Faculty of Engineering of University of Porto
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Impact Evaluation of the Large Scale Integration of Electric Vehicles in the Security of Supply

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"...Let us fight for a new world - a decent world that will give men a chance to work - that will give youth a future and old age a security...Let us fight for a world of reason, a world where science and progress will lead to all men's happiness...We are coming into a new world, a kindlier world, where men will rise above their hate, their greed and brutality."

The Great Dictator (1940) - directed by Charlie Chaplin

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Abstract

The sustainability of the transport and energy sectors has been considered the main goal in order to reduce the greenhouse gas (GHG) emissions around the world, specially, the carbon dioxide (CO_2) emissions. The massive deployment of electric vehicles (EV) and the increase of renewable energy sources (RES), in the generation portfolio, have been pointed as the main alternative to reduce the GHG emissions in both transportation and electrical energy sectors. The increase in RES and the large scale integration of EV in the power systems require flexible generation units in order to cover the variable characteristic of the wind and the vehicles' mobility needs. Apart from the hydro resource, wind has been the main renewable resource seized for the electricity industry. Countries like Portugal, Spain and Germany, the wind power has already achieved around 20-30% of the total installed capacity.

Due to forced generating unit outages, load and wind power forecast errors, an operational reserve level is required to cover these system variations. The monitoring of security of supply shall be the responsibility of regulatory entities in Europe and the long-term assessment of the security of supply can ensure that the future planned generating systems will be able to meet the load forecast in terms of their capacities.

This thesis proposes a methodology for modelling EV load behaviour based on the Poisson process, considering the mobility patterns of the population and different charging strategies, in order to be included in the adequacy evaluation of the

security of supply for generating systems with high integration of wind power. The EV models developed in this thesis account for uncontrolled and controlled battery charging, which are divided in direct, valley, controlled and vehicle-to-grid (V2G) charging strategies. The latter is seen in two perspectives: contribution for operating reserve and compensation of the wind power variation.

It is expected that, under some circumstances, the controlled charging strategies will create opportunities to the electricity sectors in order to provide ancillary services, mitigating the EV impact on the adequacy of the security of supply. This topic is exploited through this thesis assuming the existence of an aggregation entity that will be responsible to manage the EV charging, in order to deal with battery charging and stored electrical energy in the batteries. The developed EV models were included in the Sequential Monte Carlo Simulation (SMCS) method, which is a probabilistic method able to represent stochastic behaviour of the system components, taking into account the time dependence characteristic of their operational states.

The proposed models are assessed through the use of a modified configuration of the IEEE Reliability Test System 1996 and real systems such as Portugal, Spain and Greece for 2030 generating system configurations. The performance of the models were analysed through different integration scenarios with and without the deployment of EV. From the result analysis, it is possible to conclude that the massive integration of EV should be monitored through controlled charging strategies, in order to avoid the necessity of increasing the generation capacity for future years. The possibilities of controlling and injecting electrical energy back to the grid have demonstrated that it can provide an effective support for the operational reserve, maintaining the adequacy of the security of supply in the same levels as the ones estimated in scenarios with no EV deployment.

Resumo

A sustentabilidade dos setores do transporte e da energia tem sido considerada o principal objectivo para reduzir a emissão dos gases de efeito estufa (GEE) ao redor do mundo, especialmente, as emissões de dióxido de carbono (CO_2). A integração em larga escala dos veículos eléctricos (VE) e o aumento das fontes de energia renováveis (FER), no portfolio de geração, têm sido apontadas como as principais alternativas para a redução da emissão dos GEE de ambos os sectores, transporte e energia eléctrica. O aumento das FER e a integração em larga escala dos VE nos Sistemas de Energia requerem unidades de geração flexíveis, a fim de cobrir a característica variável do vento e as necessidades de mobilidade dos veículos. Para além do recurso hídrico, o vento tem sido o principal recurso renovável aproveitado pelas companhias de electricidade. Países como Portugal, Espanha e Alemanha já alcançaram níveis de geração eólica em torno dos 20-30% da capacidade de geração instalada.

Devido as falhas não programadas das unidades de geração, dos erros de previsão da carga e da potência eólica, um determinado nível de reserva operacional é necessário para atender estas variações do sistema. Na Europa, a monitorização da segurança do abastecimento é de responsabilidade das entidades reguladoras e a avaliação a longo prazo da segurança do abastecimento pode garantir que os futuros sistemas de geração sejam capazes de atender a carga prevista.

Esta tese propõe uma metodologia para a modelização da carga dos VE baseada no processo de contagem de Poisson, levando em conta o padrão de mobilidade da

população e as diferentes estratégias de carregamento dos VE. O objectivo é incluir estes modelos na avaliação da adequação da segurança do abastecimento para sistemas de geração com alto nível de integração de potência eólica. Os modelos de VE desenvolvidos nesta tese incluem os conceitos de carregamento controlado e não controlado das baterias, os quais são divididos em carregamento directo, no vazio, controlado e "*vehicle-to-grid*" (V2G). Este último, é desenvolvido sob duas perspectivas: contribuição para aumento da reserva operacional e compensação na variação da produção de electricidade a partir da energia eólica.

É esperado que, sob certas circunstâncias, as estratégias de carregamento controlado criem oportunidades de negócios para os setores de electricidade, fornecendo serviços de sistema para mitigar o impacto dos VE na adequação da segurança do abastecimento. Este tópico é explorado, através desta tese, assumindo a existência de uma entidade agregadora que será responsável pelo carregamento dos VE com o objectivo de carregar e gerir a energia eléctrica armazenada nas baterias. Os modelos de VE desenvolvidos foram incluídos no método de Simulação de Monte Carlo Sequencial (SMCS), o qual consiste num método probababilístico capaz de representar o comportamento estocástico dos componentes do sistema, levando em conta a característica temporal dos seus estados de operação.

Os modelos propostos foram avaliados através da utilização do sistema teste de fiabilidade IEEE 1996 e de sistemas reais tais como Portugal, Espanha e Grécia, para a configuração dos sistemas de geração de 2030. O desempenho dos modelos foi analisado através de diferentes cenários de integração de VE. A análise dos resultados mostra que em caso de integração em larga escala de VE, o carregamento destes deve ser monitorizado através de estratégias de carregamento controlado para evitar a necessidade de aumentar a capacidade de geração no futuro. As possibilidades de controlar e injectar energia eléctrica no sistema têm demonstrado ser um suporte efectivo para a reserva operacional, mantendo a adequação da segurança do abastecimento nos níveis estimados para cenários sem integração dos VE.

Resumé

Le développement durable des secteurs du transport et de l'énergie a été considéré comme étant le principal objectif pour réduire les émissions de gaz à effet de serre (GES), en général, et le dioxyde de carbone (CO2), en particulier. Le déploiement massif des véhicules électriques (VE) et la croissance de l'utilisation des sources d'énergie renouvelable (SER) dans la génération sont considérés comme les meilleures options pour réduire les émissions de GES dans les secteurs du transport et de la production d'énergie électrique. Cependant, la croissance de l'utilisation des SER et l'intégration à grande échelle des VE exigent un ensemble de centrales électriques avec des générateurs flexibles pour compenser les variations intrinsèques à la production éolienne et aux besoins du transport électrique. Sans considérer les ressources hydro-électriques, l'énergie éolienne est la principale SER développée par l'industrie de production d'Electricité. Dans des pays comme le Portugal, l'Espagne et l'Allemagne, les centrales éoliennes ont déjà atteint une pénétration variant entre 20% et 30% de la puissance totale installée.

Un certain niveau de réserve opérationnelle est nécessaire pour compenser les variations dues aux pannes et à l'incertitude liée à la prévision de la charge et de la production éolienne. La sécurité d'approvisionnement devrait être garantie par les institutions de régulation au niveau européen et son évaluation à long-terme peut assurer que la génération planifiée pour le futur soit capable de couvrir la charge prévue.

Cette thèse propose une méthodologie basée sur le processus de Poisson, en considérant les habitudes de mobilité de la population et différentes stratégies de charge des batteries des VE, pour son inclusion dans l'évaluation de la sécurité de l'approvisionnement dans les systèmes dont la génération connait une forte pénétration d'énergie éolienne. Les modèles de charge des VE développés dans cette thèse prennent en compte une charge contrôlée et non-contrôlée des batteries des VE qui peut être caractérisée en différentes stratégies de charge: charge directe, charge durant la période de creux du diagramme de la demande globale, charge non-contrôlée et la possibilité que les batteries puissent injecter d'énergie dans le réseau en cas de besoin. Cette dernière stratégie présente deux perspectives: contribution à la réserve opérationnelle et compensation des fluctuations de la disponibilité de l'énergie éolienne.

Dans certaines circonstances, la charge contr1ôlée des batteries des VE pourra donc être un atout, pour le système électrique, en fournissant les services auxiliaires du réseau afin de réduire l'impact des VE sur la capacité du système à garantir la sécurité de l'approvisionnement. Ce thème a été traité dans cette thèse en considérant l'existence d'une entité responsable pour la gestion de la charge des VE en mesure de contrôler l'énergie accumulée dans les batteries. Le modèle développé pour les VE a été inclus dans la méthode de Simulation Séquentielle de Monte Carlo (SSMC) capable de représenter le comportement stochastique des composants du système, en prenant en considération la dépendance temporelle qui caractérise leurs états d'opération.

Les modèles proposés ont été évalués à travers l'utilisation d'une configuration modifiée du réseau test de fiabilité IEEE 1996 et des configurations des réseaux réels du Portugal, de l'Espagne e de la Grèce planifiées pour 2030. Leur performance a été analysée en utilisant plusieurs scénarios d'intégration avec ou sans déploiement des VE. L'analyse des résultats a permis de conclure que le déploiement massif doit être géré à travers une stratégie de charge contrôlée afin d'éviter la nécessité de devoir augmenter la capacité de génération dans les années prochaines. Le contrôle de l'énergie emmagasinée dans les batteries avec la possibilité de pouvoir la réinjecter dans le réseau a démontré qu'il est possible de fournir une contribution effective en termes de réserve opérationnelle garantissant ainsi le même niveau de sécurité d'approvisionnement estimé dans des scénarios sans déploiement de VE.

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List of Acronyms

AGC	Automatic Generation Control
CC	Controlled Charging
CO_2	Carbon Dioxide
COPFT	Capacity Outage Probability and Frequency Table
COPT	Capacity Outage Probability Table
DC	Direct Charging
DOD	Depth of Discharge
EENS	Expected Energy Not Supplied
EPNS	Expected Power Not Supplied
EU	European Union
EV	Electric Vehicle(s)
EV-AL	Electric Vehicle Aggressive penetration Level scenario

EV-LL	Electric Vehicle Low penetration Level scenario
EV-ML	Electric Vehicle Moderate penetration Level scenario
F&D	Frequency and Duration
FCR	Frequency Containment Reserve
FFT	Fast Fourier Transform
FM	Failure Mode
FOR	Forced Outage Rate
FRR	Frequency Restoration Reserve
GCE	Gram-Charlier Expansion
GGS	Greek Generation System
GHG	Greenhouse Gas Emission(s)
HEV	Hybrid Electric Vehicle(s)
HL	Hierarchical Level
HPP	Homogeneous Poisson Process
ICE	Internal Combustion Engine
IEEE	Institute of Electrical and Electronics Engineers
Li-ion	Lithium-ion

LOLD	Loss Of Load Duration
LOLE	Loss Of Load Expectation
LOLF	Loss Of Load Frequency
LOLP	Loss Of Load Probability
MCS	Monte Carlo Simulation
MERGE	Mobile Energy Resources in Grids of Electricity
MTTF	Mean Time To Failure
MTTR	Mean Time To Repair
NERC	North American Electric Reliability Corporation
NHPP	Non-Homogeneous Poisson Process
NMAE	Normalized Mean Absolute Error
NOD	Number of Discharges
NSMCS	Non-Sequential Monte Carlo Simulation
ORC	Operating Reserve Capacity
ORR	Outage Replacement Rate
PBM	Population-Based Method
PGS	Portuguese Generation System

PHEV	Plug-in Hybrid Electric Vehicle(s)
PJM	Pennsylvania-New Jersey-Maryland
RBTS	Roy Billinton Test System
REIVE	Redes Elétricas Inteligentes e Veículos Elétricos (*Smart Grids with Electric Vehicles*)
RES	Renewable Energy Source(s)
RR	Replacement Reserve
RTS	Reliability Test System
SGS	Spanish Generation System
SI	Swarm Intelligence
SMCS	Sequential Monte Carlo Simulation
SO	System Operator
SOC	State Of Charge
STABALID	Stationary Batteries Li-ion Safe Deployment
US	United States
V2G	Vehicle-to-Grid
VC	Valley Charging
WFE	Wind Power Forecast Error

Chapter 1

Introduction

1.1 Context and Motivation

Over the past two and a half centuries, the societies have burnt increasing amounts of fossil fuels to be used on power machines, generate electricity, heat buildings and transport people and goods. Since the industrial revolution, in 1750, the concentration of carbon dioxide (CO_2) in the atmosphere has increased by roughly 40%, and it continues to rise [4].

Around 11% of the greenhouse gases emitted worldwide each year come from within the European Union (EU). In 2011, the latest year with available comprehensive data, EU-15 emissions stood 14.9% below their base year level. Based on estimates for 2012 by the European Environment Agency, EU-15 emissions averaged 12.2% below base-year levels during the 2008-2012 period (the target levels were 8%). This means the EU-15 over-achieved its first Kyoto's target by a wide margin. The 8% collective reduction commitment has been translated into national emission reduction or limitation for each of the EU-15 Member States under what is known as the "burden sharing" agreement [5].

For 2020, the EU has made a unilateral commitment to reduce overall greenhouse gas emissions from its 28 Member States by 20% compared to 1990 levels. The EU has offered to increase this figure to 30% if other major economies agree to undertake their fair share of a global emissions reduction effort. In consonance with these objectives, the "2020 climate and energy package" seals the EU commitment on raising the share of EU energy consumption produced from renewable sources to 20%, improving the EU's energy efficiency to 20% and reducing the greenhouse gas (GHG) emissions by 20% [6].

Portugal intends to have 60% of its generated electricity coming from RES by 2020, in order to satisfy 31% of its final energy consumption of the same year. In addition, Portugal aims at reducing its dependence on energy imports and on the use of fossil fuels [7].

Figure 1.1, which is an update of the 2000 World Resources Institute's flowchart, makes clear how much CO_2 was produced in 2010 and by whom. This figure distinguishes between sectors according to their primary energy use (coal, gas and oil), which include mainly industry, transport and energy supply sectors. This flowchart also shows that the GHG emissions are originated mainly from two sources: direct and fossil fuel related emissions.

Globally, industry sector accounts for 29% of the GHG emissions, followed by the transport and electrical energy supply sectors which account for 15% and 13% of the GHG emissions, respectively. The reduction mark for the transport sector for 2020 is 10% in EU-28 [8]. The electric vehicles (EV) are the main alternative technologies developed to achieve this goal allowing the reduction of GHG emissions by zero. From the new EV generation perspective, the hybrid electric vehicle (HEV) has been introduced in the market. This type of EV mixes the fossil fuels and electricity power sources reducing significantly, but not totally, the CO_2 emissions. The second alternative is the plug-in hybrid EV (PHEV), which beyond the fuel mix (fossil fuels and electrical energy) also uses rechargeable batteries, which can be charged from an external power source. The

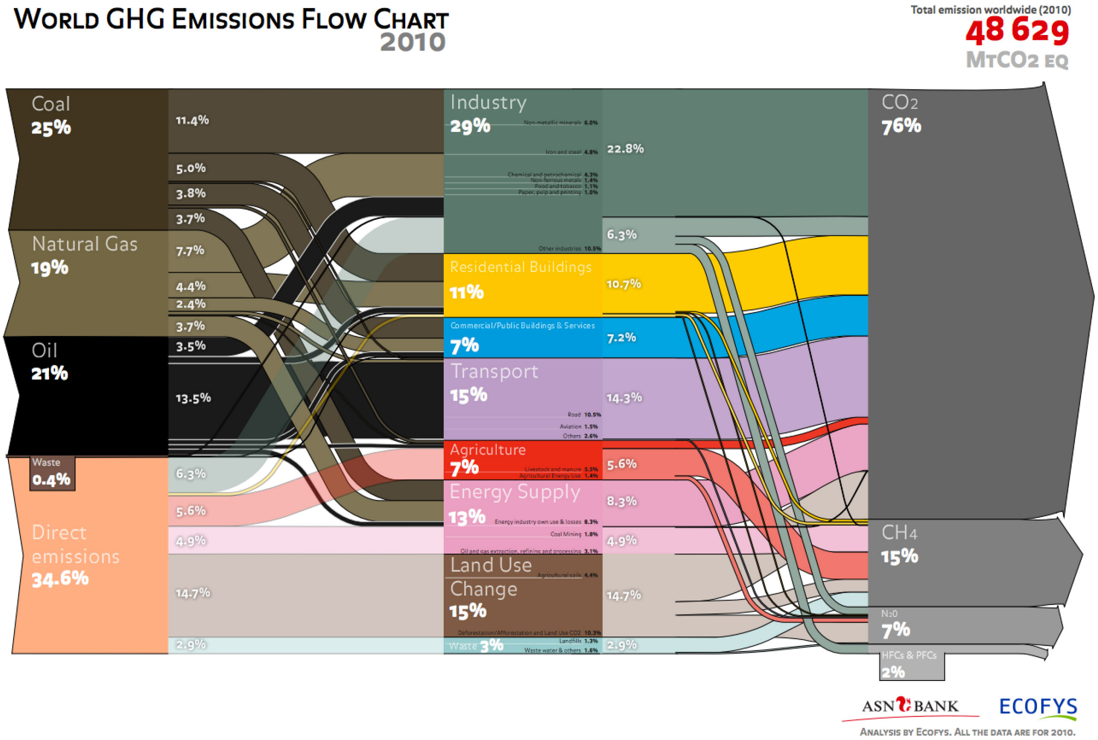

Figure 1.1: World GHG Emissions flowchart 2010 [1].

pure EV are the most recent alternative, which also consists of batteries that can be restored to full charge by connecting a plug to an external wall socket, however is the only one that has electricity as its only power source. This kind of vehicle (pure EV) plays a major role in the reduction of GHG emissions. On one hand, the EV has zero CO_2 emissions while used for mobility purpose. On the other hand, the battery charging can be controlled in order to increase the usage of renewable energy sources (RES), reducing the GHG emissions from the supply energy sector side [9].

The deployment of the RES and EV on the electric power systems will certainly affect the System Operator's (SO) decision-making in terms of operation and planning. The increase of renewable sources has been included in the power system analysis through suitable models and methodologies. The expected large scale integration of EV in the electric power systems will also require the development of adequate models to be considered in the power system analysis methodologies.

Among other issues, the security of supply at the generation system level is one of the main concerns of the European Community (EC) to achieve the implementation of a sustainable climate change policy. The monitoring of the security of supply is supported by a legal framework at the European level which is comprised in the Directive 2009/72/EC [10]. This Directive foresees that the Member States shall ensure the monitoring of security of supply issues. Such task should be delegated to the regulatory authorities. The monitoring shall, in particular, cover the balance of supply and demand on the national market, the level of expected future demand and envisage additional capacity being planned or under construction, and the quality and level of maintenance of the networks, as well as measure to cover peak demand and to deal with shortfalls of one or more suppliers [10].

Under this context, this thesis is concerned with the analysis of the EV impact on the generation systems with high integration of RES. In generation system analysis, it is usual not to include the transmission and distribution networks. Such evaluation can aid regulatory authorities to determine the need of increasing the generation capacity, identify the incentives for storage facilities to avoid wasting of renewable generation and other decisions which involve the security of supply.

The assessment of security of supply may be divided into two perspectives: adequacy and security [11]. The North American Electric Reliability Corporation (NERC) [12] defines adequacy and security as:

- Adequacy – The ability of the electric system to supply the aggregate electrical demand and energy requirements of the end-use customers at all times, taking into account scheduled and reasonably expected unscheduled outages of system components.

- Security – The ability of the electric system to withstand sudden disturbances such as electric short circuits or unanticipated loss of system elements.

Given the current context, this thesis proposes the development of EV models to be included in the adequacy of supply assessment for systems with high level of RES in generation portfolio. This analysis is carried out through the adequacy perspective and the evaluations are performed considering a long-term time horizon [13].

Usually, the adequacy of supply is analysed through the reliability evaluation of the generating systems, which in turn may be divided in two concepts: static and operating reserves. The static reserve assessment is performed by evaluating the difference between the total generating capacity and the total system load. This evaluation produces risk indices which are used to measure the adequacy level of the generating systems. Conversely, operating reserve assessment measures the requirements of the generating systems to cover short-term problems which may result from uncertainties of the RES and load forecast, and forced outages of the generating units. These concepts will be further described in detail.

1.1.1 Power System Adequacy Evaluation

The continuous electrical energy supply is affected by random failures of the electrical components. The integration of different types of generating sources to provide electricity to a wide range of customers with varying requirements is another problem that affects the continuous supply of electrical energy, mainly because of the variable behaviour of the primary energy resources.

Electric power utilities, therefore, should provide an acceptable degree of system reliability in the planning, design and operation of their systems considering the existing economical constraints. The term “reliability” when associated with a power system is a measure of the system’s ability to meet the customer requirements for electrical energy. Power system reliability evaluation has been extensively developed over the last sixty years mainly focusing on the adequacy perspective and there are many publications available on this subject [14].

The adequacy assessment of a power system can be conducted using either deterministic or probabilistic techniques. Deterministic techniques explore empirical information on how a system failure can occur or how system success can be achieved. For instance, the most common deterministic criterion, $N-1$, dictates that the loss of any bulk system component should not result in system failure. Hence, these techniques usually consist on evaluating power systems under pre-selected contingencies of important components failing to capture their random behaviour. Nevertheless, deterministic criteria are usually easier to understand by system planners, designers and operators than numerical risk indices determined using probabilistic techniques.

System behaviour is stochastic by nature, and therefore it is logical to consider probabilistic methods that are able to model the actual factors that influence the adequacy of the system. Probabilistic techniques provide quantitative indices, which can be used to decide whether the system performance is acceptable or changes need to be made. A probabilistic model of the system can be evaluated using analytical or simulation methods [15]. The stochastic characteristic of the hydro, solar, and wind resources are better assessed by simulation methods such as the Sequential Monte Carlo Simulation (SMCS), which is able to include a temporal dependency in its evaluation.

As a matter of fact, RES are receiving considerable attention in the continued growth and development of generating systems. The most integrated renewable electrical energy source at the present time is wind power. Wind power is a clean, emissions-free power generation technology. It is based on capturing the energy from natural forces and has none of the polluting effects associated with conventional fuels. For instance, 21% of the electricity produced in Spain in 2013 [16] came from wind power sources. Portugal did even better in the first three months of the same year where 27% of its electricity was generated from wind [17]. Since wind power production is dependent on the wind resource, the output of a wind farm strongly varies over time. Due to these fluctuations, the adequacy of modern generating systems is affected in different ways than conventional systems, such as those based on large thermal power stations.

Since power generation plants using wind energy are increasingly integrated into power systems, it becomes particularly important to assess their effects on the overall system adequacy. Most of the work on modelling wind power generation and on using such models for generating system adequacy evaluation has been done since 1984 [13, 18–21].

1.1.2 Electric Vehicles in the Power Systems

The transport and electrical energy sectors will become interdependent in the years to come by the expected massive deployment of EV. Figure 1.2 presents penetration scenarios of EV from 2010 to 2030 for the replacement of internal combustion engine (ICE) vehicles of the (M1) category by EV [2]. For instance, scenario 2 shows that in 2020 approximately 8% of M1 vehicles sold will consist of EV which will increase to approximately 27% in 2030.

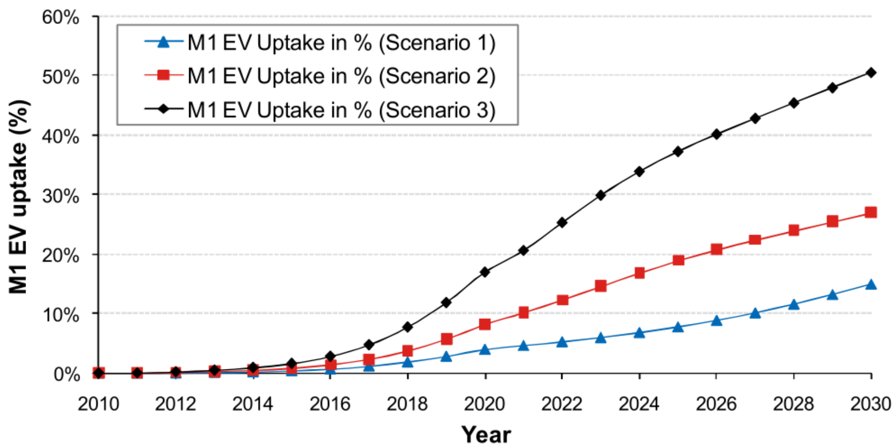

Figure 1.2: M1 EV uptake rates for each of three scenarios [2].

From the transport sector perspective, the direct benefit of EV, which is portrayed as a green vehicle implying in zero emissions, is the reduction of CO_2

emissions in the environment. However, the electrical generation portfolio of many countries continues to be composed, in its majority, by fossil-fuelled power plants. For instance, the vehicle-weighted average GHG emissions for each electrical power region in the United States (US) is presented in [22]. This paper demonstrates that, in average, each pure EV that displaces a gasoline HEV will increase GHG emissions by more than 7% (considering the increase in electric power generation to recharge EV batteries and the US generation mix at that moment). Additionally, each PHEV put in service will increase the GHG emissions by an average of 10% compared to the gasoline HEV. This problem is mainly related to the charging strategies promoted. When uncontrollable charging strategies are used, a great amount of EV owners start charging the EV batteries when they arrive at home in the evening increasing the peak load demand. To cover this demand, generating units, which are normally powered by fossil fuels, may be dispatched increasing the GHG emissions level.

This new demand must be taken into account in the long-term assessment of the adequacy of supply. On one hand, EV can be considered as an additional demand that will be added to the conventional load profile. On the other hand, this large scale integration of EV on the power systems can provide new opportunities for the electricity sector players in different areas. The possibility to increase the use of RES to cover this new demand makes the energy systems more sustainable, moving the idea of increasing the use of fossil fuel sources to meet this load demand growth away.

In order to achieve a positive impact from the deployment of EV, the charging strategies must be controlled. From the generating system point of view, two opportunities could be exploited. One, is considering the EV as an aggregated load which could be controlled through its charging rate or even moved from one hour to another promoting active demand side management. The other is taking into account the possibility of injecting electric power stored in EV batteries back into the grid, promoting vehicle-to-grid (V2G) concept.

The population mobility patterns [23] must be studied in order to obtain a methodology to calculate EV load. This methodology should have as core a suitable EV arrival distributions that is able to provide chronological aspects of this new type of load. In addition, the total load profile will also depend on the adopted charging strategy. Three different charging strategies are explored in [24]: dumb, dual tariff and smart charging. This thesis uses the same strategies, but with different names as follows: direct, valley and controlled charging.

Basically, the direct charging strategy allows the recharging when the EV arrives at some place. The EV battery charging in valley hours is represented through the valley charging strategy concept. The controlled charging strategy consists of EV battery charging in the valley hours too, however the postponement of the charging is possible when the operational reserve of the system is threatened. The charging strategies addressed in this thesis will be described in more detail.

To achieve a suitable control level, information and communication technology is necessary. From the technological perspective, battery life cycle, bi-directional charging flow, fast charging rates, and so on have been under improvement [25–27] allowing the implementation of an active interaction between EV and the power system. In this context, an aggregative entity should be created in order to manage the charging process and to establish the connection among EV, electricity market and system operation. The latter activity is the responsibility of the SO which, under some circumstances (*e.g.* when the system is threatened), can send orders, through the aggregative entity, to be followed by the EV. Reference [28] presents a review of the economical and technical management of an aggregative entity in aforementioned environment.

To sum up, the opportunities that arise from enabling the control of EV charging are:

- To use EV to maximize the integration of RES [9].

- To shift the EV load demand from peak to valley hours, which can avoid waste of RES, decrease the additional demand in peak hours and postpone reinforcements in the system.

- To contribute to the operational reserve throughout the V2G charging strategy, which can avoid load curtailment due to load variability, wind power forecast errors and unexpected generating unit outages.

This context raises the need to develop EV models that take into account the mobility patterns and different EV charging strategies in order to estimate the additional EV load. This thesis proposes two approaches based on Poisson process to construct models for the EV chronological behaviour. These models were incorporated in the RESERVE Model which evaluates the adequacy of security of supply with high integration of RES [13]. This tool is able to estimate reliability indices that measure the adequacy of generating systems and is based on the SMCS method. This method has several advantages which ranges from the possibility of representing the variable characteristic of the renewable resources, the chronological aspects of the generating unit outages and load demand to the possibility of providing probability distributions of the observed events. The background of the main methodologies used to evaluate the security of supply will be given in Chapter 2.

1.2 Research Questions

According to [10], the European requirements regarding the security of supply monitoring are:

"*...Such monitoring shall, in particular, cover the balance of supply and demand on the national market, the level of expected future demand and envisaged additional capacity being planned or under construction, and the quality and level of maintenance of the networks, as well as measures to cover peak demand and to* *deal with shortfalls of one or more suppliers...*".

From this definition and considering a massive EV deployment in the years to come, the following research questions were defined.

- Are the conventional methodologies for power system analysis adequate to assess the security of supply under a massive EV deployment within a large scale wind power integration scenario?
- Are the opportunities provided by the EV charging strategies relevant for the electricity sector?
- Does the deployment of EV provoke a negative impact on the security of supply?

These questions led to the development of hypothesis and assumptions that support the methodological approach developed in this thesis.

1.3 Main Hypothesis and Assumptions

The methodology presented through this dissertation was developed based on the Poisson process. This methodology is a stochastic process which counts the number of events (arrivals) and the time that these events occur within a given interval based on an expected average value given by the mobility distributions. Two alternative approaches were implemented: the homogeneous and non-homogeneous Poisson processes (HPP and NHPP, respectively). The basic difference between processes is that the HPP counts events with a constant rate parameter (arrivals average in an hour of a typical day) and the NHPP counts events with variable rate parameter (arrivals average dependent on the hour of the day). The NHPP approach was implemented due to the necessity of having a battery SOC (State of Charge) monitoring for each vehicle in order to develop the V2G charging strategy.

The assumptions over which these approaches were developed are:

- The numbers of arrivals counted in disjoint intervals are independent of each other.
- The probability distribution of the number of arrivals counted in any time interval only depends on the length of the interval.
- The probability distribution of the number of arrivals is a Poisson distribution.
- No counted arrivals are simultaneous.

The main consequences of these assumptions are:

- The probability distribution of the waiting time until the next arrival is an exponential distribution.
- The arrivals are distributed uniformly on any interval of time.

The advantages of the proposed methodology is that the model can be applied to any mobility pattern since the arrival average parameter is known.

Regarding the charging strategies, the assumptions are:

- Direct charging: the EV battery charging starts after an occurrence of an arrival.
- Valley charging: the EV battery charging can only be made during valley hours.
- Controlled charging: the EV battery charging can only be made during valley hours. However, it is assumed that EV battery charging can be controlled. The EV respond to a signal, postponing their battery charging if the operating reserve is threatened.

- V2G charging: the EV battery charging starts after an arrival occurs. However, the EV respond to a signal, postponing their battery charging to inject electric energy back to the grid if the operating reserve is threatened. The SOC of the batteries is taken into account.

The main hypothesis raised is that an adequate battery charging may contribute to the adequacy of the security of supply in order to mitigate the EV impact on the power systems. This hypothesis will be verified in this thesis throughout the risk indices, which also allow to assess the average load curtailment for each EV penetration scenario, estimated by the simulation process.

1.4 Thesis Objectives

The main objective of this thesis is to develop EV models capable of representing the EV charging behaviour in order to measure the EV load impact on the adequacy of the security of supply.

