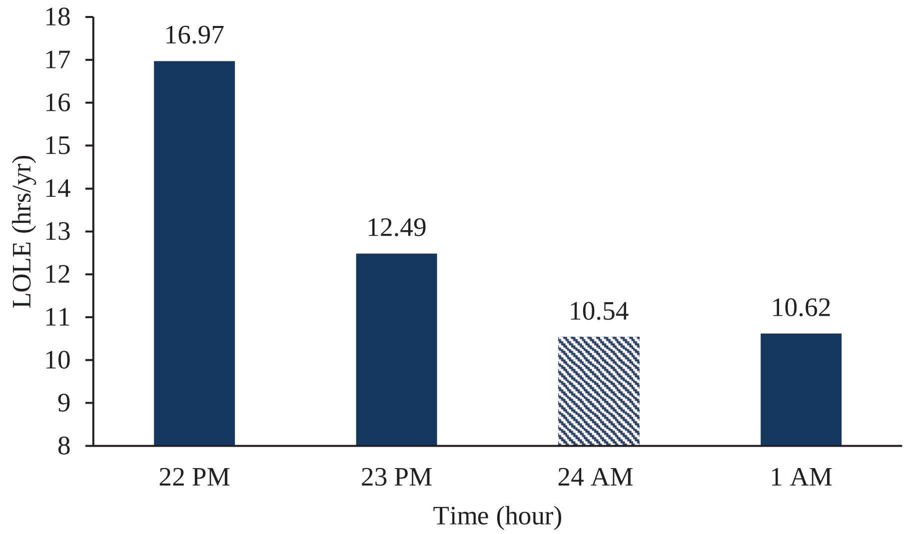


Figure 6.11 LOLE indices for different off-peak start times

Reliability indices for all seasons for all of the case studies considered are computed; the results are presented in Table 6.1. The findings for the season affected by the addition of the PEV load are highlighted and illustrated in Figures 6.12 to 6.14. The main observations stemming from a closer inspection of these results can be summarized as follows:

1) Only winter and summer weekdays are significantly affected by the addition of the PEV load. Determining the affected seasons by the addition of the PEV charging load can help planners or decision makers look at solutions specific to those seasons so that they do not waste effort and resources assessing other unaffected seasons.
2) A comparison of the base case with the case in which the PEV load is added under uncontrolled mode reveals that the system indices increase at the same rate (approximately by four times) for both the winter and summer seasons. The reliability indices for the winter season are higher than for other seasons because the peak day of the system under study (IEEE RTS) occurs during the winter.
3) Adapting the PEV load to be responsive to the proposed TOU schedules significantly reduces the system indices and helps enhance system reliability. The percentage decrease in the system indices resulting from the proposed TOU schedules is about 64 % compared with the uncontrolled PEV charging load. The LOLE index, for example, is reduced from 31.8 h/yr to 10.5 h/yr for the winter season, while that index is decreased from 9.6 h/yr to 3.6 h/yr for the

summer season. With respect to adequacy assessment, this reduction is considered significant and reveals that appropriate TOU rates can be highly beneficial for mitigating the impact on reliability imposed by the massive deployment of PEV loads.

Table 6.1 Adequacy indices for the case studies (conventional generation with 50 % PEV penetration)

Season	Day type	Base case (No PEV)		Base case plus 50 % uncontrolled PEV load		Base case plus 50 % PEV load based on the proposed TOU	
		LOLE (h/yr)	LOEE (MWh/yr)	LOLE (h/yr)	LOEE (MWh/yr)	LOLE (h/yr)	LOEE (MWh/yr)
Winter	WD	7.11	928.9	31.80	5095	10.54	1390
	WE	0.02	2.36	0.14	15.40	0.14	15.40
Spring	WD	0.04	4.17	0.44	44.35	0.44	44.35
	WE	0.00	0.00	0.00	0.02	0.00	0.02
Summer	WD	2.12	252.7	9.61	1267	3.60	446.3
	WE	0.00	0.01	0.02	1.27	0.02	1.27
Fall	WD	0.07	5.48	0.72	70.88	0.72	70.88
	WE	0.00	0.00	0.00	0.04	0.00	0.04
System		9.36	1193.6	42.74	6493.9	15.46	1968.7