In order to reach this objective the following goals were persecuted:

- The development of a methodology to build EV models capable of estimating the EV load and chronologically representing its behaviour for different charging strategies, which, in turn, affect the total system load profile.

- To estimate the power availability in the batteries that can be injected into the grid (V2G model), considering the battery SOC.

- To include the EV models in the SMCS method in order to evaluate the EV impact on the security of supply.

1.5 Thesis Structure

This thesis is structured as follows. **Chapter 1** presents the context and motivation of the problem under research as well as the assumptions and main objectives to be achieved with this thesis.

Chapter 2 presents a background and literature review about the reliability evaluation and the integration of EV in the power systems. In order to draw a framework of this thesis, a relevant discussion about short and long-term risk analysis is presented in **Chapter 3**.

The development of the EV models are divided between **Chapters 4** and **5** which describe the EV charging strategy modelling and the methodology to include the EV impact on the SMCS method.

Chapter 6 presents the results and discussions, through the use of test and real generating systems, about the performance of the proposed EV models. Finally, this dissertation ends with **Chapter 7**, where the main contributions, conclusions and future work are presented.

1.6 Publication List

International Journals

- (Chapter 3) - R.J. Bessa, M.A. Matos, I.C. Costa, L. Bremermann, I.G. Franchin, R. Pestana, N. Machado, H. Waldl, and C. Wichmann, "'Reserve Setting and Steady-State Security Assessment Using Wind Power Uncertainty Forecast: A Case Study,"' *Sustainable Energy, IEEE Transactions on*, 3(4), 827-836, 2012.

- (Chapters 4 and 5) - L. Bremermann, M.A. Matos, J.A.P. Lopes, and M.A.

da Rosa, "'Electric Vehicle Models for Evaluating the Security of Supply,"' *Electrical Power System Research*, Article accepted for publication on February 2^{th}, 2014. DOI: 10.1016/j.epsr.2014.02.001.

Conferences

- (Chapter 3) - R.J. Bessa, L. Bremermann, M.A. Matos, R. Pestana, N. Machado, H. Waldl, C. Wichmann, "Reserve and Congestion Management Using Wind Power Probabilistic Forecasting: A Real Case-Study," *EWEA - European Wind Energy Association*, Brussels, Belgium, 2011.

- (Chapters 4 and 5) - L. Bremermann, M.A. da Rosa, M.A. Matos, J.A.P. Lopes, and J. Sumaili, "Operating Reserve Assessment Incorporating a Stochastic Electric Vehicle Model," *Proceedings of PMAPS 2012 - International Conference on Probabilistic Methods Applied to Power Systems*, Istanbul, Turkey, June, 2012.

- (Chapters 4 and 5) - L. Bremermann, L.M. de Carvalho, M.A. da Rosa, M.A. Matos, J.A.L. Lopes, "Avaliação do Risco da Integração de Veículos Elétricos na Adequação da Reserva Operacional," *ENRSF - Encontro Nacional de Riscos, Segurança e Fiabilidade*, Lisboa, Portugal, May, 2012.

- (Chapters 4 and 5) - I.C. Costa, M.A. da Rosa, L.M. de Carvalho, L. Bremermann, J.P. Iria, "Identifying Benefits Between the Integration of Electric Vehicles and Renewable Power Usage," PEOCO 2014 - IEEE 8th International Power Engineering and Optimization Techniques , Maro, 2014.

- (Chapters 4 and 5) - L. Bremermann, M.A. da Rosa, M.A. Matos, J.A.P. Lopes, L.M. de Carvalho and I.C. Costa, "Adequacy of the long-term operational reserve of a system with wind power and electric vehicles under severe scenarios," *Accepted to PMAPS 2014 - International Conference on*

Probabilistic Methods Applied to Power Systems, Durham, England, July, 2014.

- (Chapter 5) - I.C. Costa, L.M. de Carvalho, L. Bremermann, M.A. da Rosa and J. Soares, “Stationary batteries performance assessment to deal with renewable intermittency,” *Accepted to PMAPS 2014 - International Conference on Probabilistic Methods Applied to Power Systems*, Durham, England, July, 2014.

Chapter 2

Background and State of the Art

2.1 Introduction

This chapter presents a literature review about the adequacy of security of supply and the impact of EV integration in the generating system. The EV deployment will create an additional electric load that might require more generating installed capacity. However, active demand side management can be provided by an aggregation entity that is able to control the EV charging rate or even postpone the battery charging to hours where the conventional load is lower. Moreover, this entity can also manage the charged batteries of the EV in order to contribute with power injection into the grid (V2G concept) [28]. A sustainable electric system must exploit these control opportunities in order to increase the integration of RES without compromising the adequacy of the security of supply.

The integration of EV on the power system analysis has been addressed in the literature mainly through two different paths: EV as uncontrollable and controllable load. The integration of EV as uncontrollable load has generated negative effects in the power system operation mostly due to the increase in the load consumption in peak load hours. Under a controlled EV battery charging, the EV becomes a flexible load capable of storing electrical energy. The EV integration under a controlled scheme has been seen as a positive way to contribute to the operational reserve, improving RES integration and avoiding, at least momentarily, system reinforcement.

In the long-term planning perspective, the monitoring of the adequacy of security of supply should ensure that the installed generating capacity meets the load forecast and the generating unit outages with an adequate level of risk. This risk is assessed through the static reserve evaluation, which consists of measuring the system balance. A complementary assessment, the focus of this thesis, relies on the long-term evaluation of the operational reserve, which is concerned with the flexibility of the generating systems to cope with the short-term uncertainties.

2.2 Regulation Reserves

The SO has the responsibility of managing the balance between generation and load to ensure a supply of energy to the final consumer with quality and continuity. Due to the removal of facilities for regular scheduled maintenance, unexpected generating unit outages and the uncertainty related to the load forecast, a reserve level must be kept in order to ensure an adequate and acceptable continuity of supply during the events with capacity shortage. In terms of short-term system operation, the effect of these events is translated in frequency imbalances and, generally, these imbalances are solved automatically and/or by giving set points to the generating units and flexible loads. The EV, under adequate charging schemes, represents a flexible load capable of contributing to the systems. This thesis will exploit this concept in Chapter 5.

The European Network of Transmission System Operators for Electricity (ENTSO-E) defines the reserve levels as follows [29]:

- Frequency Containment Reserve (FCR) - The FCR aims at stabilising the frequency after a system disturbance. For such task, synchronised generating units must respond to this imbalance.

- Frequency Restoration Reserve (FRR) - The FRR is responsible to offset the frequency deviation caused by the system disturbance. While the FCR acts to stabilise the frequency, the FRR corrects the frequency deviation to the nominal value considering one or more load frequency control areas. Generally, the FRR is given by an automatic generation control (AGC) system, which consists of setting the operating points of the generating units or change the state of flexible loads.

- Replacement Reserve (RR) - The RR is usually activated to reset the FRR level. Generally, the RR amount is composed by generating units that are able to start up quickly.

The reserve levels aforementioned are related to the short-term operation of the system. The SO should define the reserve levels required in a market environment via suitable operating planning.

The increasing integration of RES has created an additional interest on the performance assessment of the operational reserve in a long-term time frame [13]. The reserve that is spinning, synchronized and ready to take load up, is generally known as spinning reserve. When quick start generating units, such as gas turbines and hydro plants, interruptible loads and assistance from interconnected systems are taken into account and added to the spinning reserve, then the total capacity is known as operational reserve.

This long-term evaluation measures the adequacy of the security of supply considering that the operating reserve should meet the uncertainties related to the load and RES forecast errors (mainly wind power) and the generating unit outages. Hence, this thesis also focuses on the probabilistic assessment of the operational reserve in a long-term perspective. The framework of this analysis will be described in Chapter 3.

2.3 Adequacy Assessment Methods

The adequacy assessment of the security of supply can be performed using either deterministic or probabilistic methods. Deterministic methods have been widely used in the past and consider only specific configurations of the system which ignore the stochastic and probabilistic nature of the system's components. The probabilistic methods can provide risk values taking into account several operation scenarios like, for instance, the probability of the forecast load becomes greater than the generating capacity. The probabilistic methods are, usually, divided into two methods: analytical and simulation.

2.3.1 Reliability Indices

The main outcome of the probabilistic methods used to assess the adequacy of the security of supply is the reliability indices. The reliability indices have different designations regarding the system's hierarchical level (HL) involved in the adequacy assessment [30]. This thesis is concerned to the adequacy evaluation of generating systems, which is usually known as HL-1 system. Reliability indices are, generally, categorised as probability, energy, frequency and duration indices [30]. This thesis uses the traditional reliability indices, in order to analyse the adequacy of the security of supply, which are:

- Loss of Load Probability (LOLP) - this index gives the probability of the load curtailment.

- Loss of Load Expectation (LOLE) - this index represents the average of load curtailed during the evaluation period. It can be expressed in $hours/year$, $days/year$ or $weeks/year$.

- Expected Power Not Supplied (EPNS) - this index represents the average power curtailed during the evaluation period. It is expressed in MW.
- Expected Energy Not Supplied (EENS) - this index represents the average energy curtailed during the evaluation period. It is expressed in $MWh/year$.
- Loss of Load Frequency (LOLF) - this index gives the average number of load curtailment events during the evaluation period. It is expressed in $occurrences/day$, $occurrences/week$ or $occurrences/year$.
- Loss of Load Duration (LOLD) - this index represents the average duration of load curtailment events during the evaluation period. It can be expressed in $hours/occurrence$, $days/occurrence$ or $weeks/occurrence$.

2.3.2 Analytical Methods

Analytical techniques represent the system by a mathematical model and calculate by obtaining the probability mass function of the system states. Equation (2.1) presents a general formulation to calculate a given reliability index.

$$E[G(X)] = \sum_{x \in A} G(x)p(x) \tag{2.1}$$

where x is the current state of the random variable X, A is the set of all system states, $p(x)$ is the probability of the system state x, $G(x)$ is the outcome of the test function H, which is a mathematical formulation of a given reliability index, for the system state x. $E[G(X)]$ is the calculated reliability index. The main advantage of analytical methods is that they, usually, provide reliability indices in a relatively short computing time. However, the analytical model of the system requires the use of assumptions in order to simplify the problem. This is the case of almost all real power systems and real operating procedures [30]. The analytical methods are, generally, divided into enumeration, approximate and population-based methods (PBM).

Enumeration methods

Enumeration methods calculate the probability mass function of the system states. The system risk model is built through the combination between the probabilistic state model and the load model. Afterwards, the reliability indices can be calculated from the system risk model.

The main difference between enumeration methods relies in the algorithms used to obtain the probabilistic model of the states. The recursive methods were the first ones to be developed to calculate a Capacity Outage Probability Table (COPT). These methods recursively add the probabilistic model of the system components' state.

Firstly, the Forced Outage Rate (FOR) of each unit is calculated according to Equation (2.2). Afterwards, a table is recursively constructed adding the unit's capacity out of service and its probability, calculated using the FOR.

$$FOR = \frac{\lambda}{\lambda + \mu} \tag{2.2}$$

where λ is the Mean Time To Failure (MTTF) and μ is the Mean Time To Repair (MTTR) of the system's components. Then, the tables produced can be re-ordered and the probability value in the table is the probability of exactly the indicated amount of capacity being out of service. The cumulative probability of a particular capacity outage state of $X(MW)$ after a unit of capacity $C(MW)$ and forced outage rate U can be added through Equation (2.3).

$$P(X) = (1 - U)P'(X) + (U)P'(X - C) \tag{2.3}$$

where $P'(X)$ and $P(X)$ denote the cumulative probabilities of the capacity outage state of XMW before and after the unit is added. In a practical system containing a large number of units of different capacities, the table will contain several hundred possible discrete capacity outage levels.

Analytical methods have limitations on reliability evaluation due to the need of formulating multiple simplifications to represent the systems [30]. The pure recursive techniques do not give any indication of the frequency of occurrence of an insufficient capacity condition, nor the duration for which it is likely to exist. LOLP and the Frequency Methods (FM) are examples of enumeration methods. These methods were developed in order to measure the adequacy of generation, allowing the introduction of some reliability indices, such as the LOLE and the EENS as a result of bulk power system deficiencies. The most relevant method capable to include these features (given the historical relevance and extreme simplicity that allow the best performances) is the Frequency and Duration (F&D) method.

The F&D method computes the transition rates connecting the different states that comprise the Markov model. Similarly to the recursive method, the load model is convoluted with the recursively built COPT in order to calculate the reliability indices. This method is able to incorporate models for long-term load forecast uncertainty, scheduled maintenance, or even derated states of the generating units.

Reference [31] describes the F&D method in its general form. The generating units and load were represented through multi-state models and hourly data, respectively. The discrete convolutions and rounding techniques were used to build the generation and risk models. Therefore, FFT can be applied to decrease the computational effort. The operating reserve evaluation is provided through the risk indices analysis, where the LOLP, LOLE, EENS, LOLF and LOLD were calculated.

Other methods, which are based on discrete convolution [32] are available in the literature. The Fast Fourier Transform (FFT) [31, 33, 34], is extremely fast when compared to the methods based on conditional probability especially in the case of very large generating systems. Frequency and duration indices can also be obtained using discrete convolution.

Approximate Methods

These analytical methods use continuous probability expansions, like the Gram-Charlier Expansion (GCE) and Edgeworth methods, to approximate the probability mass function of the system states. Reference [35], proposes a methodology to obtain an accurate probability density function for the capacity outages through the use of a Fourier Transform method. The proposed method can also handle the derated outage states of generating units accurately. It is stated in the paper that the GCE is used to increase the accuracy of the methodology.

Despite of the efficiency of these methods, its use in smaller systems [36] has demonstrated that they can provide inaccurate reliability indices. Firstly, the expansion series are only appropriate for approximating continuous probability distributions. Secondly, there is no guarantee that the cumulative continuous probability distribution based on the Gram-Charlier or Edgeworth approximations is monotone [36].

Population-Based Methods

The Population-Based methods (PBM) seek at the state space representation with the objective to capture relevant states, for a faster index evaluation. The PBM promote an oriented-search through those states that have a certain failure probability, which is predefined through a threshold. Depending on the method applied, definitions of the threshold may differ. Some PBM techniques are mentioned as follows:

- Genetic Algorithms-based methods [37, 38].

- Swarm Intelligence-based methods [39, 40].
- Hybrid EA/SI EPSO technique [41].

The PBM does not follow the statistical sampling theorems, with both advantages and disadvantages. The advantage is that they are able to visit the states of interest must faster than other methods (*e.g.* statistically based methods and analytical methods), acquiring acceptable reliability indices earlier in the estimation process. The disadvantage is concerning to its non-statistical feature, which takes the statistical traceability unable to define an interval of confidence related to the solution obtained.

The generating components, usually, have a number of failure events much smaller than the number of success states. As the PBM visit only the failure states, this method has an extremely computational efficiency. Other techniques [41] can be used to improve the search efficacy and efficiency.

2.3.3 Simulation Methods

Over the last decades, the improvement on computation technology has seen some decisive achievements in the simulation process methods on different applications. Monte Carlo Simulation (MCS) methods, which are statistically-based, were the first simulation methods to be widely implemented. They can provide estimates of the reliability indices and an interval of confidence by simulating the stochastic behaviour of the system's components [42]. The measure for result accuracy of the Monte Carlo methodology is usually characterized by the coefficient of variation β, calculated through the standard deviation of the estimated expectation and the estimated index [42]. The mathematical equations used in reliability evaluation of power systems, through the Monte Carlo method, are addressed in Chapter 3.

Unlike the analytical methods, which try to assess all the system states contained in a state space, or approximations of such, through mathematical models and equations, simulation methods rely on a set of simulations representing the system's states.

Non-Sequential Monte Carlo Simulation

Non-Sequential Monte Carlo Simulation consists in sampling system states independently of the time periods in which they occur. The reliability indices are estimated by monitoring the state space. It is equally important to calculate the appropriate test functions for each system state as to estimate the reliability indices [43]. Each simulation produces an estimate of each of the parameter being assessed (*e.g.*, the reliability indices) through the appropriated test function.

The Monte Carlo method can be implemented in the following steps [15]:

1. Initialize the number of samples $N = 0$;
2. Sample all the components' system states from their respective probability distribution and update N;
3. Calculate the outcome of the test functions for the reliability indices to each sample system state;
4. Calculate the estimate of the reliability indices as the average of the function outcomes;
5. Calculate the coefficient of variation β [42]. If the confidence degree is acceptable then stops, if not, then goes back to step 2.

The NSMCS is not capable of handling the system's chronological characteristics. On the other hand, it is able to assess the reliability indices in less computational time and with less memory storage than the SMCS methods.

In the last decade, some researchers have tried to include a certain chronological characteristic on the NSMCS method in order to better represent some system's components. For instance, references [44, 45] present a pseudo-chronological simulation incorporating time varying loads on the NSMCS method. The objective of this attempt is to combine the efficiency of the NSMCS method with the ability to model chronological load curves in sequential simulations.

Sequential Monte Carlo Simulation

This simulation method is based on sampling the probability distribution of the component's state duration. It is used to represent the stochastic process of the system operation through the use of its probability distributions, associated with the MTTF and MTTR values of each system component. Assuming the use of the two-state Markov Model, these are the operating and repair state duration distribution functions that are usually assumed to be exponential. Other distributions, such as Weibull, Normal, and so on, can also be used to represent different behaviours [46].

Figure 2.1 presents a flowchart in order to illustrate the simulation process.

This flowchart can be described in the following steps:

1. Initiate the components' state. It is usual that all the components are in the state "*UP*". Define the maximum number of years to be simulated, N_{max} and the convergence criteria β. Set the number of years to one $N_{year} = 1$.

2. Set the simulation time to zero $t = 0$ and sum one in the number of simulated years $N_{year} = N_{year} + 1$.

3. Sample the components' system state in an annual basis (the reference period addressed in this thesis). The exponential distribution is used to approach

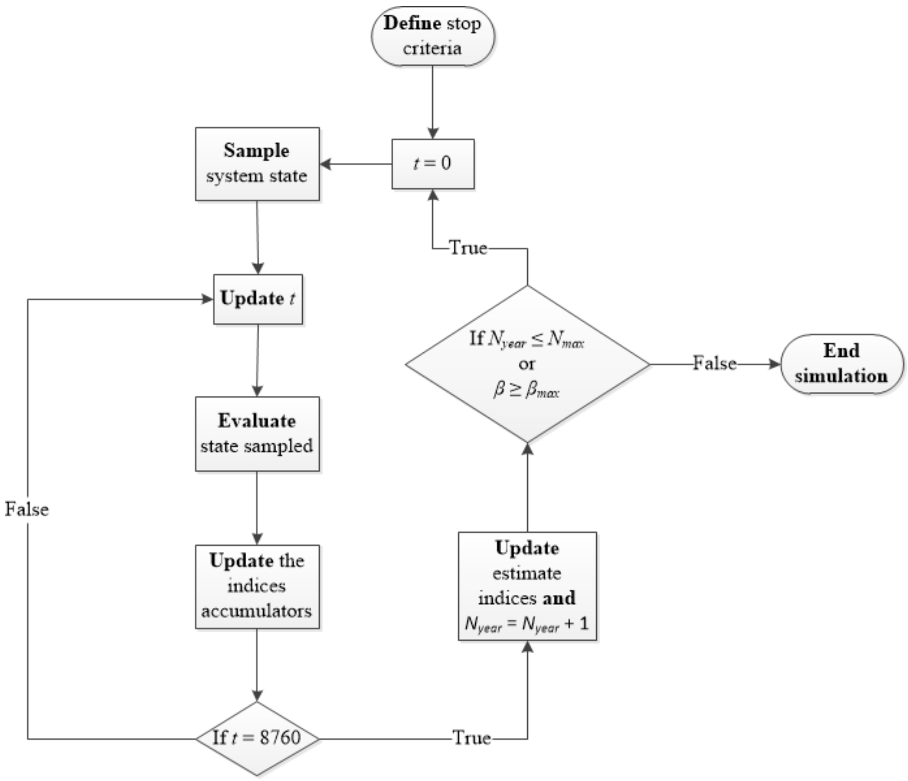

Figure 2.1: Flowchart of the Sequential Monte Carlo Simulation process.

the component's state duration and is calculated as follows:

$$T_i = -\frac{1}{\alpha_i} ln(U_i). \tag{2.4}$$

Where U_i is a uniformly distributed random number between $[0, 1]$, i stands for the component number. The MTTF and MTTR values are represented by α, and are used according to the current system's state. The load transitions occur in an hourly basis with 8760 load points.

4. Update the simulation clock t, according to the selected state transitions.

5. In order to obtain yearly reliability indices, evaluate the test function over the accumulated values.

6. Update the outcome of reliability test functions and the corresponding indices.

7. If the simulated year is not in the end, then return to step 4. Otherwise, go to step 8.

8. Estimate the expected mean values of the yearly indices as the average over the results for each simulated sequence.

9. Test the stopping criteria according to their definitions in the beginning of the simulation process. Usually, the number of sampled years and the convergence index β are the selected criteria to end the simulation process.

10. If the stopping criteria is not reached, then, repeat step 2 each time span and record the results of each duration sampled for all components. Otherwise, go to step 11.

11. End the process if the desired degree of confidence is achieved. If not, return to step 2.

The advantages of the SMCS are:

- It can easily calculate the actual frequency index.

- It considers any state duration distribution, exponential or non-exponential distributions.

- It is the only method able to calculate the statistical probability distributions of the reliability indices in addition to their expected value.

- The method is also able to represent hydro and wind series chronologically. This series bring an important season component that affects the power output of such generation technologies.

The SMCS method is the one used to evaluate the adequacy of the generating systems performed in this thesis. Therefore, more attention is given for this simulation method in Chapter 3.

2.3.4 Hybrid Methods

Hybrid methods have been developed to improve some characteristics of classic methods, and since simulation methodologies have already a complete and realistic approach, the main objective is to improve performance. Even so, the reduction of computational effort originates an almost unavoidable loss of information and of its quality.

Analytical/Simulation Methods

Reference [47] merges the Monte Carlo methodology with the LOLP technique for evaluating the reliability of an hydrothermal generating system. This approach takes into account the effect of reservoir depletion on the output capacities of the hydroelectric units. The simulation method is used to acquire the energy states whilst the analytical technique calculates the reliability indices.

An alternative hybrid method, presented in reference [48], still uses an analytical/simulation scheme, in which the recursive method is used to incorporate wind generation and hydro depletion through its hourly usage over an year interval. The presented method has the aforementioned advantages of the analytical methods, but loses, for instance, the possibility of computing the probability distributions of the reliability indices, as computed in the SMCS method.

The discussion of a new way of examining the probability distributions of the reliability indices based on an hybrid method is presented in reference [49]. The test system includes the EV impact on such analysis. The EV representation follows the basic wind power representation, *i.e.*, they are added as positive capacities on the system load.

Simulation/Simulation Methods

The quasi-sequential Monte Carlo simulation is one of the methods that combine different concepts from the Monte Carlo theory. Reference [50], presents a method based on the NSMCS. The system's components' state are sampled according to the state space representation. However, the chronology of the load is kept through the use of the multilevel non-aggregate Markov load model, instead of the traditional multi-state Markov load model that transforms the hourly chronological peak load levels into a state space representation. The quasi-sequential MCS creates a connection with the chronology aspect, by sampling the availability of the system components for each load level, which allows the inclusion of other time-dependent characteristics, like the capacity fluctuation of generating units or scheduled maintenance.

A different load model (Multi-Level Non-Aggregate Markov Load Model) is able to restore the chronological aspect and is implemented through a pseudo-chronological simulation [44]. The purpose of this approach is to use the non-sequential method to select the failure states of the system, and the sequential method is only used when there is a complete interruption of the system. The pseudo-sequential Monte Carlo simulation is described in detail in reference [44]. Despite being one of the most robust methods for power system analysis, especially for large systems, the Monte Carlo methods retain considerable difficulties in the probing process of very rare events.

Pseudo-Sequential Monte Carlo Method [51] combines the state system sampling of the NSMCS with the chronology simulation of the SMCS, processing only the failure sequences. Prior to the application of the method, a considerable amount of yearly sequences is simulated using a similar process to the one used in SMCS. A small difference occurs on Combined Pseudo-Sequential and State Transition Method [52], sequential simulation is processed through System State Transition Sampling, which leads to a lower computing time and a loss in the capture of some chronological events.

In order to suppress this problem, a Cross-Entropy based Monte Carlo method is proposed in [53]. Several reduction techniques have already been applied to power systems, with some presenting better results than others in what regards real power systems. However, rare events were still a problem deserving little discussion on reliability related literature. The proposed method in [53] serves as an optimisation algorithm for the selection of distorted parameters. The main idea is to use an auxiliary importance sampling density function, whose parameters are obtained from an optimization process that minimizes the computational effort of the MCS estimation approach. The Cross-Entropy concept is further applied to the SMCS method in [54] in order to evaluate generating capacity reliability indices. A slightly different optimisation process (still based on Cross-Entropy Method) is used. The proposed methodology suitably modifies the chronological evolution of the system in order to improve its statistical efficiency and convergence properties.

In order to decrease the computational effort, the Sequential Population Based Monte Carlo Simulation method is proposed in [41]. This method aims to create a generating states list, in which the total capacity is lower to the system's peak load, using the PBM. Then, the generation state sampled from the SMCS method are compared to those from generated list. Instead of performing the traditional SMCS procedure of composition to test the $G - L \leq 0$ to all sampled generation states, the list created in the first phase is used to identify which of them will proceed to the SMCS composition and evaluation stage. Basically, the insight was coding the generation states to build a vector with generating units that has the same capacity and the same stochastic parameters. Therefore, each entry of this vector is an integer value between zero and the number of "equal" generating units. The detailed pseudo-codes of the first and second phases can be found in [41]. The reduction of the computational effort is given, mainly, because additional time to compose and evaluate all system states is avoided.

2.3.5 Load and Electric Vehicle Load Modelling

Conventional Load Modelling

Usually, load models are developed through historical observation of the electrical demand. Depending on the power system analysis method and the necessary accuracy of the load representation, four models may be used to obtain the reliability indices. The load model is combined with the COPT or assessed by the simulation techniques. These representations are transversal for the aforementioned methods, however its usage depends on the accuracy needed.

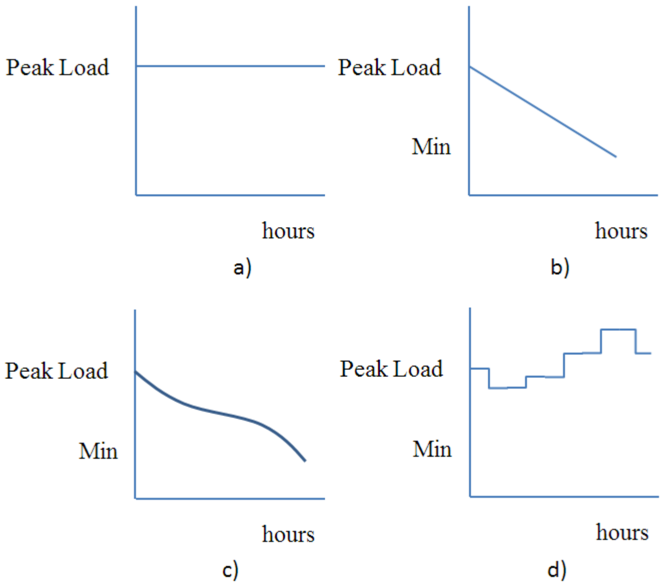

Figure 2.2: Representations of the single load curve.

Figure 2.2 presents four different load models. One considers the annual peak load for all load cycle. This means that a constant load is compared to the generation model and then, the LOLP index is determined. This method introduces excessive errors leading to a too conservative approach (see Figure 2.2 a)).

Another methodology, but still conservative, is the linearisation of a load diagram using maximum and minimum load points. This method could not capture the frequency, since, transitions disappear with the linearisation approach (see Figure 2.2 b)). Other technique is based on the daily or hourly peak demands re-ordering them to obtain a descendent curve (see Figure 2.2 c)). Nonetheless, this approach loses the chronological behaviour of the system demand.

The most common representation to index evaluation is modelling load in an hourly resolution, that is composed by load constant steps through the complete period (see Figure 2.2 d)). This model, makes possible to build a load representation with the same parameters as the generation model [31]. The load representation must be well defined, mainly because different load model representations lead to different reliability index meanings. For instance, a LOLE of 1.0 days/year obtained through the peak load demand in a daily resolution, which corresponds to a 365 points in a year, means that the generation capacity is not sufficient to meet the peak load demand in an average of 1 day in 365 days of the year. On the other hand, a LOLE of 1.0 hours/year obtained through the peak load demand in an hourly resolution, which corresponds to a 8760 points in a year, means that the generation capacity is not sufficient to meet the peak load demand in an average of 1 hour of the 8760 hours of the year.

Electric Vehicle Load Modelling

The EV brings some different approaches to modelling EV load. Reference [55] presents a methodology of optimizing power systems demand due to EV charging load. The EV load is calculated *a priori* and added (in a distributed way) to the conventional load points, maintaining it fixed during the process. The results demonstrate that EV charging load has significant potential to improve the daily load profile of power systems if the charging loads are optimally distributed. The SMCS method is used in [56] to evaluate the effects of different EV types, locations and penetration levels on the IEEE-Roy Billinton Test System (RBTS) Bus-6 distribution test system. More references will be given in the next section which is related to the literature review of the EV.

This thesis presents some EV models based on the mobility patterns and expected EV charging behaviour. Characteristics such as travel distances, battery SOC, and average time from parked vehicles are also addressed in such approaches. The resultant EV load is added to the conventional system demand to be evaluated. Then, the battery charging strategies define the EV load profile. If no charging control is provided, the EV load increases the conventional load amount requiring more capacity or operating reserve from the system. On the other hand, if charging control is provided, the EV load becomes a flexible load with storage capacity, which supports the opportunities that will be discussed and addressed throughout this thesis.

2.3.6 Wind Power Modelling

Due to the increasing integration of wind power generation in the grid, it has been addressed in the probabilistic methodologies of adequacy assessment.

Wind Power modelling for Analytical Methods

References [57, 58] have addressed the wind power generation in analytical methods. Reference [58] divides the overall system into two subsystems, containing the conventional and wind units, and a generation system model is built using a Recursive Algorithm for each of these two subsystems. The power output of the wind subsystem is calculated for each hour under study and a vector containing the hourly output of the wind power generation unit subsystem is created.

The probability model of the wind generation subsystem is modified to take into account the effect of the fluctuating energy generation. Then, the two subsystems are combined to calculate the LOLE for the desired hour. Therefore, the reliability index for the entire period is computed by the summation of all hourly values of LOLE.

Wind Power modelling for Simulation Methods

In simulation methods [13, 59–61], the wind power has been modelled through the multi-state Markov model, which is used to represent the failure/repair cycle of the wind farm's generating units. Usually, this model addresses the transitions between states as following an exponential distribution and calculated by Equation (5.1). The wind variability produces fluctuations in the power output of wind turbines, which is also represented through wind power series (generally in a hourly basis). These series capture the production of the wind farms in percentage of their total capacities. Therefore, the maximum capacity of a given wind farm is multiplied by the correspondent value of the wind power series, according to the simulation time, and taking into account the generating units' state of the wind farm, in order to produce the total wind power generation amount.

2.4 Related Studies on Electric Vehicles

Historically, the electric vehicles appeared in the beginning of the 20^{th} century. Reference [62] presents a discussion about the use of EV to correct load factor during the valley period. Curiously, the advantages of the EV had been compared with the use of horses. Instead of occupying the street and having to spend money to feed the horses, the EV owners could charge the EV batteries cheaper, during the night. Nowadays, it is expected that in a near future the EV deployment will take the place of ICE vehicles. Therefore, the EV assessment has been included in general power system references.

Market Environment

Recently, the technological improvement on the batteries and elements of the network, concepts as controlled/smart charging and V2G are discussed. In this context, the EV are able to provide electrical energy to the systems. The accumulated energy from a large group of vehicles, can be bid in the market through an aggregation entity. The reference [63] presents equations developed for calculating the capacity for grid power from three types of electric vehicles (hybrid, battery, and fuel cell vehicles). These equations are applied to evaluate revenues and costs for vehicles that are used to supply electricity to three electric markets (peak power, spinning reserves, and regulation). The results suggest that vehicles probably will not generate bulk power, both because of their fundamental engineering characteristics and because their calculated per kWh cost of energy from vehicles is higher than bulk electricity from centralized generators.

A commercial value of V2G for ancillary services is analysed in reference [64]. It is described the infrastructure considered to support the integration of EV on the distribution level. The methodology presented is used to model and analyse the load demand in a distribution system due to EV battery charging. It is stated the random characteristic of the EV behaviour and the load demand is calculated taking the SOC into account. Furthermore, the engineering rationale and economic motivation for V2G power are compelling. The societal advantages of developing V2G include additional revenue stream for cleaner vehicles, increased stability and reliability of the electric grid, lower electric system costs, and eventually, inexpensive storage and backup for renewable electricity. According to [65] to properly estimate the cost of charging/discharging EV battery, it is necessary not only to assess the operational costs, but also the impacts of the new consumption patterns in the development of long-term power plant portfolio.

The impact of EV over the market perspective is also presented in reference [28], particularly regarding the investment of conventional capacity and in the V2G role of increasing the renewable sources in the grid. References [28, 63, 66, 67] agree with the idea of V2G playing an important role in the electricity market as well as providing ancillary services to power systems.

The foreseeable increase in the use of EV led to the discussion on intermediate entities that could help manage a great number of EV. In reference [68] an aggregative agent for EV is defined as a commercial “middleman” between a system operator and EV. It is provided a bibliographic survey on the aggregative entity role in the power system operation and electricity market. The idea of an aggregation entity gives support to the use of controlled schemes to battery charging.

Power System Environment

The work presented in [69], identified essential elements of an energy distribution system that was built disregarding the EV charging capacity. Further, they examined each element, in order to determine its capacity to accommodate the additional demand that would be created by electric transportation. The EV charging impact on the electric system was assessed considering the technological limitations and therefore the charging strategies analysed were the ones that directly depend on the electric vehicle’s owner’s behaviour.

From the technological perspective battery life cycle, bi-directional charging flow and fast charging rates were already improved [25–27] allowing the implementation of an EV active interaction with the power systems. It is assumed in this thesis that the concepts of aggregation entity (from the market perspective) and communication (from the technological infrastructure perspective) presented in the literature review are adequate to make the V2G concept possible. Therefore, controlled charging schemes are addressed and discussed throughout this thesis.

The use of EV to maximize the integration of renewable energy resources in islanded grids is presented in reference [9]. The assessment was made considering two different approaches. Firstly, the EV are considered to be only in charging mode without any control scheme. Secondly, the EV are able to participate in the frequency control. From a purely technical level, the EV interfaced with the grid in a smart way can increase robustness of operation to power system dynamic behaviour. To assess the efficacy of such procedures, the grid integration of EV was pushed to its limit for each of the adopted charging management models. The study shows that the system can handle, up to a certain level, the EV integration without changes in the electricity network if a direct charging model is used. When the share of EV reaches a certain level, there is the need to reinforce the grid.

Regarding the changes in the load curve diagram caused by the large integration of EV, the impact of EV deployment will also be assessed accepting additional amounts of renewable energy in the power system [70], once EV will increase the load in the valley hours or by operational reserve that it would represent. In reference [70] the systems and process needed to pull energy from vehicles and implement V2G are examined. It quantitatively compares todays light vehicle fleet with the electric power system. This article stresses that the vehicle fleet has 20 times the power capacity, less than one-tenth the utilization, and one-tenth the capital cost per prime mover kW. Conversely, utility generators have 10-50 times longer operation life and lower operation costs per kWh.

References [71, 72] present different approaches to represent EV load. The modelling of EV made from the distribution system perspective is presented in reference [71]. The EV load value is calculated through the sum of all vehicles connected in the grid at that moment, individually. It is only considered the situation of travelling to work and returning home without considering other public areas. The start time of charging batteries is dependent on the battery SOC and has a random component to avoid the same SOC for all batteries. The charging time is according to the charging scenarios which are: uncontrolled domestic charging, uncontrolled off-peak domestic charging, smart domestic charging and uncontrolled public charging. The EV penetration level determines the total number of EV that need to be charged and the penetration level refers to the ratio of EV to the total vehicles at home or work.

Reference [72] presents a different methodology to calculate the load demand of EV in fast charging stations on a highway. First, they identify the arrival rate of discharged EV at a charging station. Then, EV charging demand is calculated with the arrival rate of discharged EV by the M/M/s queuing theory. This work lies on the distribution level considering only fast charging station points.

Under the uncontrolled domestic charging scenario, reference [73] presents a methodology to calculate the EV load taking into account the time a vehicle leaves home, the time a vehicle arrives home and the distance travelled in between. Then, the proposed methodology is applied on the national power demand of the Netherlands under different market penetration levels.

The reference [74] presents the evaluation of the EV impact in the German national grid. For such task, the authors use different charging strategies: uncontrollable charging, grid stabilization storage (pure V2G) and driven by profit maximization with V2G deployment. They affirm that the use of uncontrollable charging strategy (direct charging), increases the daily fluctuations of the national power system of 1.5%. By applying a V2G charging strategy, this is reduced about 16%. The driven by profit maximization through V2G strategy reflects in a reduction of 12% of the German power system's daily fluctuations.

Only a handful of studies considering the impact of EV in the adequacy of generating/composite systems were found. Reference [75] shows that an adequate charging strategy could support the reduction of CO_2 emissions and increase the expected deployment of EV in the grid. The EV impact on the generation mix and transmission network of the US highlighting some aspects such as the increase in natural gas generation and the reduction of the coal-fired generation imports is presented in [76]. The reference [77] presents two conclusions about the large-scale deployment of EV in the Italian power system. Firstly, the integration of EV in Italian grid will not have significant impact on its power system operation and on a fossil fuel consumption. Secondly, the energy cost and CO_2 reductions are the main benefits from the economic perspective. Reference [78] presents a reliability analysis of distribution systems to measure the impact of the interruptions in EV charging points considering adverse weather conditions. This methodology evaluates the EV impact from a customer's perspective. Under adverse weather the risk indices increase, but the main problem is related to the failure duration. While the adverse weather remains, no repair can be done and the customer is affected.

2.5 Final Remarks

This chapter presented a background and state of the art related to several techniques and methods used to evaluate the adequacy of the security of supply. The historical use of analytical methods in power system analysis is mainly given because of the predominant usage of the thermal generation and fast response. However, these methods are not able to capture the real behaviour of the electric systems' components which are, naturally, stochastic. The improvement on computational capability associated to the increase of RES integration in the generation mix led to the implementation of probabilistic methods capable of including uncertainties related to the variable characteristic of the RES and the forecast errors of their primary resources. The necessity of diminishing the computational effort provoked the emergence of hybrid methods. These methods combined the best of the simulation and analytical methods, but generally the probability distribution (for instance) is lost in exchange for the gain in computational effort.

Regarding the deployment of EV, it was stated that they have been addressed in different power system analysis. From the market perspective the V2G strategy is aim of studies. Some papers propose equations to address the revenues and costs of V2G. However, it is concluded that EV will not inject electrical energy as a conventional generation mainly because of the cost per kWh that will be much higher than conventional generation. The necessity of creating an aggregation entity to manage the storage capacity of the EV batteries is a common consensus in the related papers. This entity should bill the energy capacity provided by the EV batteries in the market environment in order to provide operating reserve for the system.

The system perspective has analysed the EV impact over the power systems. Some papers state that the EV will not impact the generation systems in the future, mainly because of the huge system capacity that is calculated in a planning phase in comparison with the load forecast. However, most of the researchers affirm that the large scale deployment of EV in uncontrolled charging mode will affect the adequacy of the power systems. Therefore, intelligent EV charging manage by an aggregation entity can provide some opportunities in order to mitigate such impact.

The V2G concept is addressed in this thesis as a charging strategy that allows the EV to provide operating reserve for the system, mitigating the EV impact on the generating systems. Another possibility is also exploited, which V2G is an inexpensive storage and backup for renewable electricity providing electrical energy to compensate the wind power variation due to the wind fluctuations.

Chapter 3

Short and Long-Term Risk Analysis

3.1 Introduction

This chapter aims at discussing the short and long-term risk analysis regarding the adequacy evaluation of generating systems. This analysis became relevant, mainly, due to the historical development of the energy market and power system.

Power systems have evolved over decades, nevertheless, the main concerns have always been to provide a safe, reliable and economic supply of electricity to the customers. The economic issue directly impacts on the degree of redundancy which should be as economic as possible. In this sense, the amount of redundant or spare capacities in generation have been inbuilt in order to ensure acceptable continuity of supply taking the failure events, forced outages of the generating units due to the scheduled maintenance into account. These considerations may lead the SO to the following questions [79]:

“how much is redundancy enough to ensure an acceptable reliability level and at what cost?"

This issue is a widely recognized problem and several criteria and techniques have been developed as an attempt to answer that. Those first used were mainly deterministic based, where typical deterministic criteria are:

- **Planning generating capacity:** installed capacity equals the expected maximum demand plus a fixed percentage of the expected minimum demand.
- **Operating capacity:** spinning capacity equals expected load demand plus a reserve which is equal to one or more largest units.

Some of that are still used in planning phase studies, however, the essential characteristic of deterministic criteria is that it does not account for the stochastic nature of the system behaviour, of customer demands and of component failures. Typical probabilistic aspects are:

- Forced outage rates of generating units.
- All planning and operating decisions are based on load forecasting techniques. Then, the uncertainties are inherent to the forecast methods which cannot be characterised in deterministic criteria.

Combining conventional generation, unconventional generation with forecast properties and consumption variability has made the task of fitting large amounts of wind generation into unit commitment procedures even more complex. Power system planners and operators are already familiar with a certain amount of variability and uncertainty, particularly because variability and uncertainty are related to the system demand. Assuming that the output from wind generation is not as dispatchable as conventional sources, the level of unit commitment uncertainty is increased, consequently, making the task of setting reserve levels more challenging [80–82].

Risk-based methodologies such as the PJM method [83] are adequate to assess short-term unit commitment risks considering intervals up to a few hours. Such evaluation is conditioned to a short period of time, and it is essentially dependent on the quality of load and wind forecasts.

Usually, these short-term concerns have been seen as a way of controlling the amount of spinning reserve, providing operators with information on operation system risks, taking the generating units available at the operation moment into consideration.

For the medium and long-term assessment, the risk evaluation must account for the available system capacity performance [13, 60] in order to meet the expected demand growth, assuring that investment options will result in more robust and flexible generating configurations that are consequently more secure.

From a technological perspective, the design characteristics of conventional hydro and thermal generators already enable the generating units to contribute to system support services, such as voltage and frequency regulation [84]. Recently, new technologies have been massively connected to the system, such as: wind and solar power. Although, the current technology allows providing a certain level of ancillary services, the level of wind unpredictability is still significant and it is not capable of fully providing the same system support as hydro and gas technologies.

Moreover, these inherent unpredictable and volatile characteristics of the wind impose additional requirements to the reserve level. Firstly, the necessary reserve to deal with the uncertainty that comes from the wind production may increase due to the fluctuating characteristic of this primary resource. Secondly, this fluctuating characteristic may also require more flexible conventional generators (hydro and combined cycle gas turbines) in order to cope with system support services [84]. To deliver both flexibility and system support services, large conventional plants could be desirable, however they usually require expensive investments [85].

Assessing reserve requirements to ensure an adequate level of energy supply is an important aspect for both expansion and operation planning of the generating systems. In the past, the planning phase concern was related to prepare the generating systems to meet the long-term load forecast, whereas the operating phase concerns were related to dealing with short-term load forecast, where sufficient generation should be scheduled in order to account for load uncertainties and sudden loss of generating units. With the massive usage of wind power technology, another set of uncertainties have been introduced on planning and operating phases.

From the short-term reserve evaluation perspective, the uncertainty linked to the wind power fluctuations brings huge difficulties to the unit-commitment and dispatch procedures of the generating systems. From the long-term reserve evaluation perspective, the uncertainty linked to the massive usage of wind power makes it difficult to prepare the future generating systems so that they can deal with large levels of uncertainty (mainly wind power and load forecasting errors) and thus meet the load forecast for the future.

In summary, the main concern of short-term reserve evaluation is measuring the unit commitment risk level. Complementary, the decisions on long-term generation management are essentially around reinforcing bulk generation. In fact, it is a common knowledge that increasing the participation of renewable power, mainly wind power, in the total generation mix means that operating and planning methodologies and standards must be revisited [86].

As the scope of this thesis is within the adequacy of power systems context, this chapter discusses the short and long-term risk analysis of the generating systems. The discussion is conducted through the use of two approaches: an analytical technique that performs an evaluation on unit commitment risk (short-term), and a SMCS method, which assesses the performance of the long-term operating reserve [13].

This chapter is organized as follows. Section 3.2 introduces short-term operating reserve evaluation. Section 3.2.1 presents the modelling of the generation unit outages. The demand and wind power forecast uncertainty models, under the short-term perspective, are presented in Section 3.2.2. The long-term operating reserve capacity evaluation is introduced in Section 3.3. Section 3.3.1 presents the modelling of the generation unit outages under the long-term assessment perspective. The long-term demand representation is addressed in Section 3.3.2. Section 3.3.3 presents the modelling of the wind power uncertainties for the long-term assessment.

3.2 Short-term Reserve Evaluation

One of the first methods that included the idea of risk to calculate generating reserve was the PJM [83]. The basic aim is to evaluate the probability of the committed generation to meet or fail to meet the expected demand during a period of time [30]. The PJM method is rooted in short-term concerns where the main uncertainties involved are load forecast errors and forced generating units outages.

The concepts are based on the assumptions that failures and repairs are exponentially distributed. The measurement obtained is a system risk index that outlines the probability which the existing generation capacity has of not satisfying the expected load demand, during time period T (lead time) and/or the probability of the operator not reacting to replace any damaged unit or using new ones [30, 60].

Therefore, the index represents a measurement of the loss of load associated with the scheduled generating reserve [30,60]. For a single unit, the probability of failure at interval $[0, T]$, *i.e.* $P_{down}(T)$, can be calculated by

$$P_{down}(T) \approx P(t_{up} \leq T) = 1 - e^{-\lambda T} \tag{3.1}$$

where λ represents the failure rate of a given generating unit. If $T << 1$, for short lead times up to some hours, then Equation (3.1) becomes $Pdown(T) \approx \lambda T = ORR$. Consequently, it is also possible to build an analytical generation model [30], with high efficiency and mainly compatible with the operating expectations in terms of time response.

Figure 3.1, shows two possible commitments in accordance with their technology predominance. The use of a merit order, to represent the generation commitment, is a common practice on the adequacy evaluation of the generating system. Even though, the generation and load are distributed over the power system network, the merit order, in a single bus representation, is based on the generating unit cost and technology in order to give a guidance of the dispatch procedure.

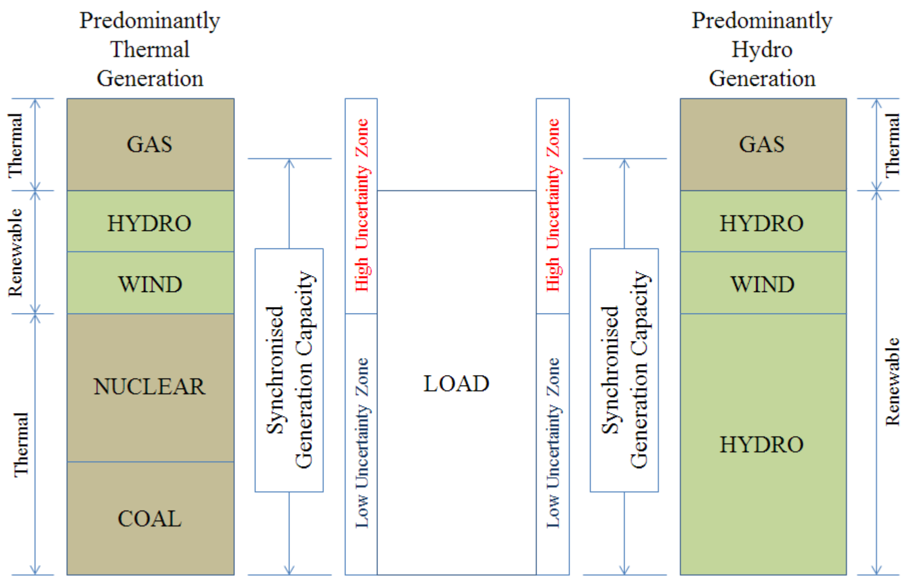

Figure 3.1: Unit commitment representation based on technology predominance.

Currently, to deal with variable generation from the operating perspective two different categories of generating systems were identified from the technological point of view: predominantly thermal generation and predominantly hydro generation.

In the predominantly thermal system, the commitment of generating units starts using less flexible technologies, such as Coal and Nuclear turbines (see Figure 3.1). These generating units deliver inertia (stability) to the system and meet a major portion of the system load. However, these units are running in the low uncertainty zone (see Figure 3.1) of the unit commitment basis due to the low costs and their inability to deliver flexibility.

In the predominantly hydro system, the commitment of generating units starts using large hydro plants which have fast response to ensure system stability. This system has high level of flexibility, however the variability of its primary resources affects the produced power requesting more installed power capacity.

The reserve capacity, which is synchronized (spinning) to take load up, is based on the generating units with more flexibility, such as gas and hydro turbines, lying in the high uncertainty zone (see Figure 3.1) of the unit commitment basis.

From a generation assessment perspective, it is usual not only to consider the synchronised units in their assessment, but non-synchronised units such as hydro and gas turbines as fast tertiary reserve.

Furthermore, for both examples and from the operating reserve evaluation perspective, the challenge is to verify whether these generating units are enough to deal with fast and enormous power variations. Usually, these power variations require a certain level of quick generation response, which are addressed by hydro and gas technologies. The flexibility of the generating system is also an issue that should be evaluated in the planning phase of the generating systems. In this thesis, flexibility is considered the feature ascribed to a system capable of accommodating generation variation.

Nowadays, there are a considerable number of flexibility sources to deal with the variability of RES [12]. Hydro predominant systems, generally have enough flexibility to integrate large amounts of variable wind power. In these cases, the main concern is to coordinate hydro and wind power in order to avoid loss of wind production, since water is storable whereas wind is not. Procedures based on water storage involving pumping facilities by wind power during convenient operation hours is one of the solutions applied to coordinate hydro and wind production from the operating perspective.

Once the system technology category is defined, unit commitment or dispatch procedures may be organized as operational decisions. In general, the operational decisions involve technical constraints related to the reserve needs and economic issues. Depending on the method used to define the level of the synchronized reserve and/or fast tertiary reserve, these operational decisions may lead to over-scheduling, which could be more reliable but also costly, or may lead to under-scheduling, which could be more affordable and yet unreliable.

Analytical-based approaches are essentially mathematical formulations based on enumeration methods. The aim of these approaches is to calculate probability density functions using generation and load risk models. In general, the reserve risk model is built considering system generation and load as independent variables. Therefore, the reliability indices are calculated through a simple mathematical manipulation. This type of approach is mostly applied for operational purposes due to its computational efficiency and simple implementation. In this context, the following sections will present an analytical method to model generating unit outages as well as the usual approaches to model load demand and wind power forecast uncertainties.

3.2.1 Modelling Generating Unit Outages

One of the analytical method advantages is to reduce the modelling dependence, where the stochastic behaviour of system's components is defined through mathematical enumerative procedures. The system load and wind power forecasts are, in this context, treated independently through dedicated systems and consequently modelled outside of the analytical model. The system risk index is calculated using a Capacity Outage Probability and Frequency Table

(COPFT) [53].

Another issue regarding this type of evaluation is related to the Outage Replacement Rate (ORR) parameter, which is similar to the Forced Outage Rate (FOR) [30] used in planning studies. The main difference between FOR and ORR is that the latter is not simply a fixed characteristic of a unit, but it is a time-dependent quantity affected by the value of the lead time considered. Hence, it is possible to build a generation model equal to the capacity and frequency outage probability table [53] in order to assess risks on hourly basis.

While the COPFT is built, it is possible to follow an intuitive process based on decoupling G (system capacity) in different subsystems, mainly to convolve all stochastic capacities G and L (system demand) at an appropriate moment of the evaluation. The information linked to resource fluctuation, such as water inflows or wind variability, is complementary to the stochastic model and, most of the time it is applied to the calculation of G [49].

To cope with short-term concerns, a COPFT is built including all committed generating units, which follows a two-state Markov Model, resulting from simple information on capacities (c_g), probabilities (p_g) and frequencies (f_g) linked to the unit commitment decision, represented as follows:

$$G = \{c_g, p_g, f_g\} \tag{3.2}$$

Time-dependent power sources, such as wind power, are rarely included in the conventional generation model. Although wind turbines behave as hydro or thermal units from the stochastic point of view, the key factors linked to wind capacity are wind speed and direction, which behave differently, for instance, from hydro depletions. Usually, wind power generation, addressed on short-term operating reserve evaluation, is a quantity provided by wind power forecast tools and, at the moment, it is considered as a complementary input in unit commitment risk evaluation.

In the same way, the value of the system load L is also provided by load forecast tools, and it is considered as a complementary input in unit commitment risk evaluation. Consequently, the reserve model will be an appropriate combination of generation model G with system load L and system wind power generation, in order to set the spinning reserve based on the pre-established risk criterion. Most importantly, this pre-established risk criterion should be followed in accordance with the operator experience.

3.2.2 Modelling Demand and Wind Power Forecast Uncertainties

Usually, conventional generation models do not comprise generation variability, like wind power. While large hydro and thermal power plants have no significant variability in their power production, the wind power generation varies with its primary resource, which in turn is different throughout time.

The variations of the wind power are often represented through a sequence of percentage values (wind series), and generally, it is given in the same basis resolution of the load, *e.g.*, 8760 capacity points. The wind series represent the seasonal wind behaviour and different annual scenarios. The probability indexed in each series gives the occurrence chance of each one. In order to combine the probabilities and frequencies of the wind power with conventional generation ones, the wind series of each wind farm is converted into impulses to perform a convolution. At least, three different manners were identified to consider the wind power's effect on reserve evaluation [31]:

- The wind capacity of each wind farm is convolved with the conventional generation.
- The summation of the total wind farm capacities is convolved, in an hourly basis, with the conventional generation.
- The wind capacity of each wind farm is added, in an hourly basis, as a

negative load on the load points.

The latter case follows an ordinary procedure of the load model, which is described in [31].

During the operation, one has to make decisions in accordance with the last information on what has occurred in the system, and taking the remaining load and wind power forecasting uncertainties into account. The demand forecast uncertainty, close to the real-time operation (up to 2 hours), is usually negligible, while the wind power forecast uncertainty is still relevant.

The Normalized Mean Absolute Error (NMAE), of the very-short wind power forecasting varies from 1-2% (10-15 min. ahead) to a maximum of 10% around 2 hours ahead, considering a time resolution of 10 min. However, it is hard to beat the persistence model performance for such a short time horizon [87]. When the time resolution increases to up to 1 hour, the improvement with respect to the persistence model is even more difficult, so it is a common practice to assess unit commitment risk using the last known wind power occurrence as the forecast for the next period, given by

$$\widehat{W}_i(t+k) = W_i(t) \tag{3.3}$$

where, $W_i(t)$ is the last known wind power generation at instant t, and $\widehat{W}_i(t+k)$ is the forecast wind power generation launched at instant t for the horizon k. Note that, the wind forecast error, from a short-term reserve evaluation is still hard to define. Therefore, the persistence method provides guidance when assessing unit commitment risk.

3.2.3 A Simple Example

From an operating perspective, one of the main concerns of a system operator is regarding the composition of the spinning reserve. This decision is usually made according to economic aspects combined with a unit commitment risk evaluation.

Table 3.1, presents a generation model built using the COPT for the entire generation system as in [53]. The generation capacities are the total installed capacity of the thermal subsystem and the total capacity of the hydro subsystem in December.

Table 3.1: Example of the PJM method application.

Capacity		Cumulative Probability Lead Times of			
In (MW)	Out (MW)	1 hour	2 hours	3 hours	4 hours
9,189	400	6.23×10^{-07}	1.25×10^{-06}	1.87×10^{-06}	2.49×10^{-06}
9,239	350	8.21×10^{-07}	1.64×10^{-06}	2.46×10^{-06}	3.28×10^{-06}
9,392	197	1.90×10^{-06}	3.81×10^{-06}	5.71×10^{-06}	7.61×10^{-06}
9,434	155	3.33×10^{-06}	6.66×10^{-06}	9.99×10^{-06}	1.33×10^{-06}
9,489	100	4.19×10^{-06}	8.37×10^{-06}	1.26×10^{-05}	1.67×10^{-06}
9,513	76	4.88×10^{-06}	9.77×10^{-06}	1.47×10^{-05}	1.95×10^{-06}
9,545	44	5.23×10^{-06}	1.05×10^{-05}	1.57×10^{-05}	2.09×10^{-06}
9,554	35	5.58×10^{-06}	1.12×10^{-05}	1.67×10^{-05}	2.23×10^{-06}
9,564	25	5.92×10^{-06}	1.18×10^{-05}	1.78×10^{-05}	2.37×10^{-06}
9,569	20	8.97×10^{-06}	1.79×10^{-05}	2.69×10^{-05}	3.59×10^{-06}
9,577	12	9.55×10^{-06}	1.91×10^{-05}	2.86×10^{-05}	3.82×10^{-06}
9,589	0	1.00	1.00	1	1

Therefore, from the total system installed capacity of 11,391 MW, the wind power installed capacity of 1,526 MW was reduced in accordance with the wind regime, as well as the effect of the hydro resources, also in accordance with hydro inflow in December, which corresponded to 276 MW. It is assumed that the latter reduction is a result of the availability of hydro resources during an operation procedure. The main idea is to characterize an operation scenario to deal with the PJM method.

The lead times of 1, 2, 3 and 4 hours and their respective cumulative probability are related to each capacity in and capacity out. The main assumption made by the

PJM is that the load will remain constant throughout the analysis period. Thus, the unit commitment risk can be directly deduced by Table 3.1. For instance, a forecast wind power production of 330 MW and a load forecast of 9,569 MW are assumed for the next hour. Using Table 3.1, it is possible to set a spinning reserve of 350 MW for a risk level of 8.21x10^{-07} and a lead time of 1 hour. In this case, the wind power generation was considered to be out of the generation model, mainly due to its hard forecast properties and chronological features similar to the load.

It is important to highlight that during the operation analysis, the unit commitment risk level assumed is a result of the generation capacity available at the moment of the operation. In fact, the operator usually uses the PJM by identifying if this generation capacity is enough to meet the load forecast with an acceptable risk level.

3.3 Long-term Reserve Evaluation

The generating systems, in a long-term perspective, are usually assessed through the evaluation of the system's balance. The comparison of the total system available capacity with the total system demand is known as the static reserve evaluation. From an operating reserve perspective, represented in the long-term evaluation, the technique relies on verifying whether the planned generation system is able to cope with the system uncertainties. The next sections will present an usual method to evaluate the static and operating reserves, in a long-term perspective.

Static Reserve Evaluation

The static evaluation aims of verifying whether a given configuration of the generating systems will be able to meet the load forecast demand for a year in the future. In order to assess the static reserve, the following equation is tested in each state transition of the SMCS process.

$$G - L_f \leq 0 \tag{3.4}$$

where G represents the total system generating capacity available and L_f is the total system load forecast. The random variable G, depends on the availability of the equipment and on the capacity fluctuations caused by hydrological and wind resources. The random variable L depends on the hourly load forecast and can be affected by both short and long-term uncertainties, as demonstrated in [13]. The test performed in Equation (3.4) determines whether or not a failure occurs. If Equation (3.4) is true, then a failure occurs and the reliability indices are calculated.

Operating Reserve Capacity Evaluation

Most recently, the massive usage of wind power as an alternative green energy resource, imposed another type of uncertainty that is directly linked to the unit commitment task. On the one hand, wind power production provides some system benefits, such as reduction in the operating costs of the system and reduction in CO_2 emissions. On the other hand, it can bring huge hourly variations in power generation in the short-term horizon.

The wind power forecasting errors directly affect the unit commitment decisions and they must be taken into account to adequately measure the unit commitment risk level. Clearly, the decisions are based on the generating units available at the moment when the decision is made, which generally happens 1 or 2 hours before the operation.

As wind power has only started being used massively a decade ago, the existing hydro and thermal generation need to cope with these current issues. Furthermore, there is a clear movement towards the use of gas turbines as flexible generation alternative, since hydro plants present more restrictions in terms of construction time and environmental awareness. Bearing in mind this transition from less to more variable generating system sources, some concepts linked to the generating system assessment were revisited considering a planning perspective.

Over the last years, the traditional long-term adequacy assessment of the generating capacity has assumed two different perspectives: the aforementioned static reserve [30] and a new perspective on operating reserve capacity [13, 60]. The operating reserve capacity evaluation is concerned with the long-term analysis of the generating system capacity and flexibility to cope with the short-term variations, which can occur during the system operation [13, 60].

The generating capacity available at each operating period is affected by planned and forced outages and by the short-term fluctuations of the primary energy resources. Moreover, this capacity must be capable of not only supplying the load, but also accommodating the difference between the actual achievement and short-term forecasts of wind power, while complying with the operational rules established by the utilities, such as minimum primary and secondary reserve levels and unit commitment priorities.

Therefore, it is possible to model some operational procedures to assess the adequacy of the operating reserve under a planning perspective, named as ***operating reserve capacity*** (ORC) evaluation, which consists of the secondary reserve plus the fast tertiary reserve available at the moment of the evaluation. The tertiary reserve is composed by those generating units capable of taking load in a short period of time, such as 1 hour.

As the ORC is an extension of the static reserve evaluation, the original static reserve equation is rewritten as

$$R_{st} = G - L_f \tag{3.5}$$

where, R_{st} is the static reserve capacity. From the operating reserve perspective, short-term problems are addressed through the system uncertainties which are represented in terms of capacities: the availability of the generating units ΔG, the load deviations due to the load forecast errors ΔL_f and the variability of the wind power ΔW_S. These new variables are addressed in the original static reserve equation, yielding the long-term operating reserve equation, as follows:

$$R_{op} = G + \Delta G + \Delta W_S - (L_f + \Delta L_f). \tag{3.6}$$

As an attempt to represent some short-term issues, the primary reserve R_P and the secondary reserve R_S are also addressed in the latter equation, resulting in

$$R_{op} = G + \Delta G + \Delta W_S - (L_f + \Delta L_f + R_P + R_S). \tag{3.7}$$

Under an unexpected situation of forced unit outage, some generating units of the system can be scheduled rapidly in order to cover this problem. The total capacity of these units is called fast tertiary reserve, because they are units that can be quickly synchronised up. From the operating perspective G means the synchronised capacity, then the variable G is suppressed and changed by G_{Sync}. Therefore, the variables L_f, R_P and R_S should be met by this synchronised capacity.

$$R_{op} = G_{Sync} + \Delta G + \Delta W_S - (L_f + \Delta L_f + R_P + R_S). \tag{3.8}$$

The Equation (3.8) is split to represent the ΔG variable which is the balance between the synchronized generating units and the summation of the system load forecast, primary and secondary reserve requirements.

$$\Delta G = G_{Sync} - (L_f + R_P + R_S) \tag{3.9}$$

The capacity of the forced outage generating units is computed during the G_{sync} scheduling procedure.

The operating reserve is, therefore, the sum of the R_S and R_T and means generating units available to be used on the deviations of the system. This balance is tested and the identification of the events of insufficient operating reserve capacity is made according to the following Equation

$$R_S + R_T - (\Delta L_f - \Delta W_S - \Delta G) \leq 0. \tag{3.10}$$

Where R_S is the secondary reserve requirement, R_T is the fast tertiary reserve capacity, ΔL_f and ΔW_S are the system load and system wind power forecast errors, respectively.