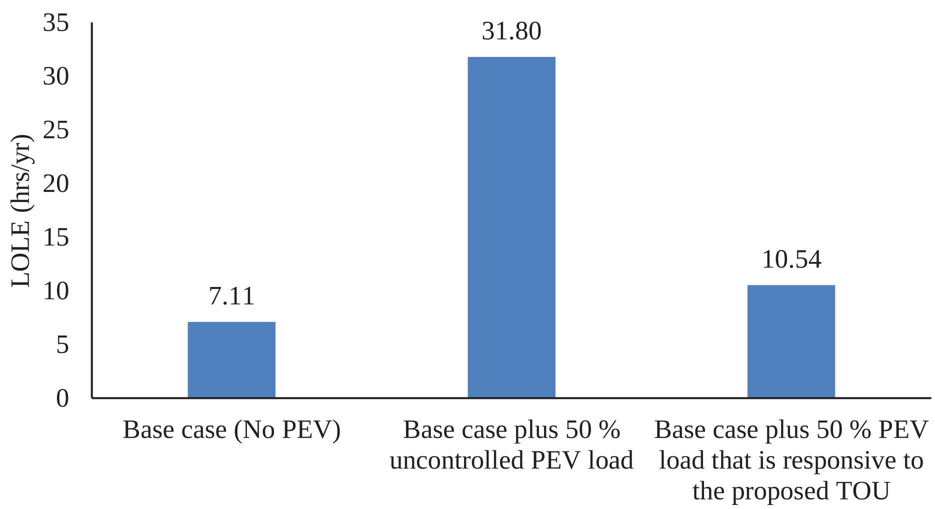


Figure 6.12 LOLE indices obtained for the winter season on weekdays

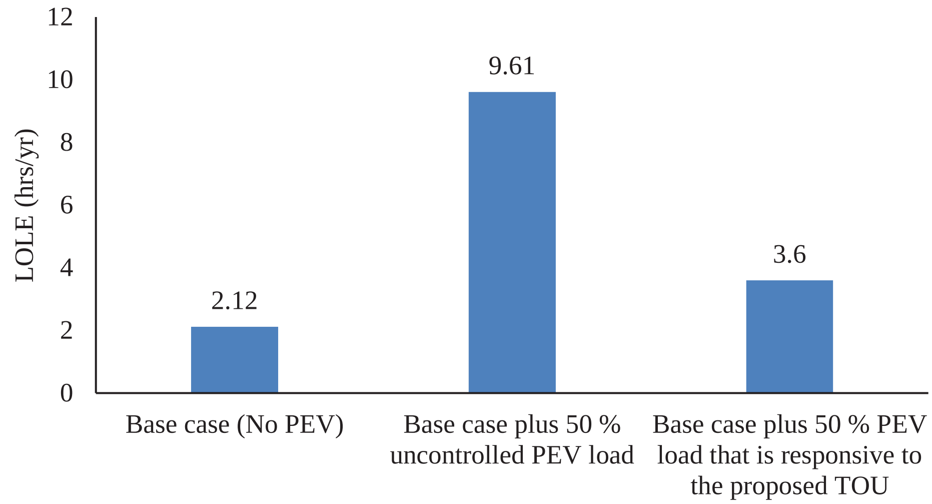


Figure 6.13 LOLE indices obtained for the summer season on weekdays

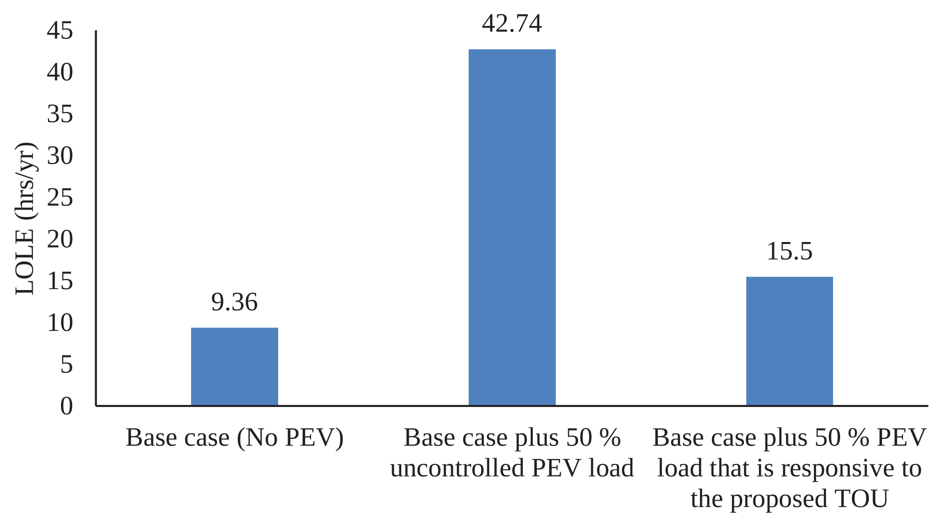


Figure 6.14 LOLE indices obtained for the overall considered system (all seasons)

6.3.2 Case 2: Wind Generation and 50 % PEV Penetration Level

The key considerations in this case are the same as for the previous case except that a 1000 MW wind farm replaces a 400 MW conventional unit. It is expected that when a high PEV penetration occurs, there will be a dramatic change in the generation type and more renewable will be deployed in the system. This case study was conducted in order to investigate the effect on the TOU schedules and reliability indices due to a massive deployment of PEV loads plus an increased share of wind power generation. From the findings presented in Figure 6.15, it is apparent that the presence of wind generation noticeably alters the TOU schedules and increases the number of the scenarios examined. This effect is due to the intermittent nature of wind generation, with its extreme dependence on variable wind speed characteristics at a particular site. It can also be observed that in addition to both the winter and summer seasons, the fall season also appeared to be affected by the inclusion of wind generation.