This new perspective may be illustrated in Figure 3.2, and can be viewed as a way to assess, in terms of flexible capacity, the future generating system to accommodate a large percentage of wind power.

As showed in Figure 3.2, the generating unit synchronisation is given according to a merit order to meet the system requirements (L_f, R_P and R_S). The secondary reserve R_S and the fast tertiary reserve R_T plus the hatched capacity (see Figure 3.2), which represents the discrete effect of the generating units scheduling, form the operating reserve capacity.

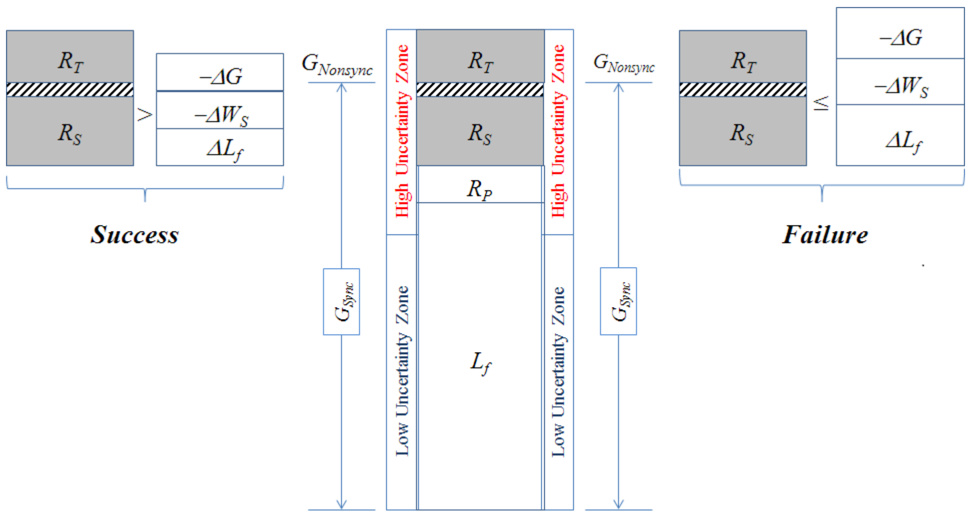

Figure 3.2: Operating Reserve Capacity evaluation.

Success and failure states are properly verified whether or not the operating reserve capacity is sufficient to compensate for the difference between load and generation deviations at each hour, during an established observation time.

Throughout this perspective, the system capacity and flexibility are evaluated in order to prepare the future generating system to cope with the entire set of uncertainties [84].

Due to the uncertainty of the system load forecast and the variable primary resources, the task of evaluating the operating reserve capacity using probabilistic methods is advisable [30]. To cope with uncertainties from a planning perspective, the Monte Carlo simulation methods are still the standard to assess the adequacy of power systems. Besides that, the SMCS, specifically, has the advantage of providing probability distribution functions associated to reserve requirements related to a set of uncertainties linked to the power balance problem.

The SMCS makes keeping track of several features related to the operating history of system states possible. Its flexibility also makes modelling uncertainty details possible, which is a valuable information for generating systems with large renewable sources in their energy mix. After evaluating each system state, performance indices are estimated using the expected value equation. As described in [15], let Q denote the unavailability (failure probability) of a system and x_i be a zero-one indicator variable which states whether or not a value equation is true.

The estimate of the system unavailability is given by

$$\widehat{E}[G] = \frac{1}{N}\sum_{u=1}^{N} G(y_u) \tag{3.11}$$

where y_u is the sequence of system states in year u, $G(y_u)$ is the reliability test function evaluated at y_u, N is the number of simulated years (samples) and G is the random variable which maps $G(y_u)$ values. The uncertainty surrounding the estimated indices is given by the variance through

$$V(\widehat{E}[G]) = \frac{\widehat{E}[G] - \widehat{E}[G]^2}{N} \tag{3.12}$$

The stochastic process convergence is tested using the coefficient of variation β as follows.

$$\beta = \frac{\sqrt{V(\widehat{E}[G])}}{\widehat{E}[G]} \cdot 100\% \tag{3.13}$$

Following the SMCS procedure, the conventional system reliability indices may be estimated. This traditional view can provide important information on loss of load events and, in this case, the simulation will monitor the success and failure states of the static and operating reserves, where the following reliability indices will be calculated [15]: LOLP, LOLE, EENS, LOLF and LOLD.

In order to illustrate the estimate of a reliability index, using Equation (3.11), the formulation of the LOLE index is exemplified. Let the LOLP of a given state x be described as

$$LOLP(x) = \begin{cases} 1, \text{ if } x \text{ is FAILURE} \\ 0, \text{ if } x \text{ is SUCCESS.} \end{cases} \tag{3.14}$$

The LOLE function can be written by

$$G_{LOLE}(y_u) = \frac{1}{8760} \sum_{n \in S} d(x_i) LOLP(x_n) \tag{3.15}$$

where x is a given state n of the system states set S in a year u. $d(x_u)$ is the duration of a given system state and 8760 is the period under analysis. Therefore, following the Equation (3.11) the LOLE index can be estimated as follows

$$LOLE = \frac{1}{N} \sum_{u=1}^{N} G_{LOLE}(y_u). \tag{3.16}$$

The LOLE is the average number of hours in a given period (in this thesis this period corresponds to one year) in which the hourly load is expected to exceed the available generating capacity.

By using the same concept presented in Equations (3.11), (3.12) and (3.13), the uncertainties surrounding the operating reserve concept might be monitored to investigate, in detail, the uncertainty impacts on the performance of the operating reserve from a long-term perspective. The following sections will introduce all of these deviations as random variables. Although the LOLE index does not indicate the severity of the deficiency nor the frequency nor the duration of loss of load, it is the most widely used probabilistic criterion in generating capacity planning studies [15].

3.3.1 Modelling Generating Unit Outages

The SMCS method is generally used to accurately reproduce the entire cycle of generating unit outages [13]. The failure/repair cycle of the generating units is represented by two-state and multi-state Markov Models (as seen in Figure 3.3) and their transitions are usually approached by an exponential probability distribution [13, 60].

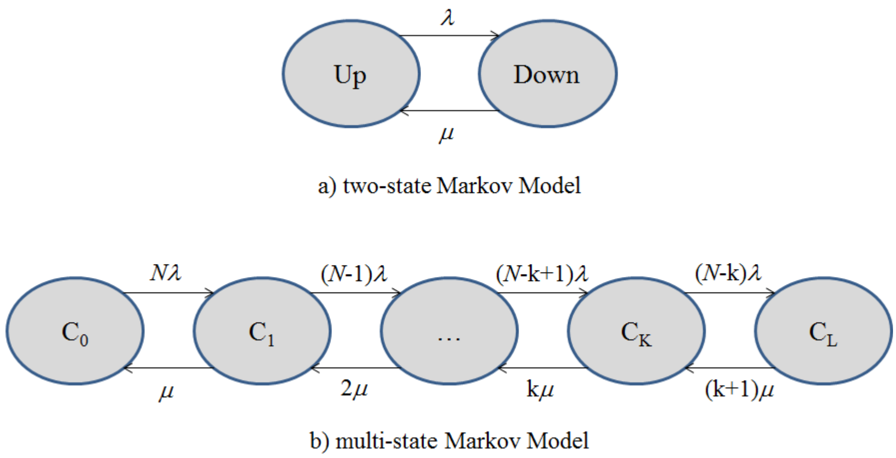

Figure 3.3: Markov Model representations.

The representation of hydro and thermal power plants follow, in general, the two-state Markov Model, as illustrated in Figure 3.3 a). Using a simplified model, hydro plants have their maximum output multiplied by their corresponding value of the hydro series [13, 60]. The hydro series are the available volume of water in the reservoir for each hydro plant region. This information can be given as a monthly average value, which will represent the seasonal water variability or even in a smaller resolution as a weekly basis. This latter, makes introducing a set of rules to the scheduling procedure possible in order to guarantee a maximum energy usage of the hydro units, for instance.

The residence time of the hydro and thermal plants representation in each state is calculated according to

$$T = -\frac{1}{\alpha} ln(U) \tag{3.17}$$

where T is the residence time of each generating unit and α assumes λ, which is the mean time to failure (MTTF), if the current state is "*Up*" or it assumes μ, which is the mean time to repair (MTTR), if the current state is "*Down*". U is a uniformly distributed random number which is sampled in the interval [0,1].

Instead to model the wind power capacity to convolve with the load (as showed in Section 3.2.2), here, it is modelled to convolve with the conventional generation. The capacity of wind turbines might be represented by a multi-state Markov Model (as illustrated in Figure 3.3 b), to characterise the failure/repair cycle of a wind farm. Then, the capacity associated to the k_{th} state is given by:

$$C_k = (N-k)C, \qquad k = 0, 1, ..., N \tag{3.18}$$

where C is the capacity of a single generating unit. N is the number of wind farm's generating units and k is the generating unit state. With the objective to reduce the number of states during the SMCS procedure, a simple truncation process defines the desired order of accuracy. Therefore, instead of $N+1$ states, a smaller number up to the capacity C_L will limit this model [43]. Similarly to the hydro depletion, the maximum output of a wind turbine is multiplied by the corresponding value of the wind series.

3.3.2 Modelling Demand Forecast Uncertainty

The seasonal characteristic of the load shapes the load profile throughout the year. For instance, due to the high temperature of the summer season, the electrical load is impacted mainly by air conditioners, whereas the electrical load in the winter season is characterised by electric heating resulting in different load profiles. In order to achieve good results in the reliability assessment of generating systems, the detailed modelling of the load is desired, however this accuracy depends on the amount and the quality of available data [45].

The load model, usually consists of 8760 load steps. In order to track the chronological characteristic of the load profile, a state space representation can be approached by Markov model. Some models keep the chronological aspects of the load tracked, contributing to the reduction of the computational effort, however the SMCS method sequentially follows these load steps during the simulation procedure process.

The error between the load forecast and the actual load is included in the load modelling, as showed in Equation (3.19). From this definition two uncertainty levels may be represented: short and long-term load forecasting errors, which can be simulated through the SMCS process. In the short-term representation, an hourly uncertainty is calculated during the simulation, whereas the long-term load uncertainty is calculated once a simulated year. The latter, causes an effect over all load profile while the short-term load forecasting error inserts a noise in the chronological representation of the load.

$$L_a(t) = L_f(t) + \Delta L(t) \tag{3.19}$$

where $L_f(t)$ is the forecast load in the hour t that comes from the chronological modelling, $L_a(t)$ is the actual load at hour t and $\Delta L(t)$ is the short-term uncertainty assumed to follow a Gaussian distribution [13] with zero mean and a standard deviation proportional to the load. The standard deviation of this normally-distributed error in Equation (3.19) is assumed to be a percentage of the load.

The main implication of this short-term load forecast is that it directly affects the decisions related to the amount of spinning reserve, as well as fast tertiary reserve.

3.3.3 Modelling Wind Power Forecast Uncertainty

The state of the art in day-ahead wind power forecasting provides a normalized root mean square error between 15 and 20% [88] of installed capacity, which in fact has an impact on the task of fitting large amounts of wind generation into unit commitment or dispatch procedures.

Some researchers have assumed normally-distributed errors for short-term forecasting [86], mainly based on the amount and the geographical dispersion of wind power [89]. Nevertheless, other researchers affirm that the distribution of the actual wind power forecasting error is not normally-distributed [90].

While wind speed distribution is generally approached through the Weibull and Beta distributions [91, 92], the analysis made over the wind speeds data for six onshore sites in Germany [91] showed that for relevant wind speed range (where the wind is useful for wind power generation), the probability density functions can also be Gaussian. On the other hand the non-linear relation between the wind speed and wind power leads the wind power prediction errors to non-Gaussian distributions.

In fact, wind speed, and therefore wind generation, is usually modelled using stochastic processes due to the complexity of wind behaviour. A simplified method based on the persistence method is presented to characterise the error of wind power due to the short-term wind forecasting procedure.

$$\Delta W_i(t) = W_i(t) - W_i(t - \tau) \tag{3.20}$$

where $W_i(t)$ is the wind production for an individual wind farm at hour t, $W_i(t-\tau)$ is the last known wind production for such wind farm, and $\Delta W_i(t)$ is the wind power deviation of this individual wind farm at hour t due to the error in the wind forecasting procedure.

After identifying the wind power deviation for each wind farm at hour t, it is necessary to define the system deviation, which will be the sum of all individual wind farm deviations.

$$\Delta W_S(t) = \sum_{i=1}^{k} \Delta W_i(t), \qquad i = 1, 2, ..., k \tag{3.21}$$

where $\Delta W_S(t)$ is the system wind deviation. The persistence method is the largest one used to represent the uncertainty of the wind power forecast, since it has a simple implementation and a adequate level of accuracy, as mentioned in Section 3.3.3.

3.3.4 Relationship between Generation and Load Uncertainties

The aforementioned system uncertainties may be viewed as a positive or negative impact on the system balance, depending on how suddenly they occur and on the magnitude and direction of the variations. Table 3.2 shows a summary of consequences (upward or downward reserve) that should be monitored during the adequacy evaluation of the generating systems concerned with these variations.

The concept of net load forecast is usually applied in the literature [93] to refer to the imbalance caused by load and wind power forecast deviations. This concept is not used here, mainly because all variation models are considered statistically independent events and an additional major variation has been modelled using the generating outages.

The effects shown in Table 3.2, reinforce the need for assessment of long-term operating reserve. These events involve not only the load and wind power forecasting errors, but also the generating outage variations. Therefore, the power balances may have negative or positive effects to the system with upward or downward reserve as consequence. As the adequacy evaluation of the generating system, performed in this thesis, is concerned to the long-term power

Table 3.2: Relationship among the system uncertainties.

Variables				Conditional	Deviation Effects	Reserve Need
Id.	ΔL	ΔG	ΔW_S	*if*	*d*	**up or down**
A	+	-	-		-	upward
B	-	-	-	$(\Delta G + \Delta W_S) > \Delta L$	+	downward
	-	-	-	$(\Delta G + \Delta W_S) \leq \Delta L$	-	upward
C	-	-	+	$(\Delta G + \Delta W_S) > \Delta L$	+	downward
	-	-	+	$(\Delta G + \Delta W_S) \leq \Delta L$	-	upward
D	+	-	+	$(\Delta G + \Delta W_S) > \Delta L$	+	downward
	+	-	+	$(\Delta G + \Delta W_S) \leq \Delta L$	-	upward
E	+	+	+	$(\Delta G + \Delta W_S) > \Delta L$	+	downward
	+	+	+	$(\Delta G + \Delta W_S) \leq \Delta L$	-	upward
F	-	+	-	$(\Delta G + \Delta W_S) > \Delta L$	+	downward
	-	+	-	$(\Delta G + \Delta W_S) \leq \Delta L$	-	upward
G	+	+	-	$(\Delta G + \Delta W_S) > \Delta L$	+	downward
	+	+	-	$(\Delta G + \Delta W_S) \leq \Delta L$	-	upward
H	-	+	+		+	downward

balance, the **downward reserve can be disregarded** since the approach used is based on the system capacities.

The first analysis from Table 3.2 is the collective event A. This event shows that the load forecast error is positive (*i.e.*, the actual load is greater than the expected one) and both wind power forecast error and the synchronised generating units are negative (*i.e.*, the amount of generating power is lower than the expected one). This collective event has as consequence an upward requirement of reserve. The event H, shows the opposite situation. The system uncertainties collaborate with the system requesting downward reserve.

The ΔG variable is the balance between the synchronized generating units and the summation of the forecast system load, primary and secondary reserves, as seen in Equation (3.9). From A to D cases of Table 3.2, ΔG assumes negative values. This means that all the synchronised generating units available are not able to meet the operating system requirements plus the system load forecast. However, this does not mean a failure state of the operating reserve capacity. For instance, this lack of capacity might be compensated by the load and wind power forecasting errors which might contribute to the system. Therefore, these possibilities lead to a downward or upward reserve, according to Table 3.2.

On the contrary, from E to H cases, the ΔG assumes positive values. This means that there is enough synchronised capacity to deal with the system requirements. Nonetheless, this situation does not imply on success state of the operating capacity reserve evaluation. As matter of fact, if the surplus of the synchronised capacity plus the fast tertiary reserve (operating reserve capacity) are not enough to meet the load and wind power forecasting errors, assuming that these uncertainties require more electric power generation, then a failure state is established. The above analysis can be expanded to the ΔL and ΔW_S uncertainties, according to Table 3.2.

3.3.5 A Simple Example

This section presents an illustrative example of the previous discussion highlighting the impact of the system uncertainties in the operating reserve capacity evaluation. Table 3.3 presents the reliability indices of the static and operating reserve capacity evaluations, which were performed through the use of a modified version of the IEEE RTS 1996 [60].

Table 3.3: Example of the SMCS method application.

	LOLE (h/y)	**EENS (h/y)**	**LOLF (h/y)**	**LOLD (h/y)**
	β(%)	β(%)	β(%)	β(%)
Static Reserve	0.3456	66.49	0.1360	2.5398
	(3.30)	(4.99)	(3.90)	-
Operating Reserve	0.7679	129.30	0.4785	1.6047
	(4.08)	(4.97)	(4.41)	-

The LOLE index of 0.34 hours per year, of the static reserve evaluation, gives an idea of the amount of time that the load is expected to exceed the total available generating capacity. From this perspective the test system can be considered quite reliable.

From the operating reserve capacity evaluation, the LOLE index of 0.7679 h/y gives an idea about the flexibility of the generating system configuration facing the system deviations. In other words, it shows the amount of time that the deviations of the system are expected to exceed the available committed capacity plus the fast tertiary reserve.

3.4 Electric Vehicle Demand Modelling

The estimation of EV load based on mobility patterns is an adequate approach, since no EV data is available, to include this type of load in the static reserve evaluation. From the operating reserve capacity perspective, the uncertainty related to the EV load estimation is not significant, but the opportunity that they arise to contribute to the operational reserve should also be taken into account.

Under an adequate charging strategy the EV charging rate can be controlled or even postponed. Analogously to Equation (3.19), the total EV load is given by

$$L_{EVtotal} = L_{EV} - \Delta L_{EV} \tag{3.22}$$

where L_{EV} is the estimate EV load, $L_{EVtotal}$ is the actual EV load, and ΔL_{EV} is the portion of EV load which is able to contribute to the system if the operating reserve capacity is threatened. This action is named as ***controlled charging strategy***.

This new variable ΔL_{EV}, directly affects the reduction of $L_{EVtotal}$ and indirectly affects the increase of operating reserve R_{op}. This action differentiates the charging strategy from the V2G procedure. Both controlled and V2G strategies are described in Chapter 5.

3.5 Final Remarks

This chapter presented a discussion about the operating reserve capacity evaluation considering a generation portfolio composed by a high integration level of RES. Two operating reserve perspectives were presented. Firstly, a short-term operating reserve evaluation was discussed and the generation units and load modelling were described. This perspective aims at evaluating whether the unit commitment of the generating units is enough to meet the load forecast through an acceptable risk level. Secondly, the long-term operating reserve evaluation was introduced as an extension of the static reserve concept. This evaluation was renamed to operating reserve capacity evaluation due to its objective of evaluating whether the available operating reserve is enough to meet the uncertainties of the system: load and wind power forecast errors, and forced outages of the generating units. The fluctuation characteristics of the hydrological and wind resources were also addressed, since they impact on the total available capacity of the generation systems.

Table 3.2 presented the analysis of the independent random variables related to the system uncertainties. The upward and downward reserves were analysed through the system uncertainties impact that, jointly, have on the ORC evaluation. As this thesis is concerned to the long-term perspective, the downward reserve is not addressed on the long-term evaluation of the operating reserve capacity.

The possibility of EV controlled charging schemes was introduced in the operating reserve capacity context. The massive deployment of EV may present opportunities to contribute to the electricity sector through the increase of the operational reserve. Uncontrolled charging schemes are addressed in Chapter 4 whilst the controlled charging strategies are described in Chapter 5.

Chapter 4

Electric Vehicle Modelling

4.1 Introduction

The gradual replacement of ICE vehicles by EV requires studies which are appropriate to measure the impact of EV in the security of supply. The EV impact depends, mainly, on the mobility pattern and charging behaviour. The EV demand will certainly impact the conventional load and perhaps compromise the adequacy of the security of supply.

Assuming that utilities and traders have interest in encouraging the EV owners to charge their vehicles in some specific hours of the day, offering lower energy prices, and/or an aggregation entity will manage the vehicles' charging, the EV can effectively contribute to reduce its impact on the generating systems.

Under this level of controllability, the EV load has been seen as a flexible load, where two perspectives are presented: EV charging under an active demand side management and EV charging as an electrical component that can inject electrical energy into the grid. These actions are known as controlled charging strategies. For a better understanding, these charging strategies are briefly commented in this chapter. The detailed description of the controlled charging models, is given in Chapter 5.

In order to represent the uncontrolled and controlled charging models, Figure 4.1 classified the EV charging strategies as follows.

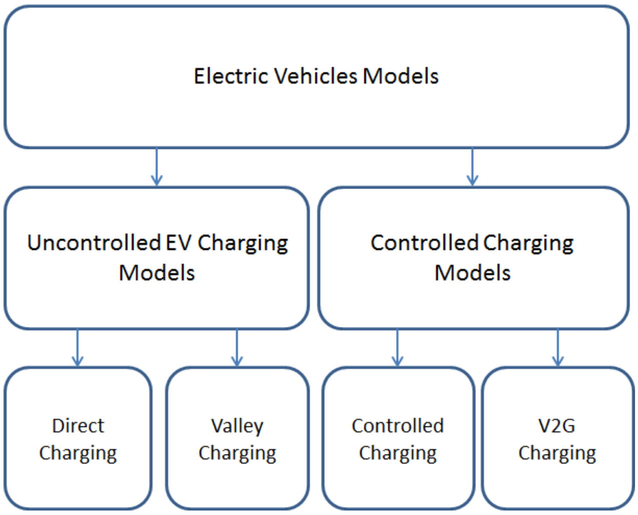

Figure 4.1: Classification of EV Models.

Where uncontrolled charging model means the EV models that do not follow a charging strategy, in fact, the decision of charging the EV batteries is taken by the EV owner instead. These models are named as the direct and valley charging strategies. The controlled charging models are the ones that the battery charging behaviour follow a strategy chosen by the driver.

This chapter presents the EV developed models and the proposed methodology to include these models in the SMCS method in order to measure the EV impact on the adequacy evaluation of the security of supply. Section 4.2 presents the mobility pattern study which provides the basic information needed to build the EV models. The counting process methodology is described in Section 4.3. The next step is building the EV load profile. For such task, a brief discussion about load shape estimation is provided. The charging strategies are described in Section 4.4 and the EV load shape estimation from the two counting process perspectives are presented in Section 4.6. Section 4.7 describes the integration of the proposed EV models into the SMCS method. Finally, the final remarks are presented in Section 4.8.

4.2 Mobility Pattern

The mobility of the population is a phenomenon closely related to the land planning, in the urban and regional aspects, the accessibility and the way how the living spaces are structured (home, work, leisure) and hence livelihoods. Mobility surveys are generally aimed to know the family lifestyle, from the perspective of demand for services and infrastructure for transport, allowing to characterise the movements of the population and how these movements are related to the structuring of the territories. These features contrast with the surveys made at the entities which provide services or transport infrastructure (private or public companies), from the perspective of supply.

In order to improve urban ordination and public transport, mobility behaviour is usually characterised throughout statistical data gathered by official government entities. Reference [94] used mobility pattern to estimate, under some assumptions, the EV load and, therefore, the EV impact on the operation and expansion of power systems. The idea proposed in this thesis is using the average number of the population arrivals, as input of the proposed methodology, to calculate, under some assumptions, the estimate of EV arrivals throughout the simulation process.

The data related to the mobility pattern used throughout this thesis is presented in [23] and, therefore, this section aims at describing, in detail, how it is gathered. The information in [23] allows to characterise the short duration mobility of the resident population from 33 counties of the north region of Portugal. This had a representation of almost 70% of the population that lives in this space. The region covers almost counties identified in areas 2, 3, 4, 5 and 6 of the Figure 4.2.

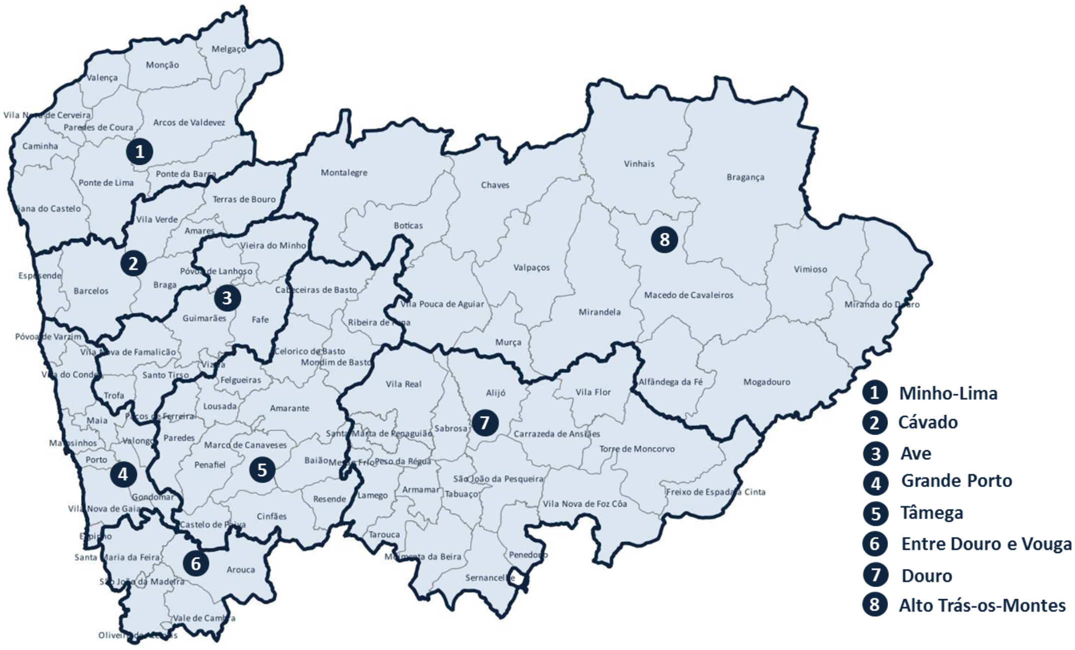

Figure 4.2: Sample of the northern regions of Portugal.

The variables of interest are organized as: number of performed trips, arrival and departure times of each trip, duration of the trips, used transportation type, transfer among different types of transport, distinction between the mobility of weekdays and weekends.

The information was obtained by direct interview, and the observation units are: household[1] and individual. This survey admits a sampling error of 10% (per county or neighbourhood) and a confidence interval of 95%.

The total interviewed population is about 213.727 individuals divided in four big regions: 27% in *Cávado / Ave*, 64.5% in *Grande Porto*, 5.5% in *Vale do Sousa / Baixo Tâmega* and 3% in *Entre Douro e Vouga*.

[1]A household consists of one or more people who live in the same dwelling and also share at meals or living accommodation, and may consist of a single family or some other grouping of people.

The total estimate for a specific characteristic in such county is given by

$$\hat{\Theta}_c = \sum_{i,j} \frac{x_{ijc}}{y_{ijc}} \hat{Y}_{ijc}. \tag{4.1}$$

where i is the gender, j is the age group, x_{ijc} represents the total of a feature in the stratum ij in the county c, obtained from the sample values. y_{ijc} is the total individuals in the stratum ij in the county c, in the sample, and $\hat{Y}_{ijc}$ is the independent estimate of the population in the stratum ij in the county c, corresponding to May 2000. The characteristics involved in the estimations are the arrival/departure times, average time and distance to make a trip for specific places, such as: work, school, leisure, home, and so on.

The accuracy of the estimator $\hat{\Theta}_c$ was evaluated in relative terms throughout the coefficient of variation, expressed in percentage and obtained through the following equation

$$C\hat{.}V. = \frac{\sqrt{v\hat{a}r\left(\hat{\Theta}_c\right)}}{\hat{\Theta}_c} \cdot 100\% \tag{4.2}$$

where $v\hat{a}r\left(\hat{\Theta}_c\right)$ is the estimate of $\hat{\Theta}_c$ variance.

The variance is calculated through the random group method[2]. Therefore, the variance estimator is given as follows

$$\hat{v}\left[\hat{\Theta}_c\right] = \frac{1}{k-1} \sum_{r=1}^{k} \lambda_r \left(\hat{\Theta}_r - \hat{\Theta}_c\right)^2 \tag{4.3}$$

where

$$\lambda_r = \frac{m_r}{n} \tag{4.4}$$

and

$$\hat{\Theta}_r = \frac{x_r}{y_r} \hat{Y}_c \tag{4.5}$$

[2]The random group method of variance estimation amounts to selecting two or more samples from the population, usually using the same sampling design for each sample; constructing a separate estimate of the population parameter of interest from each sample and an estimate from the combination of all samples; and computing the sample variance among the several estimates [95].

where k is the number of sub-samples, r is the $r-th$ random group $r = 1, ..., k$, x_r represents the total of a feature in group r, obtained through the sample values. y_r is the total individuals in group r of the sample, and $\hat{Y}_c$ is the independent estimate of the population in county c.

In order to control the quality of the survey, 5% of the sample was reinterviewed being obtained a consistency rate of 98% of the answers. Taking advantage of the data separation related to the transport mode, Table 4.1 presents the expected arrivals of the motorised population, during an ordinary weekday, divided through different reasons of making a trip in the north region of Portugal.

This table relates the citizen mobility when people go to work, leisure, shopping or home in an hourly basis. The associated percentages are the density information of the mobility and the expected arrivals parameter per hour. Note that, during the overnight, almost no vehicle arrivals happen. On the other hand, the peak periods at work hour, lunch time and return home revealed the daily Portuguese habits.

Assuming that EV owners are able to charge the EV batteries wherever they are parked, the total expected number of arrivals is the parameter used as input to the counting process. Figure 4.3 represents this arrival distribution of the total motorised population in an ordinary weekday.

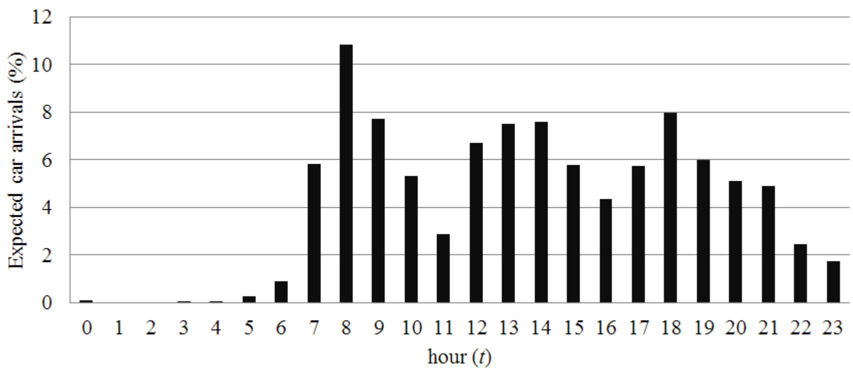

Figure 4.3: Weekday arrivals distribution.

Note that the three peak periods related to work hour, lunch time and return home, appear in the figure from 7 to 9 h., from 12 to 15 h. and from 17 to 19 h.

Table 4.1: Distribution of trips throughout the day - per reason.