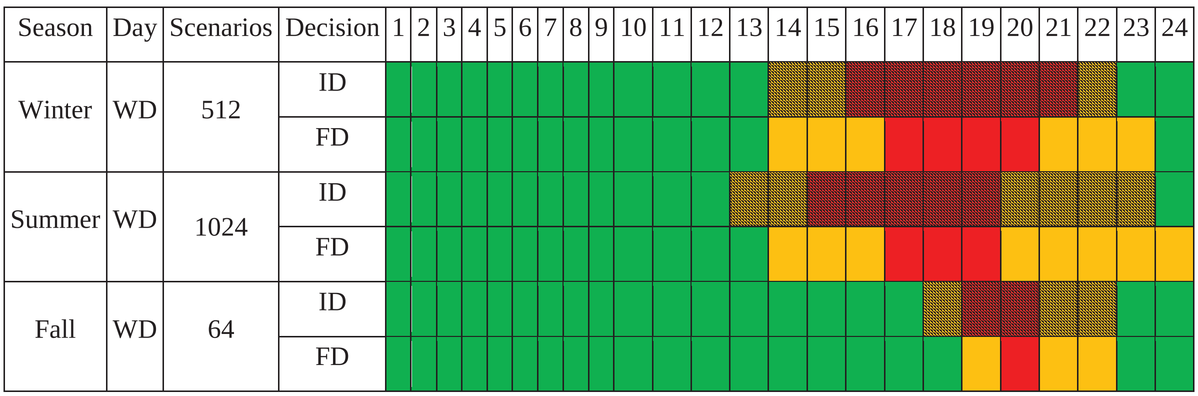


Figure 6.15 Initial and final TOU schedule decisions for the affected seasons by the addition of the PEV charging load

Table 6.2 lists the reliability indices computed for all seasons for the case studies considered. The results for the season affected by the addition of the PEV load and wind generation are highlighted. The following are the main findings to emerge from these studies:

1- When the results of the base case in this section (with wind generation and without a PEV load) are compared with the results of the base case in the previous case (with neither wind generation nor a PEV load), the system indices are relatively higher, and it is impossible to maintain the same reliability indices, even if the capacity added by the wind generation is 2.5 times greater than that of the replaced conventional unit. These results are consistent with an important consideration often stated in the literature [13]–[16]: the wind turbine capacity required to maintain a given reliability measure can be considerably higher than that of conventional units. In some circumstances, it might also be impossible to maintain a given criterion through the addition of wind generation since it is highly dependent on both site-specific wind conditions and the particular design parameters of the wind turbines.