Arrivals						
Hour	Total	Labour	Shopping	Leisure	Return Home	Others
Percentage						
0	0,1	0,0	0,1	0,1	0,3	0,1
1	0,0	0,0	0,0	0,0	0,0	0,0
2	0,0	0,0	0,0	0,0	0,0	0,0
3	0,0	0,1	0,0	0,0	0,0	0,0
4	0,0	0,1	0,0	0,0	0,0	0,0
5	0,3	1,1	0,0	0,1	0,0	0,2
6	0,9	2,6	0,3	0,3	0,2	1,0
7	5,8	16,6	1,2	2,6	0,2	8,6
8	10,9	27,4	5,7	4,4	0,6	16,3
9	7,7	10,6	11,6	4,7	0,9	10,8
10	5,3	3,2	12,8	4,7	1,6	4,4
11	2,9	1,7	4,9	2,5	3,0	2,3
12	6,7	2,0	8,9	4,8	13,9	4,0
13	7,5	13,7	4,9	6,1	6,4	6,5
14	7,6	10,5	8,8	9,2	2,3	7,3
15	5,8	2,9	9,1	8,1	2,8	6,0
16	4,4	1,8	6,9	4,9	4,1	4,1
17	5,8	1,5	6,1	4,1	10,9	6,2
18	8,0	1,3	5,8	5,7	18,8	8,3
19	6,0	0,9	4,4	5,6	13,9	5,2
20	5,1	0,7	3,7	9,8	7,6	3,8
21	4,9	0,7	3,3	14,0	3,7	2,9
22	2,5	0,4	1,2	5,8	3,8	1,2
23	1,7	0,3	0,3	2,4	4,9	0,8
Total	100.0	100.0	100.0	100.0	100.0	100.0

Analogously, Figure 4.4 represents the arrivals distribution of the motorised population, during an ordinary weekend. The figure presents an increase in the number of arrivals during the valley period in comparison with Figure 4.3. On the other hand, the decrease in the number of arrivals in the morning period confirms the expected weekend habits. Moreover, three peak periods were identified: from 23 to 1 h., from 12 to 14 h. and from 19 to 21 h.

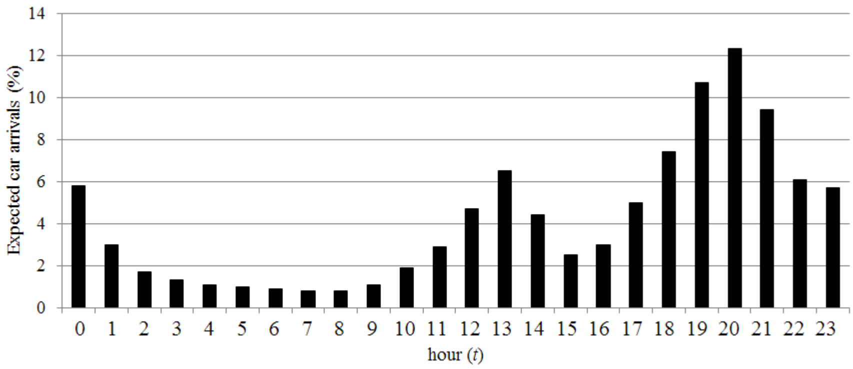

Figure 4.4: Weekend arrivals distribution.

Note that in both figures, 4.3 and 4.4, the evening period, which is related to return home, can be related to the peak demand period of the day. Therefore, assuming, for instance, that the population will start to charge the EV batteries as soon as they arrive home, then, the battery charging will increase the traditional peak period of the conventional system load.

The survey presented through this section generated the arrivals distributions showed in Figures 4.3 and 4.4. From these ones, the arrivals averages, in an hourly basis, can be used as the only parameter needed to estimate the number of EV, which will proceed to battery charging.

4.3 Proposed Counting Process Methodology

Different EV load representations have been mentioned in the literature [55, 73, 75–77, 96–99]. This thesis proposes a probabilistic technique to estimate the number of EV arrivals based on mobility pattern information.

It is assumed that the EV arrivals occur randomly, therefore, the Poisson process can be used to estimate these arrivals based only on the expected arrival parameter. The reference [100] also attests the importance of using Poisson process in many stochastic models, such as: calls arriving at a help desk centre, traffic light problems, car arrivals at a fuel station, and so on. This thesis, aims at using arrival distributions data, generally provided by mobility surveys, which can be viewed from two different perspectives leading to the development of two counting process approaches.

These approaches were developed, by the author, within the framework of two research projects, the European project MERGE (Mobile Energy Resources in Grids of Electricity) [101] and the Portuguese project REIVE (Smart Grids with Electric Vehicles) [102].

One perspective is based on the homogeneous Poisson process and its major characteristic is counting the EV arrivals using one single variable: the expected arrival rate λ. The second one was developed in order to increase the detailed representation of the EV arrivals by the inclusion of an arrival time variable in the problem. This perspective is based on the non-homogeneous Poisson process, which counts the EV arrivals continuously, using a time dependent expected arrival rate $\lambda(t)$.

The principle behind these proposed approaches, considers that cars arrive at different charging points at random moments of the day in accordance with a Poisson distribution with λ rate. It is also considered that each arrival would correspond either to different types of events, where the EV needs to connect to the grid and proceed to battery charging or to a type of event where the EV do not need to proceed to battery charging. Both types of events may be viewed as a Poisson process.

Next sections present the methodology and clarify the differences between these two counting process approaches which are the ones that define the number of EV arrivals during the SMCS procedure.

4.3.1 Homogeneous Poisson Process

The homogeneous Poisson process is characterised by a constant rate parameter λ, also known as intensity, such that the number of arrivals in time interval $(t, t+\tau]$ follows a Poisson distribution with associated parameter $\lambda\tau$. This relation is given by:

$$P[(N(t+\tau) - N(t)) = k] = \frac{e^{-\lambda\tau}(\lambda\tau)^k}{k!} \qquad k = 0, 1, ..., \tag{4.6}$$

where $N(t+\tau) - N(t) = k$ is the number of arrivals in time interval $(t, t+\tau]$. The rate parameter λ is the expected number of arrivals that occur per unit time. The HPP assumes a counting measure where the number of arrivals in an interval $(t, t+\tau]$ is independent of the number of arrivals in other interval as $(t+1, t+1+\tau]$. Figure 4.5 depicts the HPP.

In this thesis, the HPP is performed for each hour during an yearly sample of the simulation process. It means that for each hour of different days, the same λ parameter is expected. For instance, hour 1 of day 1 has the same λ parameter as the hour 1 of the day 2, and of the day 3 until the end of the year. As the EV arrivals are clustered in an hourly basis ($\tau = 1$), in order to calculate the EV load in the same time horizon of the conventional load, it is assumed that the remaining time in charging state is fixed and dependent on the technical characteristic of the

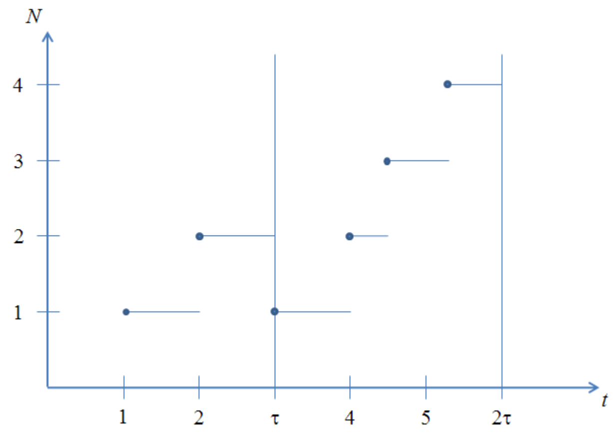

Figure 4.5: The counting process through an HPP.

battery, as capacity and charging rate. In this approach it is also assumed that the EV charging happens once a day for a fixed battery charging requirement and this happens in the end of the first trip. These assumptions can be parametrised in the inputs of the model.

Using Algorithm 1, which is based on the inverse-transform method, Figure 4.6 is generated and gives the number of arrivals per hour during the chronological simulation. In this sample, those three peak periods (see Figure 4.3) are highlighted, although the peak period of the morning presented a lower value than the expected.

where n is the number of experiments, U_n is a uniformly distributed random variable and N is a Poisson random variable which represents the number of arrivals. For fixed intervals $e^{-\lambda}\left(\frac{\lambda^n}{n!}\right)$ is the probability mass function of N and while a is greater than $e^{-\lambda}$, the number of arrival is increased by one.

Equation (4.7) gives the departure time for a fixed requirement of the battery capacity. Assuming a certain level of proportionality among the different types of EV for all samples under analysis, the total EV fleet will be proportionally divided into different EV types [2]. The departure time T_{dn} is then calculated through:

input : Expected number of arrivals λ at hour t

output: $X \leftarrow n-1$ // Number of arrivals at hour t

$n \leftarrow 0$;

$a \leftarrow 1$;

while $a \geq e^{-\lambda}$ **do**

  $U_n \leftarrow U(0,1)$;

  $a \leftarrow aU_n$;

  $n \leftarrow n+1$;

end

Algorithm 1: HPP based on the Inverse-Transform method.

$$T_{dn} = T_{an} + \frac{C_{bj}}{R_{cj}} \cdot \kappa \tag{4.7}$$

where T_{an} is the EV arrival time. C_{bj} is the battery capacity and R_{cj} is the charging rate and κ is a battery charging coefficient which ranges from $[0,1]$.

The departure time calculated through Equation (4.7) is according to the EV

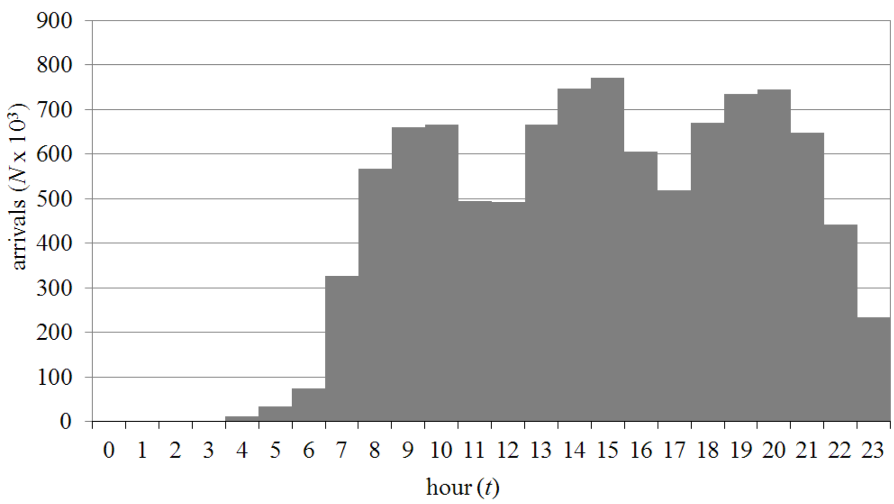

Figure 4.6: Sample of the HPP.

charging strategy. For instance, the arrival and departure time for valley charging strategy is into the valley hours range. It means that if a vehicle arrives at 9 o'clock and departures at 13 o'clock, its battery charging time will occur from 23 to 3 h, considering 23 h the start battery charging hour for this strategy.

Simple Numerical Example

Supposing an ordinary week day and a fleet of 20 EV. At 20 h, using the rate parameter λ of Figure 4.3 in the Algorithm 1, the sampled number of EV arrivals which proceeds to battery charging is achieved.

Table 4.2: Example of the HPP application.

a	n	$U(0,1)$	$a = aU$	λ	$e^{-\lambda}$	N
1.000	0	0.99	0.990	2.2	0.01	–
0.990	1	0.90	0.891	2.2	0.01	–
0.891	2	0.98	0.873	2.2	0.01	–
0.873	3	0.30	0.261	2.2	0.01	–
0.261	4	0.03	0.007	2.2	0.01	–
0.007	–	–	–	–	–	3

Table 4.2 shows 4 iterations of the counting process method until achieving the stopping criterion. At the end, 3 EV are expected to arrive at 20 h to charge their batteries according to their charging strategies.

4.3.2 Non-homogeneous Poisson Process

The non-homogeneous Poisson process consists of continuously counting the number of arrivals where the expected ones may change over time. This is characterised by a continuous rate parameter $\lambda(t)$. The NHPP has been used to describe numerous random phenomena [103] including cyclone prediction [104], arrival times of aircraft to airspace around an airport and database transaction times [105].

The NHPP assumes $N = \{N_t, t \geq 0\}$ for which the number of points in non-overlapping intervals are independent, but the rate parameter at which points arrive is time dependent. If $\lambda(t)$ denotes the rate parameter at time t, the number of points in any interval $(a, b]$ has a Poisson distribution with mean

$$\lambda_{a,b} = \int_a^b \lambda(t)dt. \tag{4.8}$$

Thus, the number of arrivals in time interval $(a, b]$, given as $N(b) - N(a)$, follows a Poisson distribution with associated parameter $\lambda_{a,b}$, and is calculated through:

$$P[(N(b) - N(a)) = k] = \frac{e^{-\lambda_{a,b}}(\lambda_{a,b})^k}{k!} \qquad k = 0, 1, ..., . \tag{4.9}$$

Note that, an homogeneous Poisson process is a special case of NHPP which consists of the rate parameter $\lambda(t)$ becomes constant. Figure 4.7 illustrates the construction of an NHPP based on the acceptance-rejection method. The idea of this method is to first find a constant rate function $\lambda(t) = max\lambda$ which dominates the desired rate function $\lambda(t)$, next generates from the implied HPP with rate $\lambda(t) = max\lambda$, and then rejects an appropriate fraction of the generated arrivals so that the desired $\lambda(t)$ is achieved. Formally a two-dimensional HPP is generated on the strip $\{(t, x), t \geq 0, 0 \leq x \leq \lambda\}$, with constant rate, and then all points are projected bellow the graph of $\lambda(t)$ onto the t-axis.

The points of the two-dimensional process can be viewed as having a time and space dimension. The arrival epochs form one-dimensional Poisson process with rate parameter $max\lambda$ and the positions are uniform in interval $[0, max\lambda]$. This suggests the following alternative procedure for generating NHPP: each arrival epoch of the one-dimensional HPP is rejected with probability $1 - \frac{\lambda(T_n)}{max\lambda}$ where T_n

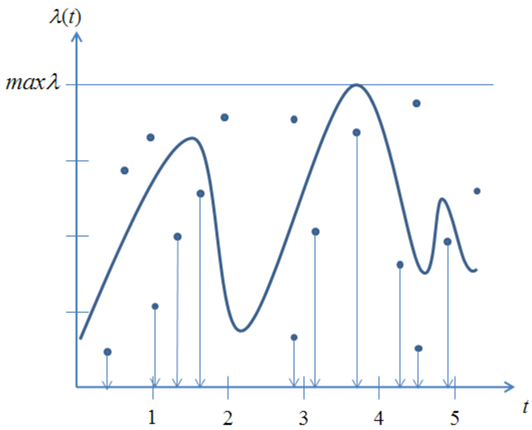

Figure 4.7: The counting process through an NHPP.

is the arrival time of the n-th event. The epochs not rejected define the NHPP. The basic difference between the counting process approaches is regarding the different time resolutions.

While the HPP model clusters the vehicle arrivals in an hourly basis, the NHPP model counts the EV arrivals continuously. The Equation (4.10) generates the EV departure time. The NHPP is performed in the beginning of the SMCS procedure generating an annual arrival and departure times vector. The characteristic of observing the individual arrivals makes sampling the SOC of each vehicle possible, as can be seen in the right side of Equation (4.10). The departure time T_{dn} of each vehicle is then calculated through:

$$T_{dn} = T_{an} + W_n \cdot \frac{C_{bj}}{R_{cj}} \tag{4.10}$$

where W_n is a uniformly distributed number between $[0, 1]$. C_{bj} is the battery capacity and R_{cj} is the charging rate. These electrical parameters are divided into different EV categories j, as can be seen in [2]. The period between the arrival and departure of an EV is the battery charging time of the battery charging requirement.

The arrival/departure vector is sorted in an ascendant order. Then, the EV load is updated through the simulation process in each arrival/departure time. From the use of the Algorithm 2, which is based on the acceptance-rejection method, and Equation (4.10), the number of EV arrival, the arrival and departure times are presented in Figure 4.8, which is a sample of this proposed approach.

input : Expected number of arrivals $\lambda(t)$
output: $X \leftarrow n$ and t_{an} // Number of arrival at instant t_{an}

$i \leftarrow 0$;
$n \leftarrow 0$;
$t' \leftarrow 0$;
$\lambda_{max} \leftarrow max\lambda(T)$;
while $t' \leq 8760$ **do**
    $i \leftarrow i + 1$;
    $U_i \leftarrow U(0, 1)$;
    $t' \leftarrow t' - \frac{1}{\lambda_{max} ln(U_i)}$;
    $V_i \leftarrow U(0, 1)$;
    if $V_i < \frac{\lambda(t)}{\lambda_{max}}$ **then**
        $n \leftarrow n + 1$;
        $t_{an} \leftarrow t'$;
    end
end

Algorithm 2: NHPP based on the Accept-Rejection method.

where λ_{max} is the maximum value of $\lambda(t)$ in period T, t' is the EV arrival time, i is the iteration counter, U_i and V_i are uniformly distributed random numbers, n is the accepted arrival, T_{an} is the accepted arrival time and N is the number of arrivals.

Figure 4.8 presents the vehicles' arrivals and departures between two hours. The NHPP approach was modelled to monitor the vehicles individually and, therefore, the number of EV load calculation is much bigger than the HPP approach, which

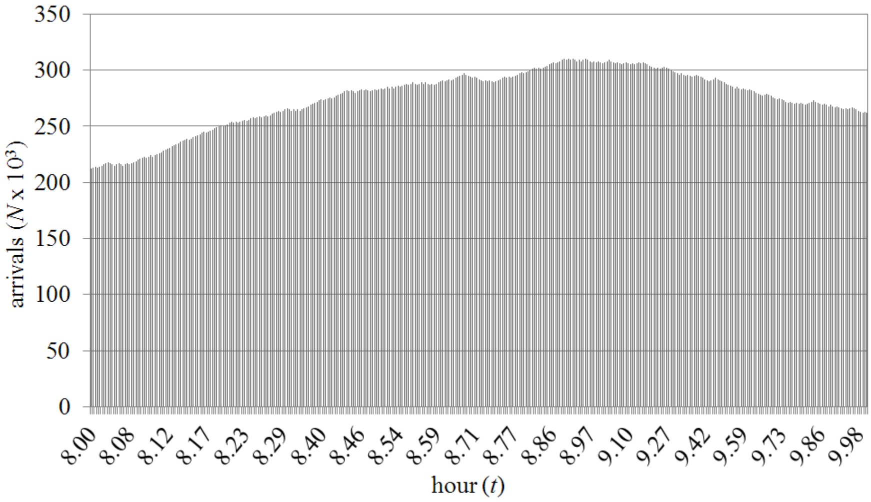

Figure 4.8: Sample of the NHPP.

clusters the EV load in an hourly resolution, resulting in a bigger computational effort, as can be seen in Chapter 6.

Simple Numerical Example

Supposing a fleet of 20 EV, the number of EV arrivals which will proceed to battery charging from 18 to 21 h is calculated using the Algorithm 2. Table 4.3 presents the counting process following the NHPP method. After 4 iterations, the method will return 1 EV arrival at 18 h, none EV arrivals at 19 h and 1 EV arrival at 20 h. Using Equation (4.10) the departure times can be calculated and the EV load is estimated. Then, the EV load profile is defined according to the battery charging strategy chosen.

Table 4.3: Example of the NHPP application.

i	U_n	$t(h)$	V_n	$\lambda(t)/\lambda_{max}$	N
0	0.83	6.14	0.58	0.26	0
1	0.23	6.23	0.18	0.26	1
2	0.42	6.38	0.81	0.26	1
3	0.75	7.54	0.19	0.10	1
4	0.09	8.05	0.27	0.70	2

4.4 Uncontrolled Charging Models

The battery charging strategy is the main characteristic that gives the shape of the EV load profile. This defines whether or not an EV will proceed to battery charging, at the moment of its arrival. Generally, two types of uncontrolled battery charging strategies are mentioned: direct and valley charging.

In this thesis, the uncontrolled models are the ones that not allow the possibility of an aggregation deal with the battery charging. Although, in valley charging, a certain level of control could be applied, allowing the EV owner to set the charging time of the EV. The uncontrolled models also allow the use of different percentages for EV battery charging strategies in the same simulation process.

4.4.1 Direct Charging Strategy

This charging model aims at representing those EV owners who will proceed to battery charging as soon as they arrive. In this context, any type of control scheme is applied to the EV charging.

Figure 4.9 is a sample of the simulation process and shows the impact on the ordinary conventional load profile of such charging strategy.

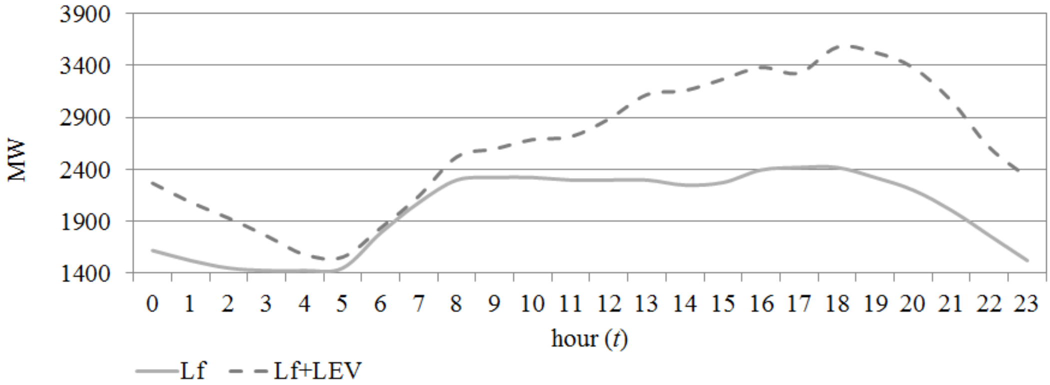

Figure 4.9: System load profile using EV direct charging strategy.

The “L_f” line represents the conventional load forecast and the “$L_f + L_{EV}$” line is the summation of the conventional and the EV load profiles. Note that, the total load profile is not proportional if compared to the conventional one. Actually, this EV load profile reflects the citizens behaviour when a direct charging strategy is applied.

Generally, this strategy leads to the increase of peak demand, which is an undesired strategy for the system operation perspective, since the EV load profile follows the human daily habits. Commonly, this type of strategy onerous the EV owner, because of the high energy prices of the day and peak periods.

4.4.2 Valley Charging Strategy

This strategy aims at giving a kind of incentive by the traders/electric companies in order to stimulate the demand side management. It is expected for lower energy prices during valley hours. At the same time it is expected a lower conventional load demand during this period. Figure 4.10 is a sample of the simulation process and shows the illustration of the EV load impact on the conventional load.

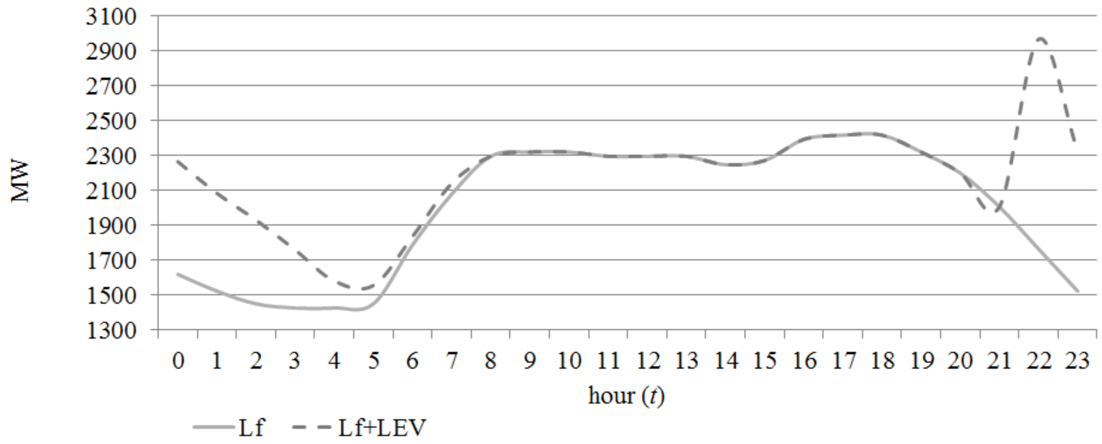

Figure 4.10: System load profile using EV valley charging strategy.

The "L_f" line represents the conventional load forecast and the "$L_f + L_{EV}$" line reflects the summation of the conventional and EV load profiles when the valley charging strategy is applied. It is supposed that all EV owners agree with this charging strategy since that there is no battery charging during the day. In this context, a low impact on the system adequacy assessment is expected, since the EV load increases the total load demand only in the valley period. However, since it is an uncontrolled battery charging strategy, above a certain EV integration level is possible to move the peak load demand to the valley hours, as it will be showed in Chapter 6.

4.5 Controlled Charging Models

The controlled charging strategies are the ones that provide some opportunities to the electricity sector. Through an aggregation entity, which would control the battery charging, the EV could either change its charging rate according to some parameters set by the EV owners (time of departure, SOC needed, and so on), promoting demand side management or could inject the electric energy stored in its battery, promoting V2G.

4.5.1 Controlled Charging Strategy

The concept of controlled charging is related to the possibility of allowing an entity to have a certain level of controllability over the EV battery charging. Generally, in the electric system distribution level, controlled charging means that the battery charger responds to a signal that changes the charger set point. This signal is interpreted by the charger and the charging rate might be controlled in order to modulate the EV load at that moment.

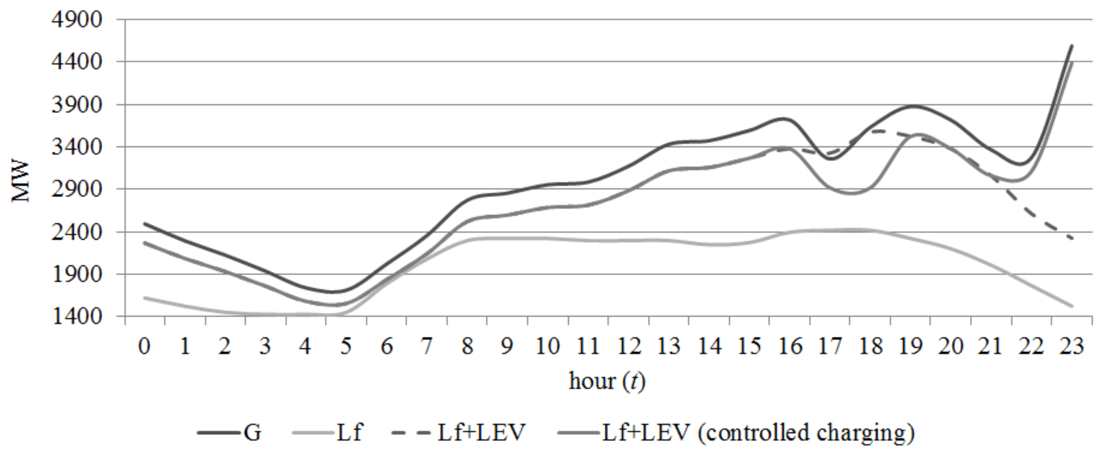

Figure 4.11: System load profile using EV controlled charging strategy.

In this thesis, controlled charging concept is the action of postponing the EV battery charging in order to release the generating units scheduled to meet the estimated EV load. Figure 4.11 illustrates the possible system state transition when a controlled charging strategy is applied.

Assuming a deficit of available generating capacity at 17 h, the "$L_f + L_{EV}(controlledcharging)$" line represents the response of the controlled charging strategy. It is capable of reducing the charging rate, releasing available generating units to meet the system uncertainties, shifting the EV charging to the valley period. Note, in Figure 4.11, that the decreased EV load at 17 h. is, therefore charged at 23 h. The detailed implementation of this strategy will be described in Chapter 5.

4.5.2 Vehicle-to-Grid Charging Strategy

The V2G concept is the ability of combining both battery charging and injection of electric energy to the system. This is possible due to a bi-directional converter which allows this level of charging controllability. From an ORC perspective, the V2G is viewed as an opportunity to increase the renewable energy source integration in the generating systems by both smoothing the wind power variability and/or providing secondary reserve to the system. Both concepts are better described in Chapter 5 where the controlled charging strategies are exploited in detail.

Figure 4.12 illustrates one probable situation of increasing the operating reserve. The "$L_f + L_{EV}(V2G)$" line represents the V2G charging strategy impact on the total system load while the "$G + V2G$" line is the V2G impact on the available generating capacity.

Assuming that the G and $L_f + L_{EV}$ lines represent the normal operation of the system, it is possible to identify a deficit of generating capacity at 17 h. Mobilising EV to inject stored electrical energy back to the grid, the system operation passes to be represented by the $G + V2G$ and $L_f + L_{EV}(V2G)$ lines.

Note that taking the EV SOC into account, the vehicles under a V2G charging strategy can effective increase the operating reserve capacity available, in order to solve the possible system failure state. The amount of injected capacity starts to charge at 23 h. Chapter 5 will present the V2G charging strategy in more detail.

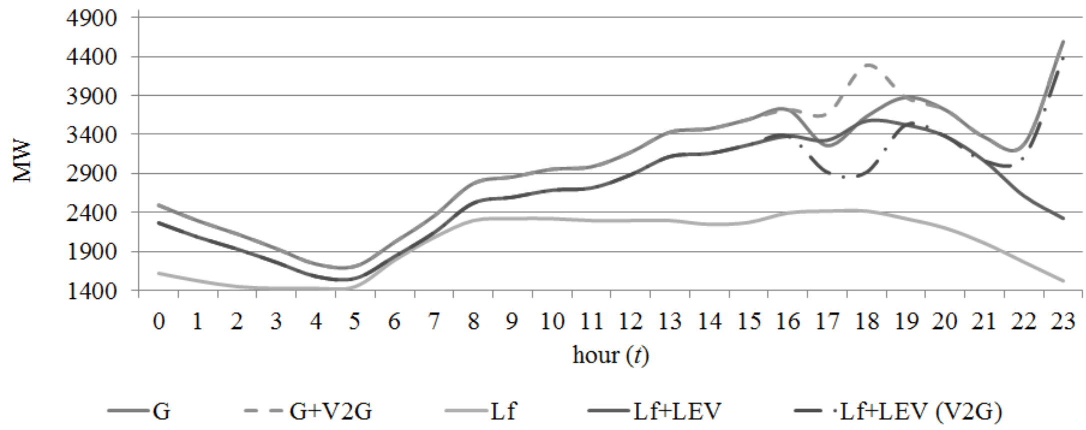

Figure 4.12: System load profile using V2G charging strategy.

4.6 Conventional Load and Proposed EV Load Estimation

Load shapes provide a means of understanding of how much energy is being used at different times of the day, week, season, or throughout a complete year. When the energy use patterns are being developed for groups of equipments with similar functions, the results are commonly referred to as end-use load shapes which represent the habit of the citizens about energy use. The most common end-use categories for the commercial, residential, and industrial classes are presented in Table 4.4.

In order to include some new end-use categories for the current classes, it is necessary to approach EV as a new load trend, which will influence the future load shapes. From these main categories, the EV charging might impact on the *Residential* and *Industrial*, since the EV owners probably will charge the EV batteries in the own place. On the other hand, the *Commercial* category, will probably use public or private infrastructure to charge the EV batteries, once they, generally, do not have an infrastructure that allows them to charge the EV battery in their own place.

Table 4.4: Common end-use categories by customer class

End-Use Category	**Commercial**	**Residential**	**Industrial**
Air conditioning	•	•	•
Space heating	•	•	•
Interior lighting	•	•	•
Miscellaneous equipment	•		•
Domestic hot water	•	•	•
Computers	•		
Cooking	•		
Refrigeration equipment	•		
Ventilation	•		•
Exterior lighting	•		•
Process equipment			•
Motors			•
Stoves / ovens / ranges		•	
Refrigerators / freezers		•	
Televisions / stereos		•	
Dishwasher		•	
Clothes washer / dryer		•	
Electric Vehicles Charging		•	•

Electric utilities have historically made large use of end-use load shapes in the energy and load forecasting. For these purposes, utilities are commonly faced to predict what their future capacity will be considering factors as: the current base load, the expected change in the number of residential homes, commercial stores, and industrial facilities, or even more, the change in equipment efficiencies over time. However, the massive EV load integration on the power systems could be viewed as a break of paradigm changing the ordinary load shapes and end-use patterns.

Based on the forecast supply and demand curves, a utility usually wishes to examine its current and future state of generation capacity under short and long-term perspectives. This thesis is proposing an alternative way to estimate EV load through the use of a counting process, based on the expected number of arrivals (mobility pattern). The EV load estimation can be calculated according to the following procedures.

4.6.1 EV Load from the Homogeneous Poisson Process

The EV counting process method gives the number of EV which proceeds to battery charging. It is assumed that all connected vehicles will charge their batteries if allowed to the chosen charging strategy. In fact, the counting process does not change with different charging strategies; on the contrary, the EV load profile changes according to the charging strategy.

In order to calculate the EV load, the battery electric parameters and the different types of EV must be taken into account. This being defined, the following procedure may be adopted

$$L_{EV}(t) = \sum_{j} L_{EVj}(t) \cdot N_j(t) \qquad j = 1, 2, ... \tag{4.11}$$

where $N_j(t)$ is the number of EV arrivals of the type j, in hour t. $L_{EVj}(t)$ is the EV load in hour t. This EV load, calculated for each hour of the simulation process, remains in charging mode until the departure time, calculated in Equation (4.7), is reached. Therefore, the adequacy evaluation of the generating systems is analysed for each transition (hourly) of the EV charging mode.

Figure 4.13 illustrates the procedure to calculate the EV load using the HPP. In this illustrative example, the different colours are the EV arrivals counted through the HPP.

At 19 h. one EV arrival is identified and it is assumed that this vehicle connects to the grid to charge its battery during 3 hours. At hour 20 h, two EV arrive in a certain place to be charged and their consumption is added to the demand of the last vehicle already in charging mode. At 21 h, four EV are in charging mode.

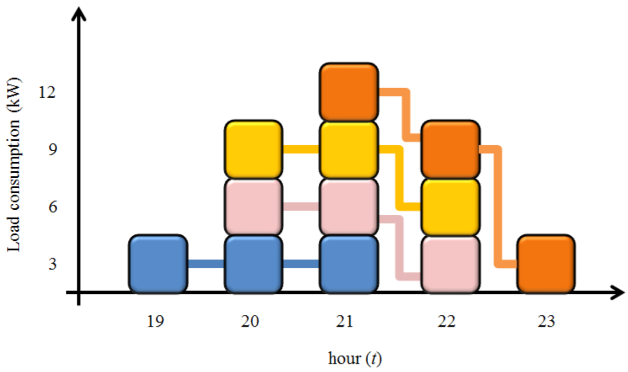

Figure 4.13: Illustration of the EV load calculation through HPP.

Note that for illustrative purposes, a fixed battery charging requirement needs a charging time of three hours. Then, because of the chronological characteristic of the EV arrivals, the load increases as the arrivals happen, assuming that the EV owners will charge the EV batteries as soon as they park. However, after three hours the EV is already charged and is disconnected to the grid, decreasing the EV load as showed in hour 22 and 23 h of Figure 4.14.

The Figure 4.14 gives the total EV load profile for each hour, according to the direct charging strategy. Moreover, this load is added in each system load state transition of the SMCS, chronologically.

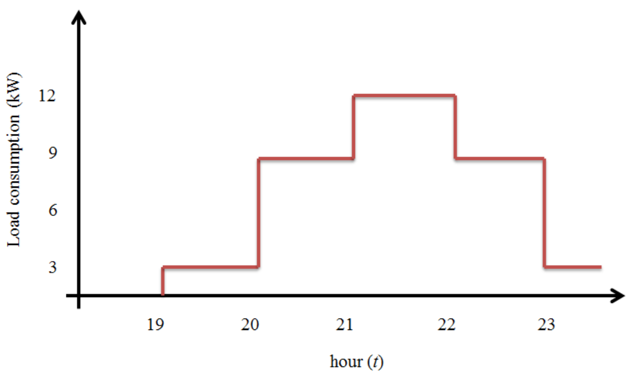

Figure 4.14: EV load profile using HPP and direct charging strategy.

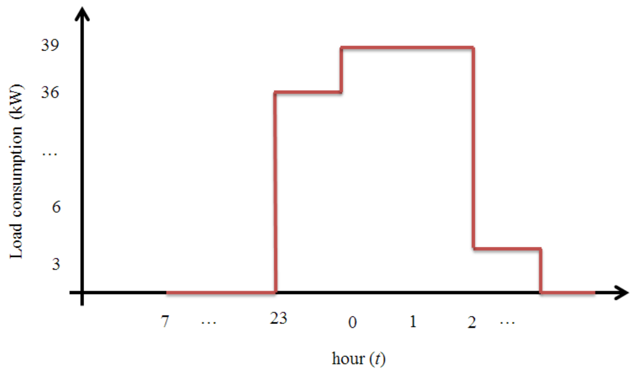

Figure 4.15: EV load profile using HPP and valley charging strategy.

Now, imagine the same previous illustrative example. However, let the direct charging strategy be changed by the valley charging strategy. Figure 4.15 gives an idea of the EV load.

The EV arrivals occurred during the daylight, are connected to charge the EV batteries in the valley hours (for instance, at 23 h). Then, this EV load is added on the system load, chronologically. As the system load is lower in the valley hours, it is expected a low EV impact when this charging strategy is applied.

4.6.2 EV Load from the Non-homogeneous Poisson Process

The EV load curve of the NHPP, is performed for all samples under analysis integrating the area formed by the arrival and departure times (see Figure 4.16). Therefore, the EV load is given by the following equation

$$L_{EV}(t) = \sum_{j=1} \int_{T_{an}}^{T_{dn}} L_{EVj}(t)dt \tag{4.12}$$

where T_{an} and T_{dn} are the arrival and departure times, respectively. As mentioned before, the arrival and departure times form a sorted vector in time. Therefore, the adequacy evaluation of the generating systems is analysed in each transition

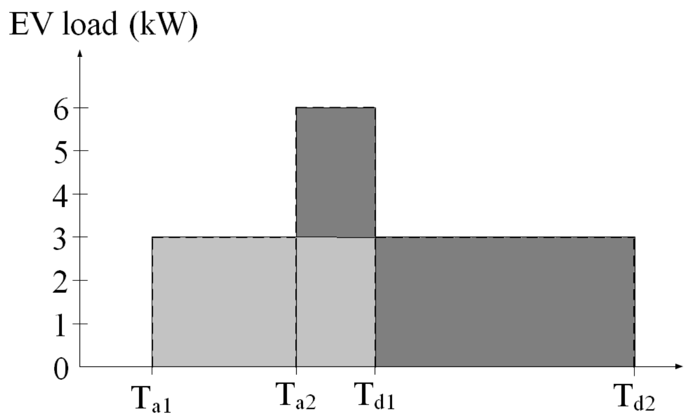

Figure 4.16: Illustration of the EV load calculation through NHPP.

(arrival or departure) of the EV charging mode.

Figure 4.16 illustrates an EV arrival which proceeds to charge the battery at T_{a1} and left the charging mode at T_{d1} when the SOC is achieved. A second EV arrival happened at T_{a2} and left the charging mode at T_{d2}. The integration of the hatched curve is the EV load. In this case, the SMCS evaluates each transition instant, in order to keep a continuous tracking of the load. As mentioned before, the detailed description of the active charging models is given in Chapter 5 under the contexts of the homogeneous and non-homogeneous Poisson processes.

4.7 Proposed EV Models Integration on SMCS Method

As the electric system components, the EV load is chronologically represented through the SMCS method. This method relies on repeated random sampling to obtain numerical results by running simulations many times over in order to calculate those same probabilities heuristically. The main advantage of this method is the possibility to generate probability distribution of the events. The

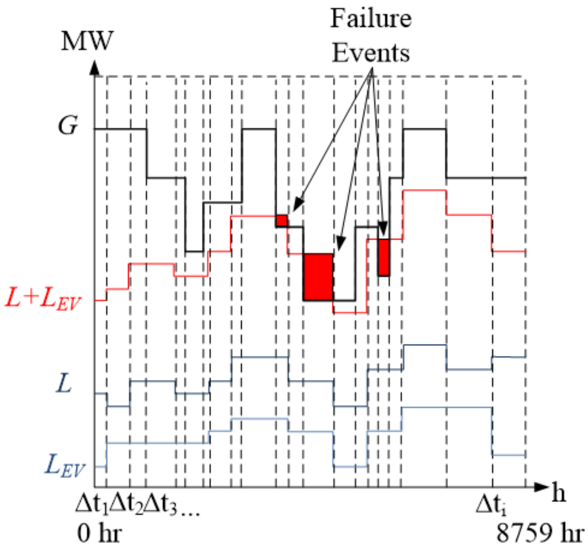

Figure 4.17: Chronology of the Sequential Monte Carlo Simulation.

chronological procedure of the generating system adequacy evaluation is illustrated in Figure 4.17.

From the static reserve evaluation perspective, Figure 4.17 shows system failure state in three moments. As previously mentioned, the evaluation is conducted from two different perspectives: static reserve and operating reserve capacity evaluations, as in [13]. The objective is to evaluate the impact and opportunities for uncontrolled and controlled charging strategies that EV could have in the future generating systems.

4.7.1 Static Reserve Evaluation with Electric Vehicles

The Equation (3.4) presented in Chapter 3 is used to measure the level of risk in which a future generating system configuration is able to meet the forecast load.

In order to include the effect of the EV load in this generation assessment, the

Equation (3.4) is then modified according to Equation (4.13)

$$G - (L_f + L_{EV}) \leq 0 \tag{4.13}$$

where L_{EV} is the total EV load calculated through the EV models.

4.7.2 Operating Reserve Capacity Evaluation with Electric Vehicles

Originally, Equation (3.10) is set to assess the risk indices associated to the long-term operating reserve. It captures the risk of forecast errors linked to load and wind power generation, as well as the forced outages of the generating units. The inclusion of EV in the generating system should also be represented in the ORC evaluation. Therefore, the Equation (3.9) is then modified in order to meet this new random variable according to Equation (4.14).

$$\Delta G = G_{sync} - [(L_f + L_{EV}) + R_P + R_S] \tag{4.14}$$

where L_{EV} is the total EV load, as previously stated. This change is illustrated through the Figure 4.18, where the expected EV load is added on the conventional system load.

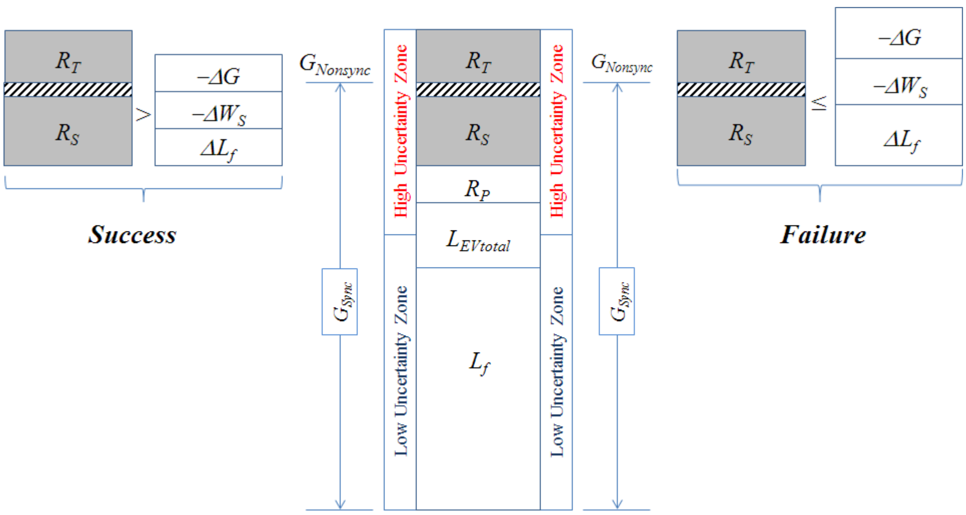

Figure 4.18: Operating Reserve Capacity evaluation with EV.

Figure 4.18 is a general representation of the operating reserve capacity evaluation. The synchronised generating units meet the system requirements as in Equation (4.14). The hatched block, represents the discrete effect of the scheduling procedure. Then, as stated in Equation (3.10) the available capacity sinchronised R_S plus the fast tertiary reserve R_T should meet the system deviations. From the left to the right side of Figure 4.18, the system moves from a success to a failure state.

Regarding the EV integration in SMCS method, the Figure 4.19 shows the flowchart of the entire procedure. Basically, the simulation process is divided into five stages: system composition, system state selection, state evaluation, EV load control and end of the simulation process.

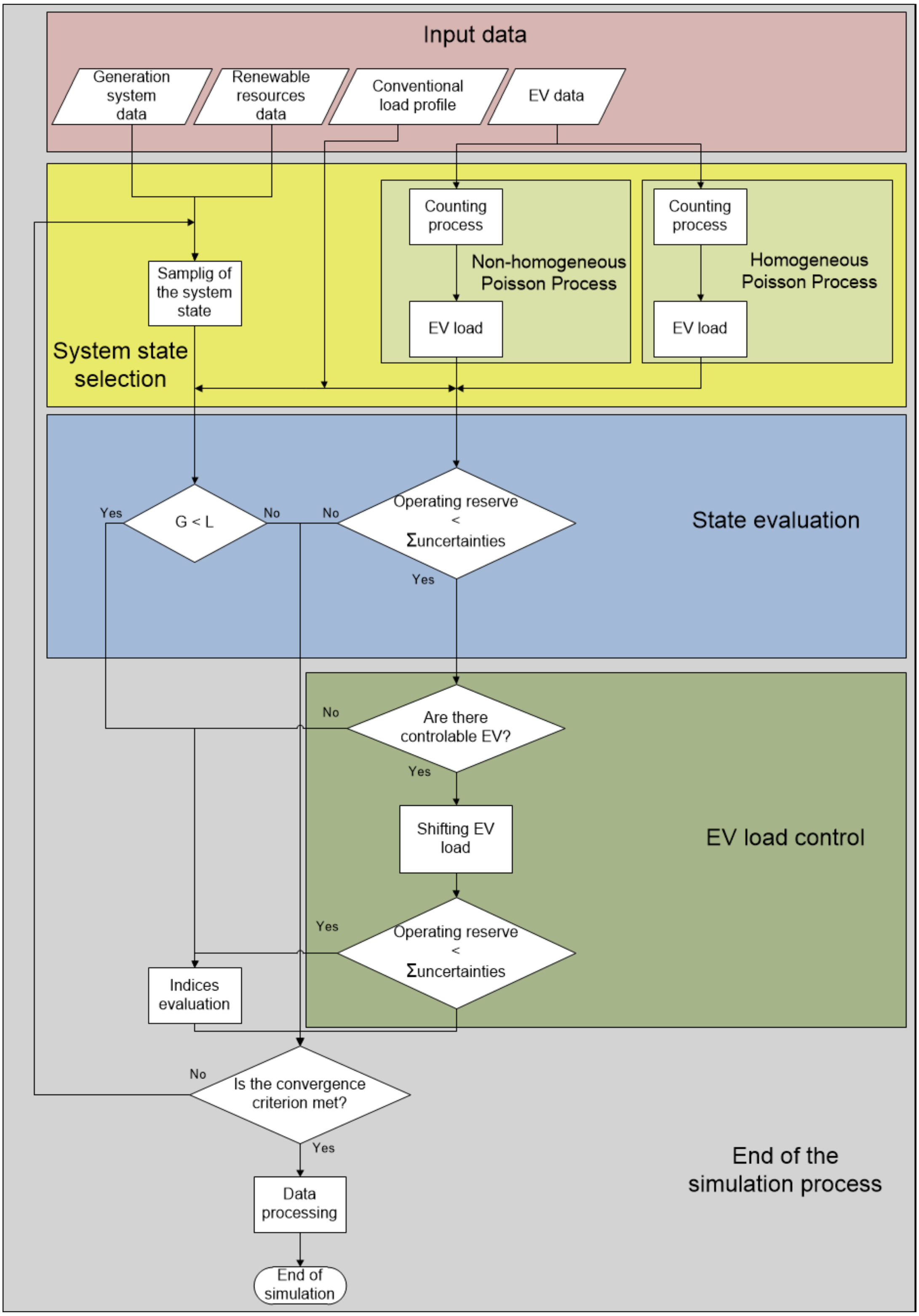

Figure 4.19: Flowchart of the system adequacy evaluation.

The **Input data** gives all data information needed to proceed to the simulation. The inputs are:

- **Generation system data:** the generation system data consists on gathering all required information such as generating unit identification, generating type (thermal, hydro, wind, and so on), rated power, maximum power, minimum power, production cost, region identification of the renewable sources (in order to meet the resources series according to their location), MTTF, MTTR, scheduled maintenance, model type (two or multi-state Markov model), initial state and mobilization (units able to participate of the fast tertiary reserve).

- **Renewable sources data**: this input data is related to the variable energy resources. For instance, the hydro generation is dependent on the water availability in the reservoir of each hydro plant. The wind generation is dependent on the wind series available in each region of the wind farms. The solar incidence also varies according to the region of the solar plant. Therefore, these input data enhance the results provided by the methodology.

- **Conventional load profile**: generally, the conventional load profile is given in an hourly basis in p.u. as a percentage of the annual peak load. Then, this input data is generally composed by 8760 load points.

- **EV data**: analogously to the conventional load, the EV data is given through its rate parameter λ which is the distribution of the expected EV arrivals in an hourly basis. This information might be characterised for an ordinary weekday and/or weekend day.

It is a common knowledge that, the accuracy of the assessment is dependent on the accuracy of the input data.

The **System state selection** samples the generating units system state. This stage calculates, for instance, the yearly sample states of the generating units defining their up and down cycles. It is in this stage that the effect of the long-term load uncertainty is included in the conventional load annual sample. The renewable energy series are also selected (sampled) in this stage.

Afterwards, the simulation process evaluates each system state, in the **State evaluation** stage, according to each system component transition, chronologically, as showed in Figure 4.17. The evaluation consists of testing the Equation (4.13) for the static reserve evaluation and Equation (3.10) modified by the Equation (4.14) for the operating reserve capacity evaluation.

According to the static and operating reserve capacity concepts, at this moment the static reserve evaluation goes to the end of a simulation process stage where the indices are computed and processed if the convergence criterion is reached.

The ORC evaluation may need to pass by the **EV load control** stage, where the EV is able to contribute to the system when this one is threatened, i.e., the Equation (3.10) is true. Finally, after all indices have been computed and when the convergence criterion is reached, the simulation process ends.

4.8 Final Remarks

This chapter has presented the EV model to be included in the adequacy evaluation of the generating systems. The models were based on two different approaches of the Poisson process: the homogeneous Poisson process and the non-homogeneous Poisson process. In general, both HPP and NHPP follow the next assumptions:

1. $\mathbf{N(0) = 0}$ – There is no arrival event in time $t = 0$.

2. **Independent increments** – The proposed approaches are modelled under the assumption that each rate parameter λ happens in totally independent intervals. It means that the numbers of occurrences counted in disjoint

intervals are independent of each other.

3. **Stationary events** – Regarding the first approach, the HPP is performed for each hour independently. It is assumed that the probability distribution of the number of occurrences counted in any fixed time interval only depends on the length of the interval (one hour in this case).

4. **Probability distribution of** $N(t)$ – From the arrivals characteristic of the motorised population, it is assumed that $N(t)$ is a Poisson distribution.

5. **Counted occurrences** – No counted occurrences are simultaneous.

As a consequence of these assumptions, it is expected that the probability distribution of the inter-arrival time becomes an exponential distribution. The main difference between the EV models approached by the HPP and the ones approached by the NHPP are the departure time estimate and the individual EV arrival. The departure time defines the charging time. Therefore, the charging time estimated through the NHPP is according to Equation (4.10), which estimate different charging requirement for each EV. The charging time estimated through the HPP is according Equation (4.6), which assumes a fixed charging requirement for all vehicles that arrive at a certain place in the same hour.

Regarding the battery charging models, a summary of their assumptions is provided.

1. **Direct charging strategy** – This strategy, for both HPP and NHPP approaches, considers that EV proceed to battery charging after an arrival occurrence.

2. **Valley charging strategy** – This strategy, for both HPP and NHPP approaches, considers a fixed period in the valley hours for EV charging battery.

3. **Controlled charging strategy** – This strategy, for both HPP and NHPP approaches, is only applicable in ORC studies.

4. **Departure time in HPP** – The characteristic of clustering the EV arrivals in an hourly basis leads this approach to consider the departure time fixed and total dependent on the battery parameters.

5. **Departure time in NHPP** – The battery SOC is sampled and consequently, the departure time of each vehicle is different.

The chart showed in Figure 4.20, presents, step by step, an overview of the EV models.

This structure is applied during the SMCS process and, at the end, the conventional load is affected by the EV load. Next chapter, describes in more detail, the controlled and V2G charging strategies which are the ones that might

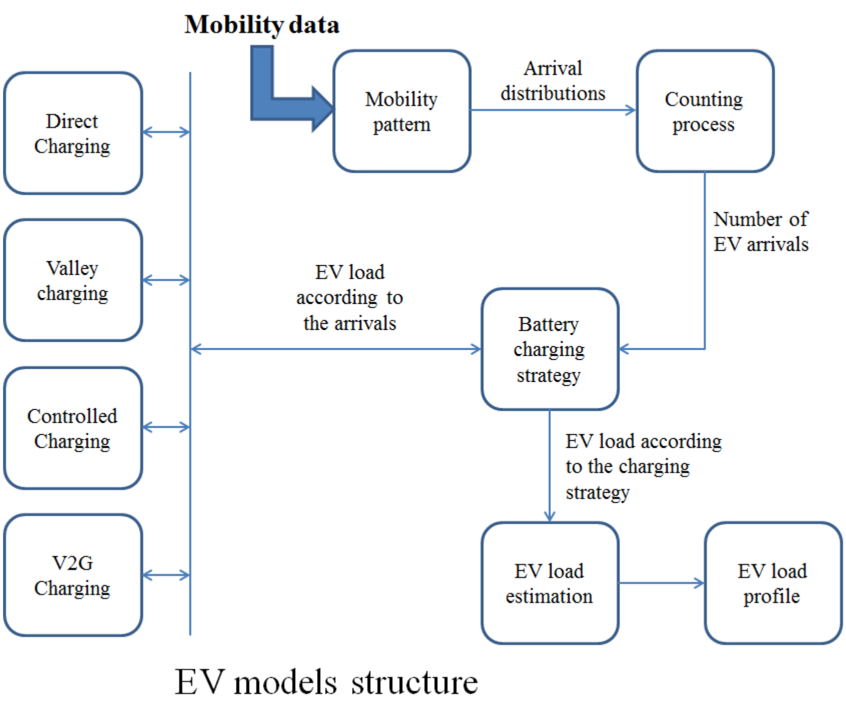

Figure 4.20: General structure of the EV models.

contribute to the electric systems in order to mitigate the EV impact and/or increase the participation of the renewable energy sources in the generating systems.

Chapter 5

Controlled Electric Vehicle Charging Modelling

5.1 Introduction

The uncontrollable charging strategies, addressed in the previous chapter, represents the EV as a conventional load, the EV owner being free to charge the vehicle at any time of the day. The main difference of the EV load profile is related to the periods of the day in which the EV owners will charge the battery. These strategies do not account controlled models, which could effectively manage the EV battery charging.

From [106] the electric vehicles could provide system support in 81% of the time, when charging spots are available at home and at work. Then, smart charging schemes are desirable in order to mitigate the EV impact and to exploit EV as an electrical component that is able to provide ancillary services for the system.

The main challenges of the integration of electric vehicles as active components of the electric system are the infrastructure, management and control sectors.

From the technological point of view, the expected large scale deployment of equipments on the grid such as the energy boxes, the transformer controllers and the improvement of the distribution management systems (DMS) is viewed as an opportunity to create active demand side management solutions and control strategies to reduce the EV impact on the power systems, taking advantage of their ability to provide ancillary services through an aggregation entity.

The smart electronic devices record consumption of electric energy in intervals of an hour or less and communicate that information at least daily back to the utility for monitoring and billing purpose. They also enable a two-way communication between the device and the aggregation entity. These aspects make these charging schemes possible, at least, from the technological infrastructure perspective.

The charging process of these structures can take less than half an hour (for fast charging rates) up to 8 hours (for slow charging rates). In this sense and, assuming a higher price to charge the EV battery in fast charging stations, it is expected that EV will be connected to the grid for large periods of time, being potentially possible to exploit their storage capacity to enable a grid support service.

Since the choice for controlled charging schemes will always be a decision taken by the EV owners, this thesis addresses two possible charging schemes which fit the EV owners' needs and the system requirements. In one hand, an active demand side management strategy is implemented in order to contribute for the provision of the operating reserve capacity, which is named as **controlled charging strategy**. On the other hand, a **V2G charging strategy** is developed to mobilise enough electric power capacity to increase the operating reserve in moments where conventional generation capacity is not available and to compensate the impact of the wind variability on the operating reserve capacity.

In normal operating conditions, a commercial aggregation entity is expected to manage and control the EV charging in controllable mode. The main objective is clustering the EV, and exploit business opportunities in the electricity markets to provide reserve. Throughout this thesis, the definition of reserve is an amount of available electric energy capacity to meet unexpected variation on load, renewable power and generating capacity due to forced outages.

In order to successfully respect the agreements, both with the clients and with the electricity market, the EV aggregator must be capable of sending set-points to the charging points related to rates of charge. In [67], an optimization approach to support the aggregation agent participating in the day-ahead and secondary reserve sessions is presented. The aggregator will be responsible for managing the EV charging; therefore, whenever the security of operation is threatened, it is able to mobilise EV to provide operating reserve in order to aid the system.

Before the description of the proposed EV models, two sections are included to give technological support for the controlled charging schemes: an overview on the specifications for the EV charging interface, communication and smart metering technologies and a life cycle study which is a matter of interest in V2G studies. Each model were developed in the framework of the European projects MERGE and STABALID, respectively.

This chapter is organised as follows. Section 5.2 presents an overview on the active charging framework for V2G strategy. The controlled charging model is described in Section 5.3. The reliability aspects of V2G are presented in Section 5.4. Section 5.5 presents the V2G charging model approach and in Section 5.6 presents the final remarks.

5.2 Active Charging Framework

Technologically, the achievement of a plug-and-play capability for the interface linking electric vehicles and grid is desirable. This interface must be able to access identical charging points (CP) across Europe, for instance, that can be used by any equipped vehicle, just as the roaming technology for cell phones.

Basically, this plug-and-play should consist of a **power stage** and an information and communication technology (**ICT**) stage. A power stage embraces the physical connections and functionalities between EV owner (user) and charging point. The ICT stage communicates between, at least, five identified parties: the user, the EV itself, the charging point, the SO and the aggregation entity. Figure 5.1 shows an illustrative representation of this relationship.

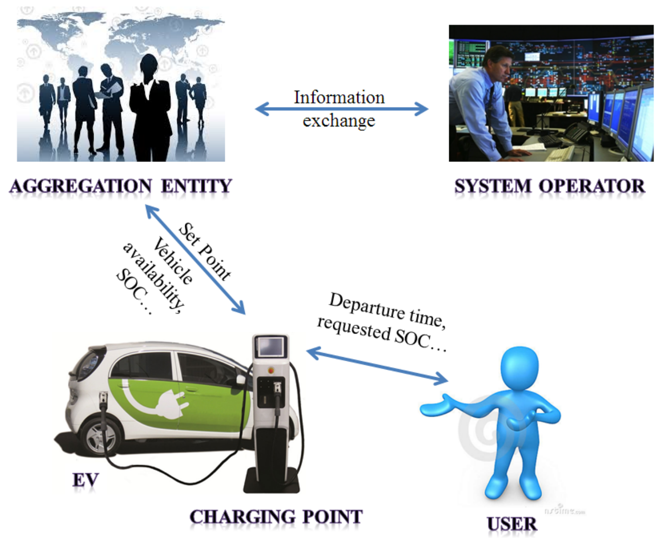

Figure 5.1: Information and Communication Technology scheme.

The definitions for the identified parties are:

- The **charging point** is the equipment containing the electrical and communication connection to the EV owner, electricity grid, system operator and aggregation entity. It is composed by the electricity meter, the communication modules, the electronics and software needed to control the charging process, a main control board, and a connector for the charging cable to be plugged into.

- The **electric vehicle** interacts with the charging point in order to give the needed information: state of charge and charge/discharge rate. The charging electronics (AC-DC converter, AC-AC converter, power electronics etc.) are embedded in the EV as an option of the vehicles manufacturers.

- The **EV owner** (user) needs to provide the inputs needed by the charging point software: departure time, how many kilometres the user needs to drive or desired SOC.
- The **system operator** is the responsible entity for the transmission/distribution system, and the one that provides electrical power for such charging point.
- The **aggregator** is the entity that manages the EV charging and mobilises the EV in order to provide operating reserve to the system.

These features define the basic framework to an aggregation entity provides the controlled charging schemes. Next sections present the **controlled charging model** and the **V2G charging model** for adequacy evaluation of generating systems.

5.3 Proposed Controlled Charging Modelling

Differently from the conventional flexible loads, the EV have batteries capable of storing electric energy to be used later. Through the vehicles mobilisation, an aggregation entity may supply reserve for the system. This action needs to consider a predefined SOC that must be guaranteed to ensure the EV usability.

The main objective of the controlled charging strategy is to avoid the impact that uncontrolled charging strategies may have on the electric systems and, at the same time, to provide operating reserve to the grid releasing generation capacity to meet the system variations.

Figure 5.2 illustrates such situations. After the system requirements have been met, through the synchronised generating units, the Equation (4.14) is tested. In situation (a), it is showed that the operating reserve capacity (ORC) is sufficient to cover all system uncertainties, resulting in a **success state**. However, due to the variation of the wind power, the load forecast error and the forced outages of the generating units, situation (b) presents a system **failure state**, where the result of Equation (4.14) becomes true.

Thus, assuming that the EV battery charging can be quickly interrupted, by decreasing the EV load, as showed in situation (c), the operating reserve $R_S + R_T$, is increased through the release of pre-scheduling generating units. These units were synchronised to meet the additional load that EV represents. Since, these EV stopped and the EV can effectively contribute to the operational reserve of the system and perhaps change the system state from a **failure** to a **conditioned success state**. Note that the released pre-scheduled generating units are part of the ones scaled to meet the additional EV load demand.

Therefore, this action makes possible to take advantage of load shifting instead of the ordinary load curtailment. In turn, the EV, which releases reserve for the electric system, will be charged at another hour, when no generation deficit is expected.

Moreover, as the ORC evaluation has the objective to measure the system flexibility when dealing with the system variability, through the already mentioned risk indices, the management of a massive EV charging may avoid or postpone the generating system reinforcement. On the other hand, the simulation process using different charging strategies may provide, through the risk indices analysis, a notion of the charging strategy required in order to maintain the system reliability when an EV fleet is integrated in the electric system without changing the desired generating system configuration.

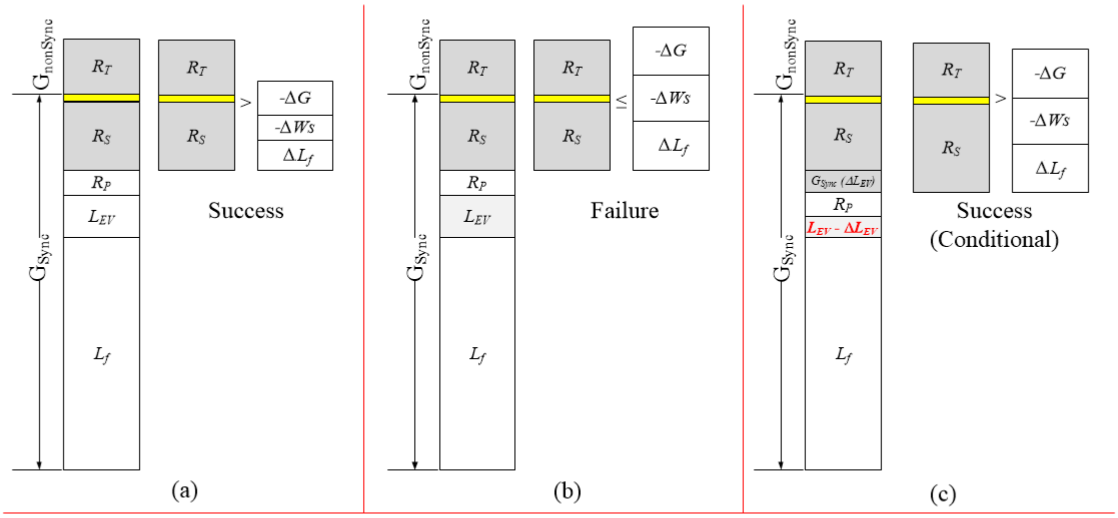

Figure 5.2: Operating Reserve Capacity evaluation with controlled charging strategy.