2- In confirmation of the results from the previous case study, when 50 % PEV penetration is added under uncontrolled mode, the results obtained in this section also show that the winter and summer weekdays are significantly more affected than in other seasons. The indices obtained for these seasons are increased by more than three times compared with the base case. As previously mentioned, a possible explanation for the increased reliability indices for the winter season is that the peak day of the system under study (IEEE-RTS) occurs during the winter. It can also be observed that the indices for a fall weekday are somewhat affected by the increased share of wind generation.

3- When the PEV charging load is responsive to the proposed TOU tariff, a significant decrease in the system reliability indices results. For all seasons affected by the addition of the uncontrolled PEV load, all of the indices are reduced by approximately 70 % if the proposed TOU tariff is well designed and followed. These results are very encouraging with respect to establishing the TOU program as one effective solution for mitigating the impact of PEV charging loads and maintaining an acceptable level of reliability.

Table 6.2 Adequacy indices for the case studies (conventional and wind generation and 50 % PEV penetration)

Season	**Day type**	**Base case (No PEV)**		**Base case plus 50 % uncontrolled PEV load**		**Base case plus 50 % PEV load based on the proposed TOU**	
		LOLE (h/yr)	LOEE (MWh/yr)	LOLE (h/yr)	LOEE (MWh/yr)	LOLE (h/yr)	LOEE (MWh/yr)
Winter	WD	10.49	1351.0	42.98	7073	14.38	1880
	WE	0.03	2.53	0.21	23.23	0.21	23.23
Spring	WD	0.10	6.64	0.73	77.63	0.73	77.63
	WE	0.00	0.00	0.00	0.02	0.00	0.02
Summer	WD	3.75	414.5	17.28	2215	5.59	636.9
	WE	0.00	0.11	0.03	2.28	0.03	2.28
Fall	WD	0.17	12.80	1.37	141.87	0.61	56.33
	WE	0.00	0.00	0.00	0.02	0.00	0.02
System		14.53	1787.6	62.60	9533.1	21.75	2696.29

6.4 Summary

This chapter has presented a reliability-based framework for designing TOU schedules in order to mitigate the impact of an uncontrolled PEV charging load. The proposed framework involves the use of different stochastic simulation models, visualization approaches, and expert rules that help determine appropriate TOU schedules for the PEV charging load. Different TOU schedules are designed for the season affected by the deployment of the PEV load. The process of designing these schedules incorporates consideration of the realistic random behaviour of system elements, including random component failure, the stochastic nature of wind generation, and the variability and uncertainty of the load. To demonstrate the performance of the proposed framework, a number of case studies were applied using the IEEE-RTS. The results reveal that charging PEVs in accordance with the proposed TOU schedules would considerably mitigate the impact on reliability that would otherwise be expected when PEVs are charged in uncontrolled mode.

Chapter 7
Conclusion, and Future Work

7.1 Summary and Conclusion

Electrification of the transportation sector and the widespread implementation of PEVs are expected to impose more challenges and complications for electrical systems. One such challenge is the quantification of the new supply infrastructures or reinforcements that are required for existing facilities to meet this new mobile load. In addition, the future profiles of these types of loads entail numerous uncertainties, including the intrinsic randomness in driver behaviour, lack of knowledge related to PEV penetration levels, and the unknown future of upcoming technological developments and charging infrastructures.

Current power system facilities are neither well designed nor sufficiently prepared to accommodate these new types of loads with high penetration levels and uncertain characteristics. Before encountering these issues, essential actions should be taken into consideration: 1) the development of thorough research that can carefully address the issues imposed by PEV charging loads in order to realistically evaluate their impact on the reliability and performance of generation systems; 2) an investigation into solutions to smoothly accommodate widespread implementation of PEV charging loads while maintaining overall system reliability. In summary, a consideration of PEVs with regard to reliability is a timely and challenging task that needs to be thoroughly studied, and therefore represents the main motivation for the research presented in this thesis.