The flowchart presented in Figure 4.19, was modified to include this charging strategy. Figure 5.3 shows a new flowchart for the SMCS process, which can be described by the following steps:

1. Initiate all the component state. Commonly, it is assumed that all the components are in the state *UP*. Define the maximum number of years to be simulated, N_{max} and the convergence criteria β. Set the number of years to one $N_{year} = 1$.

2. Set the simulation time to zero $t = 0$ and sum one in the number of simulated years $N_{year} = N_{year} + 1$.

3. Define the EV model approach desired. If HPP is the chosen one, go to step 4. Otherwise, go to step 5.

4. Sample the current state duration of each system's component. If using an exponential distribution to approach the state duration, then it is calculated as follows:

$$T_i = -\frac{1}{\alpha_i} ln(U_i). \tag{5.1}$$

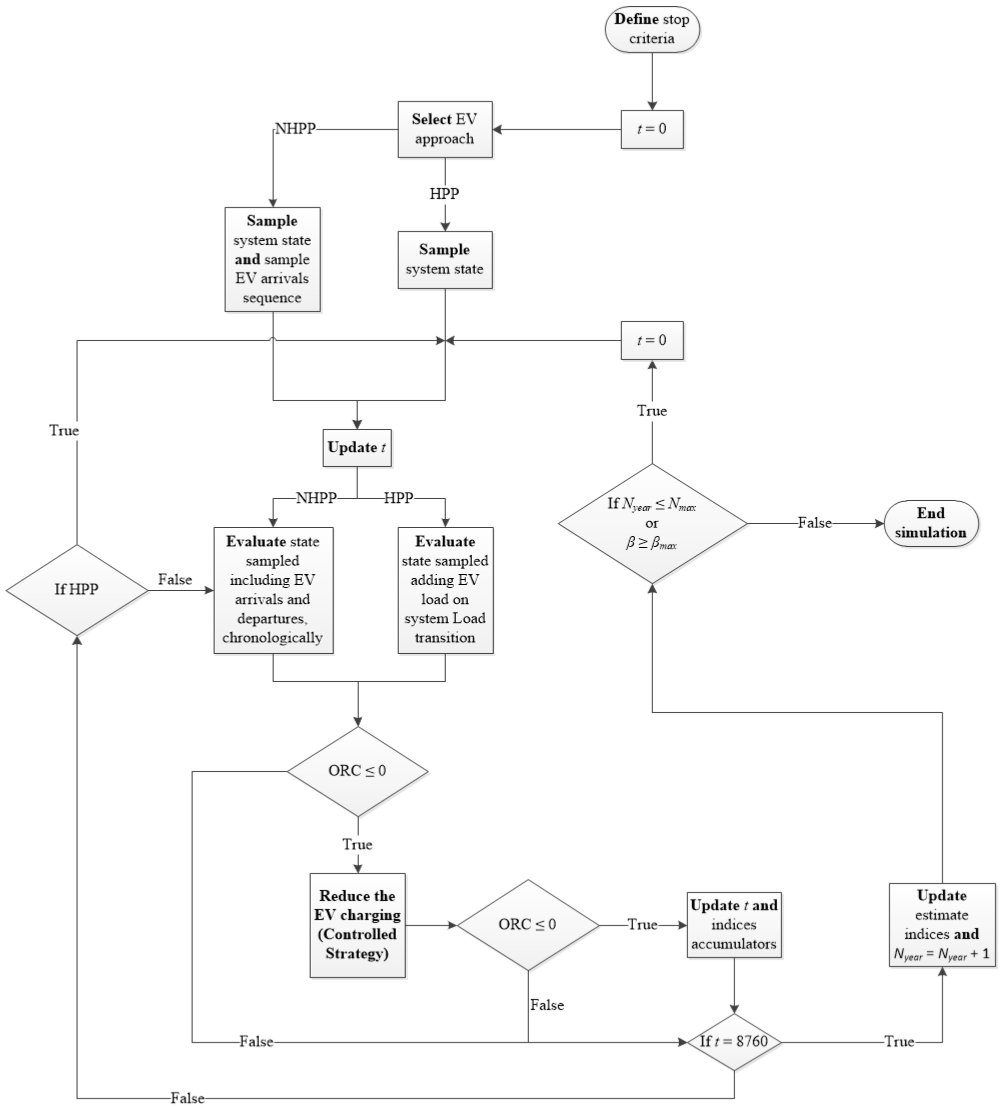

Figure 5.3: Flowchart of the SMCS with the EV controlled charging strategy.

Where U_i is a uniformly distributed random number between $[0, 1]$, i stands for the component number. The MTTF and MTTR values are represented by α according to the current system's state. The load transitions occur in an hourly basis with 8760 load points. Go to step 6.

5. Sample the current state duration of each system's component through Equation (5.1). Sample the EV arrivals and calculate the departure time of

each one, according to Equation (4.10). The load transitions occur in an hourly basis.

6. Update the simulation clock t, according to the selected state transition. If using the NHPP approach, each arrival is considered as a state transition. Otherwise, the EV load is added in each system load transition.

7. In order to obtain yearly reliability indices, evaluate the test function over the accumulated values. If a failure state occurs, then go to step 8. If a success or conditional success state occurs, go to step 10.

8. Reduce the EV load of the vehicles in controlled charging mode to be charged later after the departure hour defined before the failure occurrence. Return to step 7. If there is no EV in controlled charging mode, go to step 9.

9. Update the outcome of reliability test functions and the corresponding indices.

10. If the simulated year is not in the end, then return to step 4 or 5, according to the EV model approached chosen. Otherwise, go to step 11.

11. Estimate the expected mean values of the yearly indices as the average over the results for each simulated sequence.

12. Test the stopping criteria according to their definitions in the beginning of the simulation process.

13. If the stopping criteria is not reached, repeat the step 2 each time span and record the results of each duration sampled for all components. Otherwise, go to step 14.

14. End the process if the desired degree of confidence is achieved. If not, return to step 2.

5.4 Reliability Aspects of Vehicle-to-Grid

The variable characteristic of some primary renewable resources, especially wind, and the fact that, in general, renewable generation units are not capable of fully providing secondary reserve services, has been pointed out as a difficulty in integrating it in the power systems without additional investments to guarantee system stability.

In order to overcome these problems, technical solutions that enable the management of the energy produced by RES should be considered and implemented. Among the possible solutions, large stationary batteries installed at strategic points of the electricity network can be used as a solution that allows a larger integration of RES while keeping the power systems stability and quality of service levels unchanged and, at the same time, reducing the renewable energy wasted. Although these battery systems are distributed over the networks, this thesis uses the aggregated capacity provided by them, in order to evaluate the security of supply from the operating reserve capacity perspective.

From all different large stationary batteries, Li-ion technology is considered as one of the best solutions due to its intrinsic characteristics, providing an energy-to-power ratio adequate to be used in combination with the various types of RES. However, the lack of experience by the end-users, especially for large scale integration levels, raises a number of questions related to the safety and performance of these battery systems at the considered scale.

Smaller Li-ion batteries are already being used for other purposes, such as cell phones and portable computers, what lead to the definition of several standards (UL, UN, IEEE, and so on.). The emerging interest on hybrid and electric vehicles also lead to the definition of several other standards (SAE, IEC, and so on.). Since in the industrial framework, the deployment of large Li-ion batteries is just at an initial stage, there are presently no available standards for this specific field of application. Considering this conjecture and in order to regulate safety issues and increase market acceptability, a specific standard focused on safety testing for stationary Li-ion batteries is necessary and is an issue addressed in the STABALID project [3].

The STABALID project intended to deliver a proposal for a new standard, defining the most appropriated testing methodology for stationary Li-ion batteries. According to [107], this storage system is composed of 10 parallel strings, each one comprising 29 battery modules, delivering a nominal 700 V and a rated energy of 40, 56 or 60 kWh. In addition, each string is controlled by a Battery Management Module (BMM). This component guarantees that the charging and discharging of the strings do not violate the operating limits. Moreover, it can continuously monitor the state of charge (SOC), the state of health (SOH) and other vital data of the Li-ion modules, such as temperature.

The SBS also contains a Master Battery Management Module (MBMM), which is responsible for monitoring and controlling the 10 parallel battery strings, and an active cooling system that maintains the temperature of the modules within optimal operating boundaries. A fire prevention system is also available to prevent destructive consequences, such as fire or explosion.

These storage systems have been developed by different companies, such as ABB Group, A123 Systems and SAFT Batteries among others. These three companies have already installed their stationary SBS, to support the wind power plants, as presented in Figure 5.4 which gives an overview of some real storage system facilities.

Figure 5.4: Stationary Storage Battery Systems.

The main issue regarding V2G is the charge/discharge of the vehicle's battery, which impacts on its life cycle. Next section presents the development of a methodology to evaluate the life cycle of LI-ion batteries.

Life Cycle Analysis of Batteries

The Li-ion battery provides an adequate energy-to-power ratio to be used in combination with the various types of RES. The literature shows that the outage probability of Li-ion batteries increases as the battery wears out [108]. For that reason, the Li-ion battery was submitted to different number of charging and discharging cycles until an outage occurs. The following procedure is applied in the battery life cycle study.

Let the random variable X, which follows the Weibull distribution (see Figure 5.5), be the number of discharges at 80% DOD (Depth of Discharge) that a battery experiences until the occurrence of a forced outage. The probability density function of this distribution is

$$f\left(x,\alpha,\beta\right)=\frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1}e^{-\left(\frac{x}{\alpha}\right)} \tag{5.2}$$

where $\alpha>0$ is the scale parameter and $\beta>0$ is the shape parameter. Figure 5.5 illustrates different probability density functions according to the the number of discharges X.

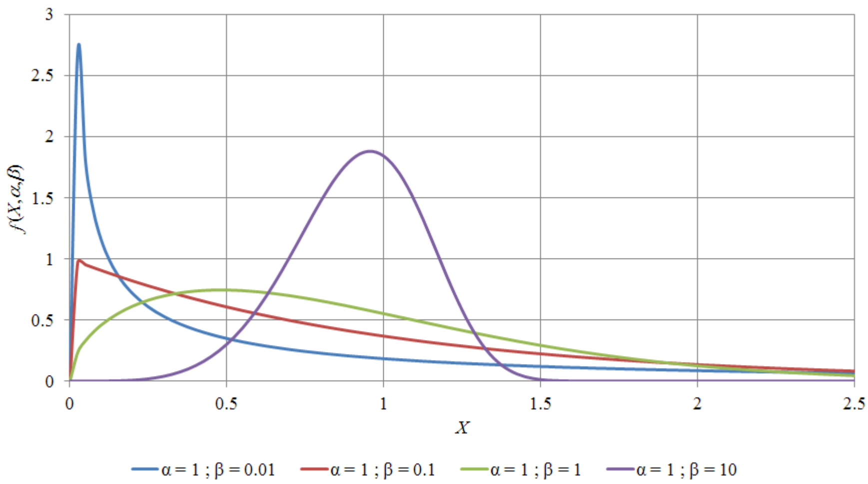

Figure 5.5: Potential risks of the Li-on battery to failure [3].

α and β can be computed from a reliable source of data by using a curve fitting analysis for each type of failure mode (FM) that a battery may experience. The FM considered in STABALID project refers to possible problems occurred during manufacture, packing, transport and installation phases. The FM were divided into 6 categories:

1. Irreversible "Damage": Failure but no leakage, no venting, no fire or flame, no rupture, no explosion, and no thermal runaway.
2. Leakage: Light smoke, no venting, no fire or flame, no rupture, no explosion and no thermal runaway.
3. Venting: Heavy smoke, no fire or flame, no rupture, no explosion and no thermal runaway.
4. Fire or Flame: No rupture and no explosion.
5. Rupture: Disintegration of the battery but no explosion.
6. Explosion: Explosion, i.e., high thermal and kinetic energy release.

After sampling an outage which, is according to the two-stage random sampling procedure based on the probabilities calculated in [3], the number of discharges at 80% DOD until the outage actually happens is drawn from the respective Weibull distribution. The shape of the cumulative probability distribution (CDF) of the number of discharges at 80% for each failure mode is depicted in Figure 5.6.

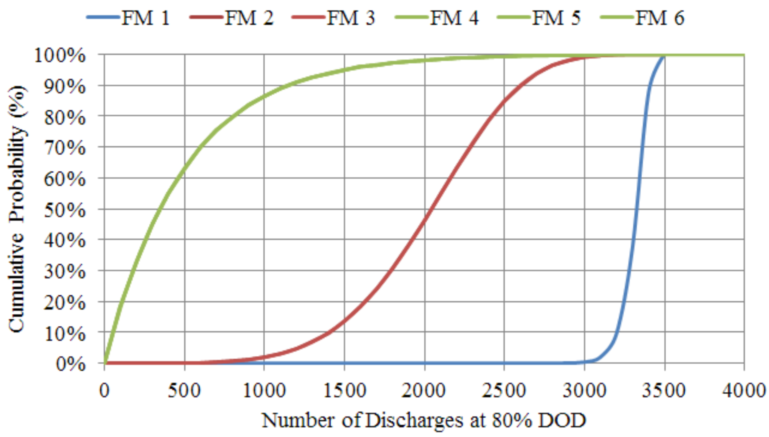

Figure 5.6: Cumulative risks of the Li-on battery to failure.

After this two-stage sampling procedure, the sequential Monte Carlo simulation method is used to count the number of discharges of the strings. For creating a realistic representation for the charging and discharging process of the strings of the SBS, the maximization of the usage of wind power was selected as an operation strategy. According to this strategy, the energy stored in the Li-ion battery system is injected into the grid, when, after the dispatch of the conventional generating units, the load is greater than the wind power available.

The maximum discharge rate, the minimum SOC of the battery, the discharging efficiency, and the duration of the system state sampled are taken into account to determine the quantity of energy to be injected into the grid. On the other hand, the Li-ion battery system is charged when the system load is less than the wind power available, which configures the most common condition for battery charging. The amount of energy stored is calculated based on the battery electrical characteristics previously mentioned.

As a simple example, Figure 5.7 illustrates the charges and discharges of the SBS during a 5-hour-operation. These operations depend on the wind power variations and on the system load behaviour, which are random variables that also depend on time (see Figure 5.7). Consequently, the detection of the number of discharges at 80% DOD until the occurrence of the forced outage previously sampled is only possible through sequential Monte Carlo simulation.

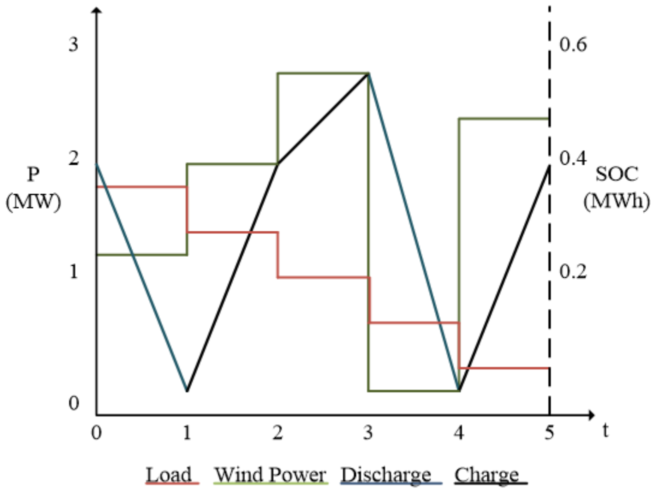

Figure 5.7: Sequential charging and discharging of a SBS.

Every time there is a discharge, the respective accumulator is updated. For this purpose, the following equation is used

$$NOD := NOD + \frac{DOD}{80\%} \tag{5.3}$$

where NOD (Number of Discharges) stands for counting the number of discharges and the DOD is the difference between the SOC at the beginning and the SOC at the end of the analysed period in percentage of the maximum SOC of the string.

The loss of storage capacity of the strings over time until the maximum number of discharges at 80% DOD (MNOD) is reached was also modelled in this approach.

For the purpose of this work, it was assumed that the decrease of capacity follows a linear curve, as depicted in Figure 5.8.

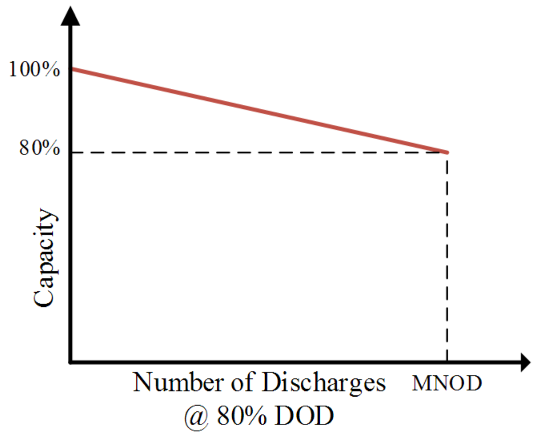

Figure 5.8: Decrease of the battery capacity.

From the proposed methodology, it is possible to estimate the life cycle of the LI-ion battery for different operation purposes. The one described in this section relies on the assumption that the SBS are able to compensate the wind power variations.

Next section presents the proposed V2G model. Some aspects of the V2G model (battery parameters, time of charge/discharge and SOC estimation) follow the model developed in the STABALID project, however, the life cycle methodology is not addressed in the adequacy evaluation of the generating systems. It can be performed separately using the type of the EV battery parameters.

5.5 Proposed Vehicle-to-Grid Charging Modelling

Due to the necessity of having a battery SOC monitoring, the modelling of the V2G strategy was addressed through the NHPP approach, which is able to obtain the EV arrivals and the time in charging mode for each vehicle. Therefore, the update of the energy available in each vehicle's battery is carried out for each evaluation moment.

Figure 5.9 presents an illustrative example of a possible system configuration in a single bus representation. The figure is composed by the conventional generation, renewable energy sources (as wind power), conventional and EV loads and storage battery systems.

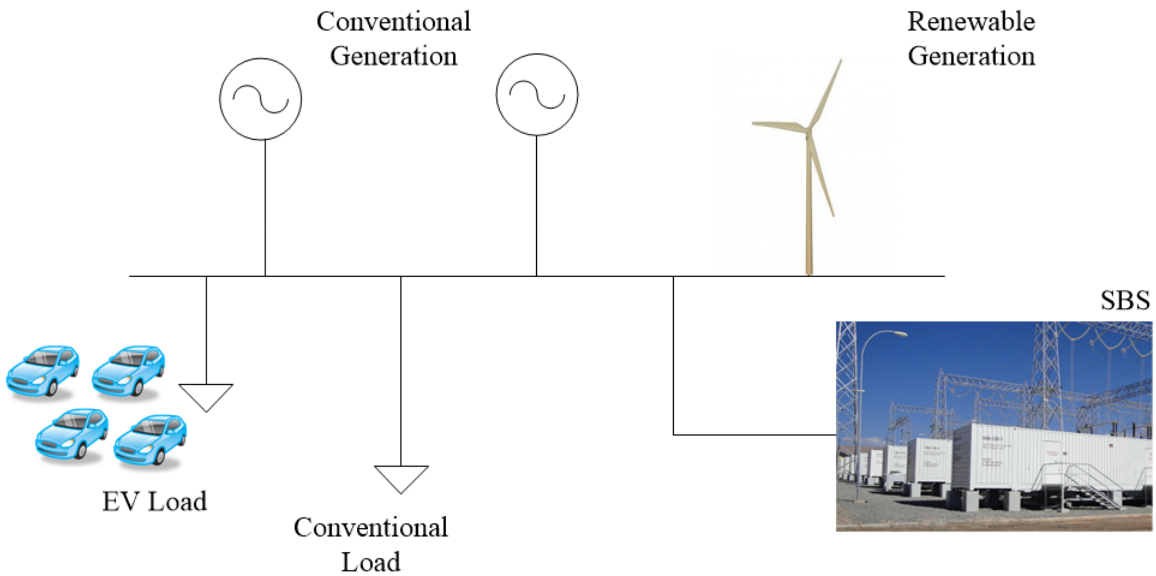

Figure 5.9: Electric components of a single bus representation.

In the operating reserve capacity context, the V2G strategy is divided in two perspectives. Firstly, the V2G charging model provides operating reserve capacity to the power systems throughout the mobilisation of connected vehicles in periods where the deficit of generation capacity is foreseen. Secondly, the V2G charging model supports the electric systems as a SBS, compensating the impact of the wind forecast error in the operating reserve level.

When the simulation process starts, it is assumed a 100% battery SOC, *i.e.*, the EV battery is fully charged. Then, if a discharge is necessary the SOC is updated according to (5.4).

$$SOC_i(t) = SOC_i(t - \tau) - \frac{\Delta R(t) \cdot d}{NB(t) \cdot \eta_{discharge}} \tag{5.4}$$

Where, $SOC_i(t)$ is the state of charge at the moment t for each vehicle i, $SOC_i(t-\tau)$ is the last known SOC of the battery for each vehicle i. $\Delta R(t)$ represents the capacity needed to cover a failure state of the operating reserve or the wind power forecast error in the moment t according to the V2G selected mode in the beginning of the simulation and d is the duration of the actual system state. $NB(t)$ is the number of EV available to inject electrical energy in the grid connected at time t and, $\eta_{discharge}$ is the discharge efficiency related to the battery technical parameters.

The discharged vehicles are relocated to charge their batteries later and the departure hour is postponed in order to guarantee the EV battery requirement. In this case, the updating of the SOC is given according to

$$SOC_i(t) = SOC_i(t - \tau) + \frac{\Delta R(t) \cdot d}{NB(t)} \cdot \eta_{charge} \tag{5.5}$$

Where η_{charge} is the charge efficiency related to the battery technical parameters.

The operational limits of the batteries are also taken into account. All batteries have a minimum SOC and a maximum SOC which are considered as the delivering energy limits to the system. The simulation parameters can be changed, nonetheless it was assumed, for all EV batteries, 30% and 80% as minimum and maximum battery SOC, respectively.

The total available energy for V2G charging is given by the summation of the EV batteries' SOC of all connected vehicles that are in V2G mode at the evaluation moment. Usually, just a percentage of the total vehicle fleet is considered to be in V2G charging mode and this value is a parameter of the simulation process.

The maximum charging/discharging times are also limited by the charging/discharging rates of the EV batteries and are updated every time a charging/discharging event occurs. These values are calculated through the following equations

$$maxtmpCharge(t) = \frac{SOC_{max}(t) - SOC(t)}{\epsilon} \tag{5.6}$$

$$maxtmpDischarge(t) = \frac{SOC(t) - SOC_{min}(t)}{\epsilon} \tag{5.7}$$

where ϵ is the charging/discharging rate of the battery. The operation purposes of the V2G model is presented in the next sections.

5.5.1 Vehicle-to-Grid for Operating Reserve Capacity

The EV mobilisation provides operating reserve for the system when a deficit of available generating capacity is identified. The available energy stored in the EV batteries can be injected in the grid through a signal sent by the aggregation entity to the EV in V2G mode.

The discharge of the EV batteries occur according to an identified system failure state. Figure 5.10 shows an illustrative example of such situation. A failure event

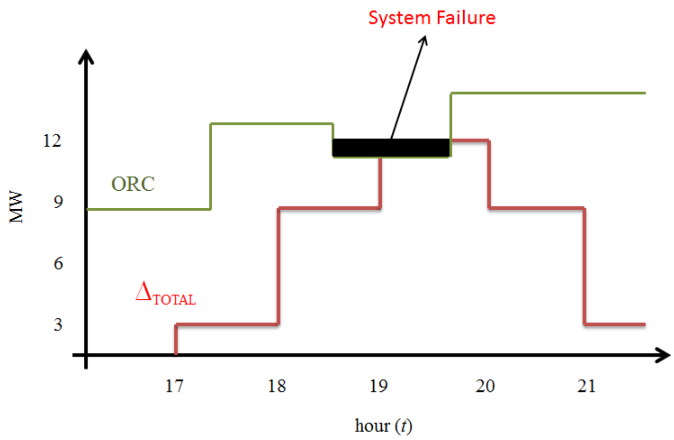

Figure 5.10: Illustration of the expected ORC failure state.

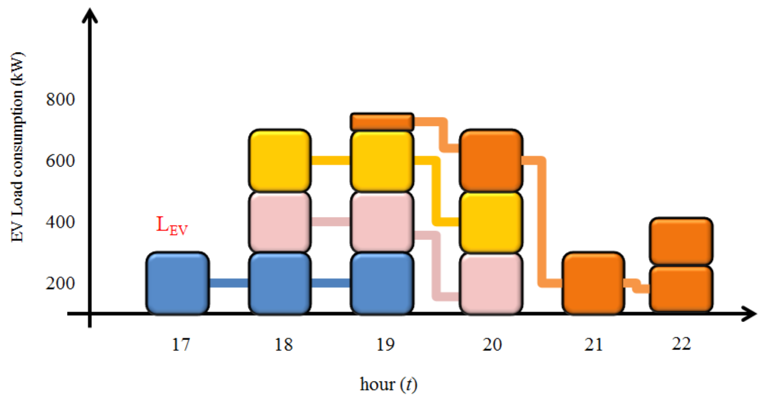

Figure 5.12: Battery charging according V2G strategy for ORC.

is identified between 18:30 and 20 hours. This means that the available operating reserve capacity is not able to meet the system uncertainties.

Supposing that the aggregation entity had mobilised vehicles to provide reserve, according to the parameters given by the EV owners, Figure 5.11 shows the reduction of the expected EV load (dashed box), the increase on the operating reserve provided through the V2G strategy (in blue), and the amount of EV load postponed to be charged in another period where no system failure state is foreseen.

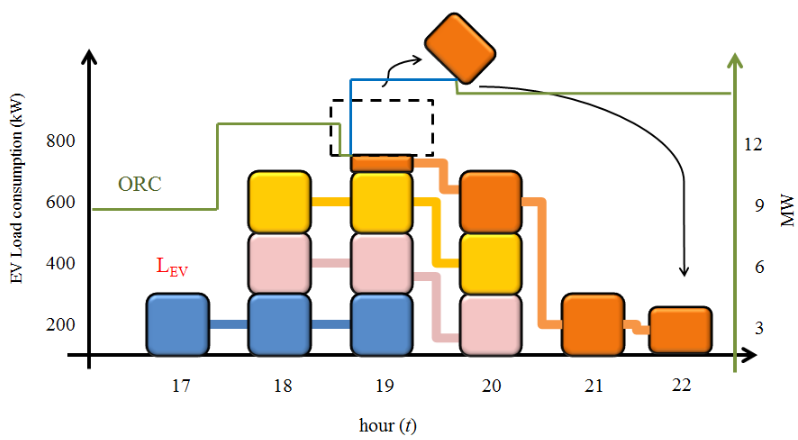

Figure 5.11: Energy injected and postponement of the battery charging.

Figure 5.12 shows the final situation for this example. Note that, the aggregation entity needs to respect a SOC threshold set by the EV owner in order to guarantee the usability of the vehicle.

On the other hand, at the moment where a system failure event is foreseen, the user needs to maintain the EV connected in the grid in order to provide reserve for the system.

Figure 5.13 summarises the conditional success state due to the V2G charging strategy. The blue line indicates the increase in the operating reserve through the mobilization of EV.

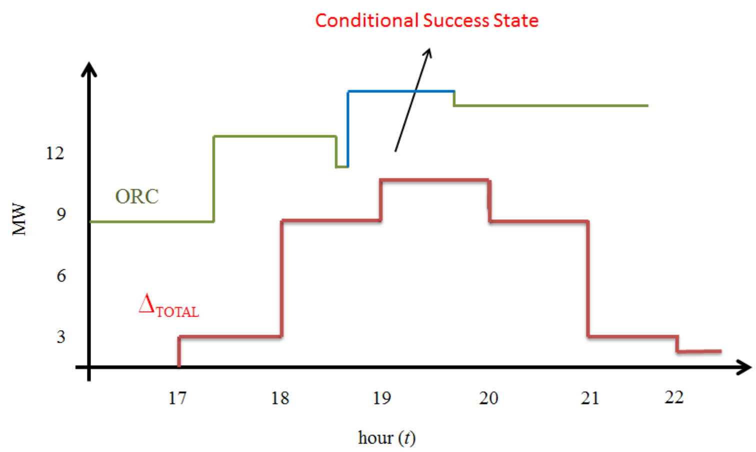

Figure 5.13: Illustration of the conditional success state due to V2G strategy.

5.5.2 Vehicle-to-Grid for Wind Power Generation Balance

Due to the variability effect of the RES on the operating reserve, this model intends to compensate the wind forecast error, mitigating the impact by an increase usage of wind power in the generation portfolio. In order to illustrate this effect, a simulation is performed in a test system by removing the constraints of the battery technical parameters, *i.e.*, the vehicle has no limits for the battery charging/discharging rates and capacity. Therefore, this scenario should result in a fully correction of the wind power forecast error by the injection of the electric energy stored in the EV batteries.

Figure 5.14 presents the performance of the V2G strategy (in a daily period), the annual average values of the EV battery capacity and the wind forecast error (WFE) before and after the wind power compensation. The negative values of the "WFE - before" line, mean that the wind power production is lower than the expected one, therefore it is necessary to inject electric energy from the EV batteries to correct such situation. This is highlighted by the "EV SOC" line, where the negative slopes mean the discharges of the batteries.

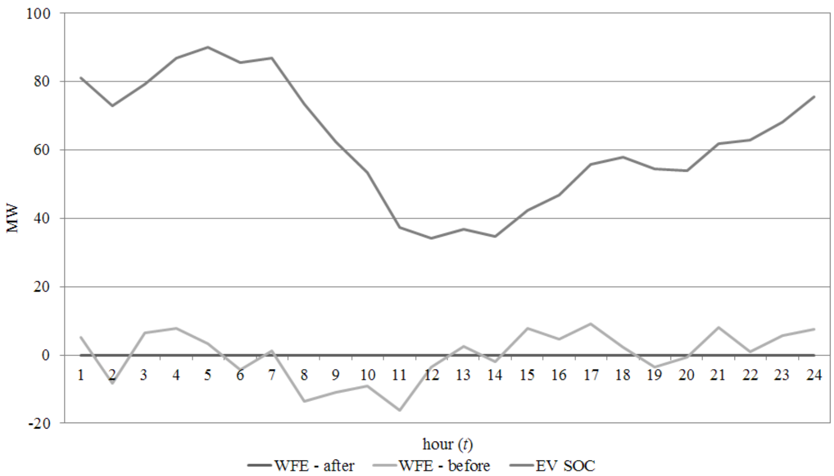

Figure 5.14: Performance of the V2G charging strategy for wind generation balance.

On the other hand, the positive values of the "WFE - before" line, mean that there are surplus on the wind power generation and it could be used to charge the EV batteries that are connected in the system, as showed through the positive slopes of the "EV SOC" line.

As there are no battery operational constraints, the "WFE - after" line is zero for all period. This means that, when necessary the V2G strategy is able to meet the wind power variation throughout the injection of electric energy into the grid.

One supposition based on this operation strategy is that the large-scale integration of electric vehicles could support the integration of more renewable energy sources in the generating systems. Consequently, the EV can charge its batteries through the use of this renewable energy, decreasing the renewable energy waste.

5.6 Final Remarks

This chapter presented the developed active charging strategies, controlled and V2G models, in order to mitigate the EV impact on the security of supply and provide system support through the existence of an aggregation entity.