Chapter 2 in this thesis presented a brief background to some basic definitions, reliability measures, and common approaches that are used to evaluate the reliability of the power system. This is followed by a general review of PEV types, PEV load characteristics, and associated uncertainties, together with a discussion related to previously developed models that discuss the inclusion of PEV charging modeling and wind generation into the adequacy assessment problem. In Chapter 3, a statistical evaluation study on different collections of PDFs is presented in an attempt to find the best model that reflects the variable characteristics of driver behaviour. The most commonly used PDFs, along with some advanced PDFs, have been verified against sample data pertinent to different variables of driver behaviour based on a consideration of well-known goodness of fit statistical tests. This statistical study has identified that Dagum, Burr, and Johnson are among the best-fit PDFs for all random driver behaviour variables. These PDFs, which are statistically validated to represent realistic description models for the variables of driver behaviour, can be used directly in the simulation process of estimating PEV charging load profiles.

Chapter 4 provided a comprehensive reliability evaluation framework that incorporates an adequate representation of all the factors that influence PEV charging loads and offers a realistic assessment of their adverse impact on the reliability performance of generation systems. A stochastic model based on the Monte Carlo simulation (MCS), combined with fitted PDFs, was deployed to explicitly take into account any underlying uncertainties and to generate a wide range of potential PEV charging scenarios. The proposed framework, which was applied to a well-known test system (IEEE-RTS), offers a thorough investigation into the reliability impact of different PEV charging characteristics, including the effect of penetration levels, charging levels, and PEV types with different battery specifications. Within the proposed framework, particular attention was paid to investigating the capability of current TOU rates, designed for residential loads, to mitigate the reliability impact of uncontrolled PEV charging loads.

From the results of the case studies outlined in Chapter 4, it is noted that penetration level, charging level, and battery capacity are clearly major factors that affect uncontrolled PEV charging load profiles and, ultimately, computed reliability indices. Therefore, it is important for planners or researchers to acknowledge the consequence of either neglecting or representing these factors in an excessively simplified manner. The results also reveal that the massive integration of PEV load under uncontrolled mode is very likely to draw considerable load and significantly increase the reliability indices. The reason for this significant increase lies in the trend that a large proportion of PEV owners arrives and starts charging during peak system hours. The results also show that the application of current TOU rates with respect to PEV loads is no longer an effective solution but one that can adversely impact system reliability, particularly with the use of charging level-2.

While the importance of developing appropriate models for measuring the reliability impact of the different characteristics of PEV charging loads must be recognized, investigating potential solutions for mitigating the anticipated impact is also crucial. A novel reliability-based framework for the application of dynamic critical event programs for use with PEV charging loads was proposed in Chapter 5. The framework comprises two main models, the first of which determines the time and duration of critical system events as well as the amount of PEV demand not supplied in the case of a shortage of supply. The second model examines the existing flexibility in PEV loads to respond to critical events. The proposed framework entails new indices, and these indices provide highly essential information about system behaviour that can be used for managing PEV charging loads.

The results of the proposed framework highlight important findings, including: 1) There is enough flexibility in a PEV load to respond to critical system events without violating driver behaviour limits. 2) A considerable reduction in the system peak was achieved and the adequacy indices at all penetration levels, and for both charging levels, were significantly reduced. An important conclusion made in this chapter is that although the dynamic DR program (critical event call program) is a very promising alternative that is worthy of consideration for managing PEV charging loads, the application of these programs thus far for residential use involves major challenges. The successful deployment of these programs depends strongly on: 1) The availability of a well-designed infrastructure to facilitate information sharing and communication between electricity utilities and a significantly high volume of residential customers; 2) The development of automation technologies that would assist residential customers to respond and keep track of hourly price changes.

The TOU program is the common DR program at residential and small business load levels. The TOU is designed to be static over a season, thus helping residential customers to easily understand and follow. However, designing such a static program that is valid for the whole season and that, at the same time reflects the realistic random behaviour of the system, is very challenging. Addressing these challenges was the core contribution of Chapter 6, which relates to the development of a proper reliability framework for designing TOU schedules for PEV loads. The proposed framework comprises different simulation models, a visualization method, and expert rules to simplify the assessment analysis and decision process for determining the type of each hour (off-, mid-, or on-peak). The models developed to design the TOU schedules consider the random behaviour of the system elements, including random component failures, the stochastic nature of wind generation, and load variability and uncertainty. Detailed studies are applied to the IEEE-RTS to demonstrate the applicability of the proposed framework. The results of these studies support the idea of developing TOU schedules specifically designed for PEV loads, hence TOU can be considered as a viable and practical option to lessen the adverse impact of uncontrolled PEV charging loads on system reliability.

7.2 Research Contributions

The main contributions of the research presented in this thesis can be summarized as follows:

1- A statistical evaluation study among a wide range of available theoretical PDFs was conducted to determine the best model that reflects the random characteristics of each driver behaviour variable. This study is very useful for system planners and researchers as it provides compact, easy, ready-to-use equations for directly describing data relevant to driver behaviour variables.

2- PEV charging load models have been developed in a novel and detailed manner for use with uncontrolled and TOU-based strategies. The models are based on a Monte Carlo simulation (MCS) combined with fitted PDFs to manage inherent uncertainties and generate multiple scenarios. For an accurate determination of the impact on reliability, both models were based on the use of high-quality data and realistic estimates of factors affecting the charging process.

3- The PEV charging load models are included in the reliability assessment problem to enable thorough investigations into the effect of PEV charging characteristics on the reliability and performance of generation. Also provided are a detailed analysis and better understanding of the behaviour of reliability indices with respect to PEV charging characteristics: driver behaviour, penetration levels, charging levels, battery capacities, and customer response to TOU pricing.

4- A reliability framework is proposed to assess the flexibility of PEV charging loads in response to system-critical events. The framework is built upon two aspects: the first determines the time, duration, and amount of shortage for critical system events, when system supply facilities are unable to meet PEV loads, while the second assesses the feasibility of PEV owner response to critical events.

5- A novel reliability based framework is proposed to help design a TOU schedule that is well-adapted to PEV charging loads. The proposed framework involves the use of different stochastic simulation models, special data treatments, statistical tools, and expert criteria to simplify the decision process and determine the type of each hour (off-, mid-, or on-peak).

7.3 Future Work

Based on the work presented in this thesis, the following suggestions represent areas for future investigation:

1- The assessment framework proposed in Chapter 4 is a solid foundation to build upon in order to include transmission line facilities and conduct a composite reliability assessment. Therefore, the effect of a PEV charging load on nodal system indices (bus-wise indices) can be assessed. This would enable system planners to focus on identifying solutions for only buses affected by the presence of PEVs.

2- It is assumed in this thesis that PEV charging occurs at home since in practice this is where people's vehicles are available and parked most of the time. However, improving the accessibility and viability of public charging facilities (e.g., charging stations, work parking lots, or shopping parking lots) is crucially important. Further research needs to be conducted in order to include public charging facilities in the proposed models and to assess their impact on system reliability.

3- The model-based DR programs developed in Chapters 5 and 6 can be further extended to evaluate the economic benefits of implementing these programs and to compromise their benefits with the expected reliability improvement. This can be achieved by improving the present framework to include a planning cost model that would measure the benefits of such programs together with traditional planning options such as new supply units, as well as system upgrades and reinforcements.

Appendix A
IEEE-RTS Load Data

Table A.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	100.0
26	86.1	52	95.2

Table A.2 Hourly peak load in percent of daily peak [76]

	winter weeks		summer weeks		spring/fall weeks	
	1 -8 & 44 - 52		18 -30		9-17 & 31 - 43	
Hour	Wkdy	Wknd	Wkdy	Wknd	Wkdy	Wknd
12-1 am	67	78	64	74	63	75
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	95	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	93	91
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 A.3 Daily peak load in percent of weekly peak [76]

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

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