The controlled charging strategy was thought as an active demand side management scheme that through the aggregation entity the load shift is carried out in order to release synchronised capacity of the power plants to meet system uncertainties. The impact of this strategy could be measured evaluating the operating reserve capacity through the reliability indices provided in the SMCS process. The main assumption of the controlled charging strategy is that the vehicle used to provide operating reserve will be charged during the valley hours due to the characteristic of low load demand in this period.

The V2G charging strategy was modelled through the NHPP approach due to the necessity of the individual battery SOC monitoring. Firstly, the V2G strategy provides an increase of the operating reserve when a system failure state is foreseen. In this sense, the aggregation entity has the responsibility of guaranteeing the parameters given by the EV owners to ensure vehicle usability. On the other hand, the EV owners need to guarantee that the EV remain connected on the grid while this one is providing electrical energy back to the grid. Secondly, the V2G charging strategy has the purposes of compensating the wind power forecast error impact on the wind power variation. The increase on the operating reserve capacity and the decrease of the renewable energy wasted can be achieved through the use of a V2G charging strategy.

Chapter 6

Simulation and Result Analyses

6.1 Introduction

This chapter discusses the impact of electric vehicle charging on the security of supply through the adequacy evaluation of the generating systems. The proposed methodology, described in Chapters 4 and 5, is applied by simulating different generating systems, which are divided into test and real systems.

Regarding the test system, this chapter presents the analysis of the adequacy evaluation of the modified IEEE Reliability Test System 1996 using the proposed models. This system was modified [60] in order to include a higher level of renewable energy sources in the original generation portfolio. Firstly, hydro series were included in order to represent the seasonal hydrological condition of the hydro plants. Secondly, a thermal unit was substituted by wind power plants in order to increase the renewable sources in the system.

Several simulations were performed in the framework of the MERGE and REIVE projects. In this thesis, the simulations of the Portuguese, Spanish and Greek generating systems using a forecast scenario for 2030 with and without deployment of EV are discussed. The simulation result analyses are presented according to the approach (HPP or NHPP) and the battery charging strategy[1]. Then, the risk indices are presented and discussed from the static reserve and operating reserve capacity perspectives.

The chapter is organised as follows. As the forecasted scenarios were built from past systems, Section 6.2 describes the test and real system references. Firstly, the original IEEE RTS 1996 is described in Section 6.2.1. Secondly, the descriptions of the generating systems for Portugal 2010, Spain 2010 and Greece 2009 are given. The IEEE RTS 1996 HW and the Portuguese, Spanish and Greek generating systems as well as the EV penetration scenarios for 2030, are presented in Section 6.3.

Regarding the validation of the tool, it is carried out in the modified RTS-96, and the results are presented in Section 6.4. Afterwards, reference reliability indices are given using the test and real generating system scenarios in order to build a comparison basis. These results are presented in Section 6.5.

Section 6.6 presents the results of the static reserve and operating reserve capacity evaluations for the test and real systems according to the proposed EV models. This section is divided into different modelling approaches (HPP and NHPP). Section 6.7 presents a brief comment about the computational burden of the presented simulation cases. Finally, the Section 6.8 outlines the final remarks.

6.2 System Descriptions

This section gives a brief description of the IEEE Reliability Test System - 1996 (RTS-96) and the Portuguese (PGS), Spanish (SGS) and Greek (GGS) Generating

[1]In order to simplify the result tables and figures, the direct, valley, controlled and vehicle-to-grid battery charging strategies are tagged as **DC**, **VC**, **CC** and **V2G**, respectively

Systems, which are used throughout this chapter.

6.2.1 IEEE Reliability Test System - 1996

The report described in [109] presents an enhanced test system (RTS-96) to be used in bulk power system reliability evaluation studies. The objective of a test system is the possibility of new and existing reliability evaluation techniques being compared to the benchmark studies performed on these systems. The test system was developed based on the original IEEE Reliability Test System (named as RTS-79) to reflect changes in evaluation methodologies and to overcome perceived deficiencies.

The original configuration of the RTS-96 consists of 96 generating units divided into five different technologies with a total installed capacity of 10,215 MW and the annual peak load of 8,850 MW. Figure 6.1 depicts the installed capacity of each technology.

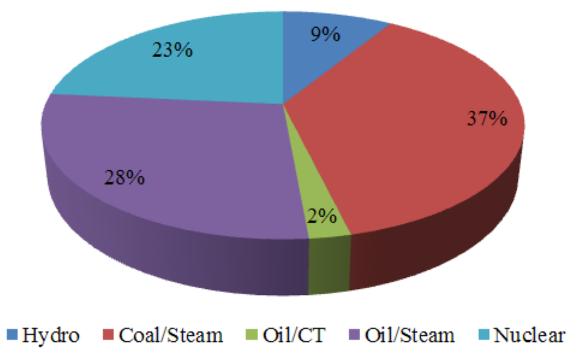

Figure 6.1: Original generation technology sharing for the RTS-96.

The static reserve corresponds to 16.3% of the total generation installed capacity. From the renewable point of view, 900 MW are based on hydro power plants, which consist of 8.8% of the generation portfolio. Moreover, 9,315 MW are divided into different thermal technologies (see Figure 6.1).

6.2.2 Real Generating Systems

This section describes the configuration of the real generating systems. The objective is giving reference to the forecast scenarios that will be presented later.

Portuguese Generating System - 2010

In 2010, the Portuguese Generation System had about 18 GW of installed capacity in which more than 25% consisted of hydro power plants. The thermal generation was over 40%, highlighting the natural gas technology (21%), which has been increasing significantly, mainly due to the flexibility that needs to cope with wind variations.

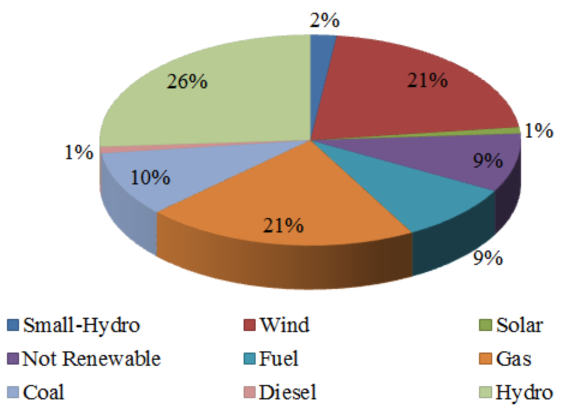

Figure 6.2: Generation technology sharing for the PGS-2010.

Regarding the "Special Regime", which consists of electricity generation through mini-hydro, co-generation, biomass and wind power, it accounts for 33% of the total generation installed capacity in Portugal in 2010, where wind power accounts for more than 20% (see Figure 6.2).

As a matter of fact, Portugal has been one of the European countries with great deployment of renewable energy sources. In 2013, Portugal achieved 27% of its electricity generated from wind resource [17].

Spanish Generating System - 2010

In 2010, the Spanish Generation System increased about 3,717 MW, resulting in 97,447 MW of total generation installed capacity. This significant amount of generation capacity is strongly linked to the commitment of new renewable energy facilities, consisting of more than 27% of the total generation installed capacity, where 20% comes from wind power and 7% comes from other renewable technologies (see Figure 6.3).

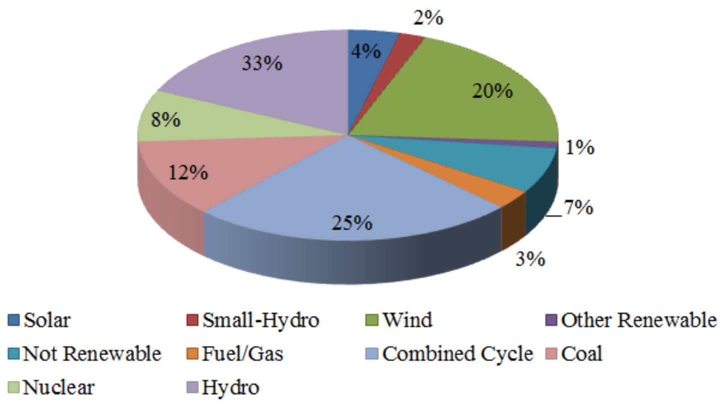

Figure 6.3: Generation technology sharing for the SGS-2010.

However, in order to preserve the generating flexibility and to deal with wind variations, an amount of 25% of the generation installed capacity comes from the combined cycle power plants [110].

During this year, Coal power plants were 12% of the total generation portfolio, due to the unusual decrease of the demand and a generating system review face to a large diffusion of renewable production. In the same year, fuel and gas production remained only 3% of the total energy production. Hydroelectricity increased to 35%

considering the small-hydro power plants. Spain has 8 nuclear power plants placed over six different locations, which represent 8% of the total generation installed capacity.

Greek Generating System - 2009

The Greek interconnected system serves the needs of the mainland and a few interconnected islands. Gross electricity demand during 2009 was about 53.7 TWh. The compound annual growth rate of electricity demand reached about 4% in the last decade. The demand is met mainly by thermal power and large hydro plants, which together achieved 97% of the total generation installed capacity, 13,344 MW at the end of 2009. Figure 6.4 presents the different technologies of the GGS in 2009.

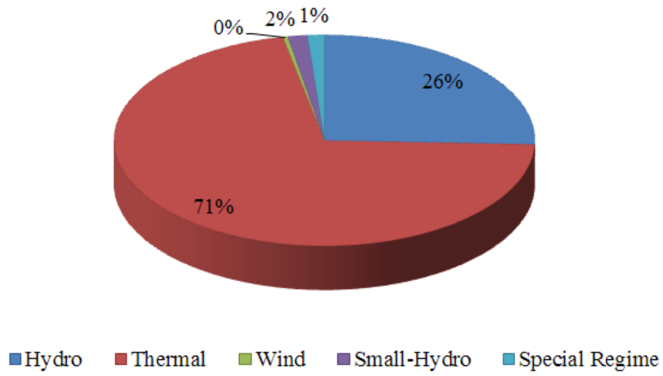

Figure 6.4: Generation technology sharing for the GGS-2009.

The main production centre is situated in the North-West of Greece in the vicinity of a lignite rich area. Significant hydro production takes place in the North and Northwest of the country, while some lignite production is also available in the South of Greece (Peloponnese peninsula). Small-Hydro shares 2% of the generation installed capacity whilst the special regime is almost 1%.

Wind farms reaches a total of 0.4% of the generation installed capacity, most of which is in the island of Evia and in Thrace. These wind farms contributed to about 3% of the electricity needs during 2009.

A number of islands, such as Crete, Rhodes and others are not connected to the mainland system. These autonomous systems represent approximately 8% of the electricity demand in Greece [111]. The electricity generation on these islands relies on petroleum products and, to a much lesser extent, on RES. The system is interconnected with Albania, Bulgaria, and F.Y.R.O.M. via three 400-kV tie lines of a total Available Transfer Capacity of 600 MW and to Italy via an asynchronous 400-kV AC-DC-AC link with a transfer capacity of 500 MW.

The system is also connected with Turkey with a 400-kV line since the summer of 2008, but the commercial operation of this interconnection had not started in 2009, as the Turkish system was synchronised with ENTSO-E only in September 2010.

6.3 Scenarios Description

Different scenarios are presented in order to perform the reliability studies. In the test system, changes were made to increase the participation of renewable energy sources and include hydro power monthly variation. In the real system scenarios, the generating system configurations are forecasts for the year of 2030.

6.3.1 IEEE Reliability Test System - 1996 HW

The first version of the IEEE Reliability Test System was developed in 1979 by the Application of Probability Methods (APM) Subcommittee of the Power System Engineering Committee [112]. This system was developed to test and compare results from different power system reliability evaluation methodologies based on a standardised data. In 1986, a second version of the RTS was developed and published [113]. The experience with RTS-79 helped by including critical additional data requirements and the need to include the reliability indices of the test system.

The RTS-86 expanded the data system related to the generating system. This was marked by the increase in the number of generating units and the inclusion of data, such as unit derated states, unit scheduled maintenance, load forecast uncertainty and the effect of the interconnection. The major advance of the RTS-86, was the publication of the system reliability indices obtained through the use of rigorous techniques without any approximations in the evaluation process.

Several changes in the electric utility industry have taken place since the publication of the RTS-79. These changes along, motivated the task force[2] to suggest a multi-area RTS incorporating additional data.

The RTS-96 was developed to represent as much as possible all the different technologies and configurations that could be encountered on any system. However, since 1996 the renewable energy sources gained a significant participation on energy mix for several countries, namely EU countries. Then, a modified version of the RTS-96 was proposed in [60].

This system was named as IEEE Reliability Test System 1996 HW (RTS-96 HW). "H" is related to the changed made to cope with the monthly variation of the stored water in the basins, which affects the hydro power capacity and "W" refers to the substitution of a 350 MW coal unit by 1526 MW of wind power. The ratio between $350/1526 \approx 0.23$ is a capacity factor to cope with wind power variability.

The original generation installed capacity was 10,215 MW, from this total 900 MW are hydro power units and 9,315 MW are from thermal sources. The annual peak load is 8,550 MW. The changed made increased the generation installed

[2]Co-Chairmen: C. Grigg and P. Wong; P. Albrecht, R. Allan, M. Bhavaraju, R. Billinton, Q. Chen, C. Fong, S. Haddad, S. Kuruganty, W. Li, R. Mukerji, D. Patton, N. Rau, D. Reppen, A. Schneider, M. Shahidehpour, C. Singh.

capacity to 11,391 MW, and the percentage of renewable power has increased to 21.3% (between hydro and wind power plants). Figure 6.5 shows the generation technology sharing for the RTS-96 HW.

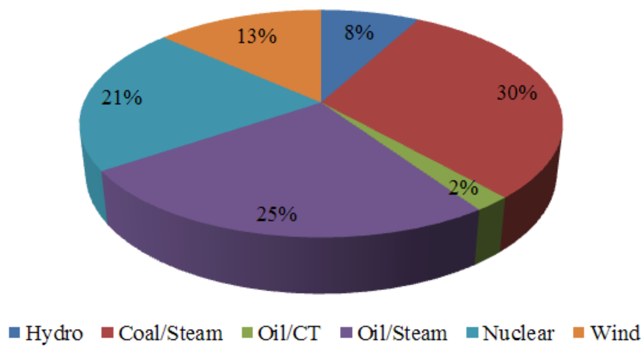

Figure 6.5: Original generation technology sharing for the RTS-96.

The thermal generation subsystem has 78 units with capacity varying from 12 up to 400 MW, totalling 9,315 MW (almost 79% of the total generation installed capacity). The hydro generation subsystem is composed by 18 units of 50 MW each, distributed in three power stations. The capacity variation of these units is simulated according to five hydro series, which is referred to the average monthly power capacity, with the same probability of occurring. The wind power subsystem has 763 units of 2 MW, distributed among three regions with different wind characteristics: region I and III have 267 units each one and, region II has 229 units.

The wind power fluctuation is characterised through three wind series for each wind region. The series reflects the variability of the wind power average, in an hourly basis. These series are classified as favourable, average and unfavourable, and their corresponding probabilities of occurrence are 25%, 50% and 25%.

6.3.2 Real Generating Systems Scenarios

The Portuguese, Spanish and Greek generating system configurations studied in this thesis are the ones forecasted for year of 2030. This section presents these future systems in detail and afterwards, the EV scenarios for 2030 are also described in order to be included in the adequacy evaluation of the real generating systems.

Portuguese Generating System - 2030

The forecasted peak load for 2030 is 14,384 MW while the planned generation capacity is 28,339 MW, which is composed by 4,589 generation units with capacities ranging from 1 MW to 557 MW. Figure 6.6 depicts the generation portfolio for 2030.

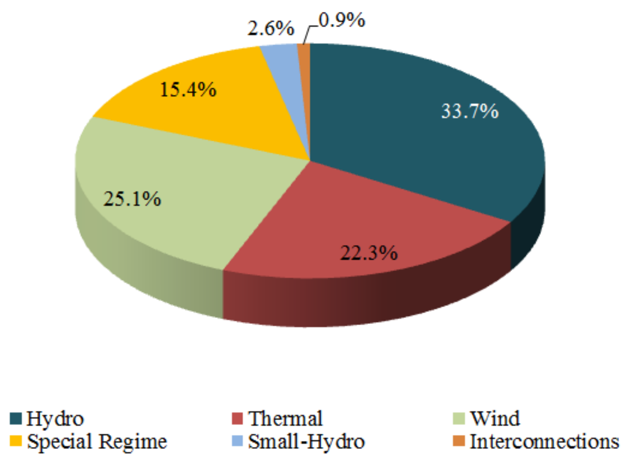

Figure 6.6: Generation technology sharing for the PGS-2030.

The primary reserve is set to 53 MW and the secondary reserve is 650 MW. The tertiary reserve is composed of 100 hydro units and 2 thermal units, that are able to be started in less than one hour, totalling 12,423 MW. However, this amount may vary according to the dispatch, once these units can be used to meet the load or the primary/secondary reserve requirements. The short and long-term uncertainties of the load are 5% and 0%, respectively.

Wind, small-hydro and special regime units are always scheduled for production prior to any other units. Hydro and thermal units are scheduled subsequently. The scheduling priority between thermal and hydro units vary with the strategy selected at the beginning of each sampled year.

Spanish Generating System - 2030

The SGS accounts for 139,357 MW of generation installed capacity, which comprises 25,411 generation units with capacities ranging from 1 MW to 1,087 MW. The expected peak load is 64,000 MW. Figure 6.7 depicts the technology sharing of the Spanish generation portfolio.

The primary and secondary reserves are set to 351 MW and 900 MW, respectively. The tertiary reserve is calculated according to the generating units available to,

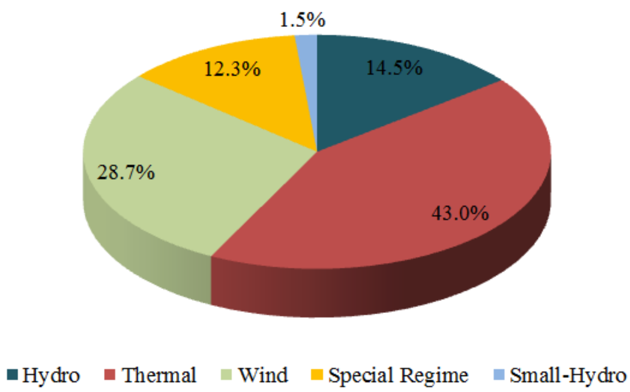

Figure 6.7: Generation technology sharing for the SGS-2030.

rapidly, take load up at the moment of the evaluation. To give an idea, the total generation capacity of these selected units is 24,983 MW and consists of 436 hydro and 48 thermal units. The short and long-term uncertainties of the load are 4% and 2%, respectively.

The first units to be scheduled for production are the wind generators. Small-hydro and special regime units come second and third in the scheduling priority, respectively. Hydro and thermal units are used only after all the aforementioned units. The scheduling priority between thermal and hydro units vary with the strategy selected at the beginning of each sampled year. Pure pumped storage hydro units are the last ones to be scheduled.

Greek Generating System - 2030

The configuration of the GGS for 2030 consists of an expected peak load of 15,665 MW and 26,461 MW of generation installed capacity, which consists of 8,321 generation units with capacities ranging from 17 kW to 600 MW. Figure 6.8 illustrates the Greek generation portfolio for 2030.

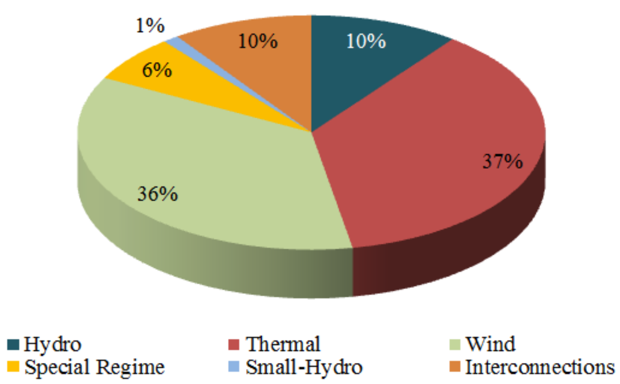

Figure 6.8: Generation technology sharing for the GGS-2030.

The primary reserve is set to 80 MW and the secondary reserve is 615 MW. The units that compose the tertiary reserve are 33 hydro units and 17 thermal units totalling 4,688 MW. This amount may vary according to the available generating units at the moment of the system state evaluation. The short and long-term uncertainties of the load are 2% and 6%, respectively.

The first units to be scheduled for production are the wind and the special regime generators. The small-hydro and the thermal units come second and third in the scheduling priority. Hydro units are the last ones to be used.

Analysis of the Real Generating Systems

Figure 6.9 presents the main generation technologies for each country from the reference to the forecasted generating systems. Portugal had an increase of 8% and 3% in the total installed hydro and renewable technologies, respectively, from 2010 to 2030. On the other hand, the total installed thermal technology decreases about 12%.

Regarding the total generation capacity in Spain, the 2030 scenario presents a reduction in the hydro capacity of 4%. The thermal technology remains the same whilst the renewable technology increases about 4%.

The Greek system presents an expected reduction of the hydro and thermal technologies about 6% and 30%, respectively. On the other hand, the renewable technology increases 36% from 2010 to 2030.

The trend in increasing the participation of renewable energy sources is verified in these countries. However, the thermal generation remains the greatest technology used in Spain and Greece cases. Portugal is the one that, apparently bet on a more balanced and flexible generation system.

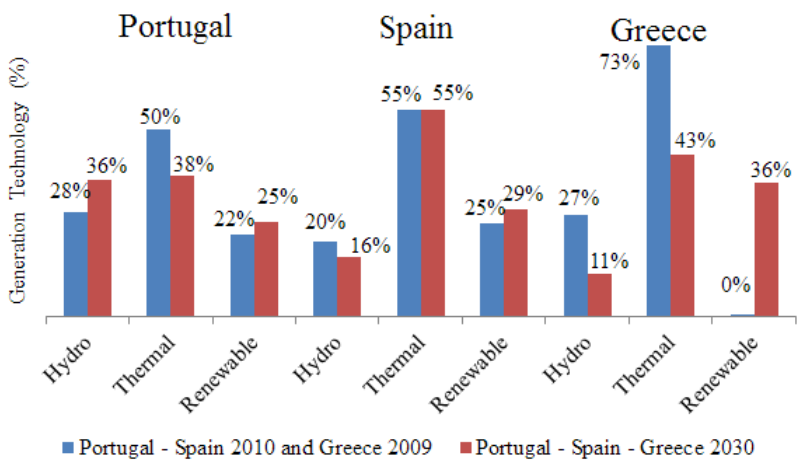

Figure 6.9: Expected generation technology growth.

6.3.3 Electric Vehicle Scenarios

The forecasted EV scenarios were defined in [2], in the framework of the MERGE project. In this report, three EV penetration levels were achieved, from 2010 to 2030, for five countries: Germany, UK, Spain, Portugal and Greece. This thesis will present the performances of the EV models considering the EV scenarios related to Portugal, Spain and Greece.

Following these statements, three EV penetration scenarios and corresponding EV uptake rates (annual sales percentage) are defined with an explanation of the key drivers that underline them.

- Scenario 1 is an estimate of EV uptakes that is the most likely of the three scenarios to occur in reality.
- Scenario 2 is a more aggressive EV uptake scenario than is expected to occur. It was recommended as the prime focus for the MERGE project partners to use in their studies as it will provide better information on the effects of mass integration of EV on the grid.

- Scenario 3 is a very aggressive EV uptake scenario. It is unlikely that the number of EV in this scenario will be exceeded.

Historical vehicle sales and attrition rates are showed in [2]. Although the information provided is related to the year 2010 to 2030, the data used in this thesis is related to the EV penetration scenarios for 2030, as presented in Table 6.1. The percentage value is the EV estimate of the total vehicle fleet.

Table 6.1: EV fleet scenarios for 2030.

Scenarios	Portugal	Spain	Greece
Low	209,254 (2.64%)	1,187,477 (3.60%)	287,432 (3.75%)
Moderate	446,700 (5.64%)	2,534,935 (7.69%)	605,003 (7.90%)
Aggressive	870,955 (11.00%)	4,942,510 (15.00%)	1,148,379 (15.00%)

The penetration levels name (scenario 1, scenario 2 and scenario 3) of reference [2] are changed to low level (EV-LL), moderate level (EV-ML) and aggressive level (EV-AL) scenarios. These scenarios names are referred throughout this chapter.

Controlled models scenario

In order to present the performance of such models, the simulations using the test system considered 100% of the vehicle fleet, in controlled charging mode, of the aggressive scenario. Regarding the V2G strategy, it was considered 70% of the total vehicle fleet of the aggressive scenario. These strategies must have a significant number of vehicles in order to mobilise a considerable amount of electrical energy capacity. Depending on the SOC available, but in the sense of giving an idea for the reader, 70% of the aggressive scenario means about 1812 GWh, considering the battery parameters of the M1 passenger car [2].

6.4 Validation of the Adequacy Evaluation of Generating Systems Tool

As benchmark results can be found in [60], the RTS-96 HW is the chosen test system to perform the validation of the adequacy evaluation of generating systems tool.

For such task, a simple simulation reproducing the Case 2, in [60], was performed using the *Normal scenario* (see [60]), and disregarding the EV models. Table 6.2 presents the static reserve evaluation published in [60] and the ones obtained through the tool used by the author.

Note that only the LOLE index is presented in [60] and, therefore, only the LOLE index reached through the used tool is presented in Table 6.2.

Table 6.2: Validation case of the Static reserve evaluation.

Scenario	**LOLE (h/y)**	β **(%)**
Reference	0.3449	3.34
Proposed tool	0.3456	3.30

Assuming reference [60] as a benchmark case, the comparison between LOLE values leads to the validation of the tool.

As the operating reserve evaluation presented in [60] follows a different approach, the risk indices cannot be compared; however, the risk indices presented in Table 6.3 were estimated using the same scenario of the static reserve evaluation performed for the validation case.

Table 6.3: Operating reserve capacity evaluation of the RTS 96 HW.

	LOLE (h/y)	EENS (MWh/y)	LOLF (occ/y)	LOLD (h/occ)
ORC risk indices	0.7679	129.30	0.4785	1.6047
β (%)	(4.08)	(4.97)	(4.41)	-

This simulation does not consider the short and long-term load uncertainty, however, the wind power forecast error and the generating units forced outages are taken into account.

6.5 Reference Cases Analyses

This section presents the performance of the reliability indices with no EV in the grid. The objective is providing reference values to build a comparison basis.

6.5.1 Reference Case of the IEEE Reliability Test System - 1996 HW

This system follows the description provided in Section 6.3.1. Additionally, the short and long-term uncertainties of the load are included in the simulation parameters. The short-term load uncertainty is 2% whilst the long-term load uncertainty is 0%. The primary and secondary reserves are set to 85 MW and 315 MW, respectively. The static reserve evaluation with no EV, provided the following risk indices.

Table 6.4: Reference case of the Static reserve evaluation.

	LOLE (h/y)	EENS (MWh/y)	LOLF (occ/y)	LOLD (h/occ)
Static risk indices	0.6115	124.08	0.3433	1.7813
β (%)	(3.47)	(4.99)	(2.75)	-

The increase in the reliability indices, from Table 6.2 to Table 6.4, is due to the added load uncertainty in the simulation parameters. Therefore, the expectation that the system load will exceed the available generating capacity is, in average, 0.6115 h/y.

From the ORC evaluation perspective, the additional information about the load uncertainty for the short and long-term increases the risk indices from 0.7679 h/y (see Table 6.4) to 1.6463 h/y.

Table 6.5: Reference case of the Operating reserve capacity evaluation.

	LOLE (h/y)	**EENS (MWh/y)**	**LOLF (occ/y)**	**LOLD (h/occ)**
ORC risk indices	1.6463	388.65	1.2300	1.3384
β **(%)**	(4.03)	(4.99)	(3.62)	-

The LOLE of 1.6463 h/y is the expected average that the system uncertainties exceed the synchronised plus the available fast tertiary reserve capacity.

6.5.2 Reference Cases of the Real Generating Systems

This section presents the performance of the real generating systems with no EV in the grid. Their generating systems configurations for 2030 follow the description given in Section 6.3.2. The stopping criteria for both, static and operating reserve capacity evaluations, is a β convergence of 5% for all risk indices or a maximum number of 10,000 sampled years.

Portuguese Generating System - 2030

Table 6.6 presents the static reserve and ORC evaluations for the PGS 2030 configuration.

Table 6.6: Reserve capacity evaluations - Portuguese reference case.

	LOLE (h/y)	**EENS (MWh/y)**	**LOLF (occ/y)**	**LOLD (h/occ)**
Static risk indices	0.0196	4.40	0.0213	0.9220
ORC risk indices	1.0570	548.31	1.2000	0.8808

The low risk indices indicate a robust configuration for the PGS 2030, from the static reserve and operating reserve capacity perspectives.

Spanish Generating System - 2030

The performance of the SGS for 2030 for the static reserve and ORC evaluations is presented in Table 6.7.

Table 6.7: Reserve capacity evaluations - Spanish reference case.

	LOLE (h/y)	**EENS (MWh/y)**	**LOLF (occ/y)**	**LOLD (h/occ)**
Static risk indices	0.0012	1.31	0.0016	1.25
ORC risk indices	0.2190	190.10	0.3417	0.6409

The high percentage of thermal generation of the SGS for 2030 (see Figure 6.9) is reflected by the low risk indices estimated in this reference case.

Greek Generating System - 2030

The adequacy evaluation of the GGS 2030 provides the reference risk indices used through this chapter. The result of the static reserve and ORC evaluations are presented in Table 6.8.

Table 6.8: Reserve capacity evaluations - Greek reference case.

	LOLE (h/y)	EENS (MWh/y)	LOLF (occ/y)	LOLD (h/occ)
Static reserve	0.6421	346.04	0.3230	1.9879
ORC	2.2090	1,313.08	2.3380	0.9448

From the static evaluation perspective, the low risk indices indicate a robust configuration for the GGS of 2030. Although the LOLE of 2.2090 h/y estimated by the ORC evaluation is still low, some utilities may consider it a system indicator that this configuration is not flexible enough to cope with the system variabilities.

Next section presents the simulation results considering the EV penetration scenarios on the test and real system simulations. These simulations also take into account the different battery charging behaviours. The result comparisons give support to the discussions.

6.6 Results and Discussions

In this section, the EV scenarios were included in the systems configurations described in Section 6.3. This section is organised as follows. Section 6.6.1 presents the results for the static reserve evaluation of the real generating systems under uncontrolled battery charging strategies and for the ORC evaluation of the real generating systems under uncontrolled and controlled charging models. Section 6.6.2 presents the results for the static reserve and ORC evaluations for the RTS 96 HW under uncontrolled charging models using both HPP and NHPP approaches. The use of the controlled charging models for the previous system is presented in Section 6.6.3.

6.6.1 Real Generating Systems

The direct, valley and controlled charging strategies were developed in the framework of the MERGE project. The EV models included in the Sequential Monte Carlo Simulation are the ones that were developed through the HPP approach. An important issue is related to the battery charging coefficient of Equation (4.7) which, in the framework of the MERGE and REIVE projects, was set to 1.0 in order to represent the worse scenario. This value means that a fully battery capacity requirement is assumed for all vehicles that arive at a certain place in the same hour, during the simulation process. The percentage of vehicles in controlled battery charging strategy was also modified regarding the one presented in Section 6.3.3 to 70% with the objective to represent a more realistic situation.

Static Reserve Evaluation - Direct and Valley Charging Strategies - HPP Approach - Portuguese Generating System 2030

This section aims to present the reliability indices of the simulations regarding the PGS for 2030 scenario with and without EV on the grid. Tables 6.9 and 6.10 present the static reserve indices considering direct and valley battery charging strategies in all three scenarios of EV integration.

Table 6.9: Results for the static reserve evaluation of the PGS 2030 - Direct charging strategy.

	EV penetration levels			
	No EV	Low	Moderate	Aggressive
LOLE (h/y)	0.0196	0.0611	0.2110	1.3940
EENS (MWh/y)	4.40	17.61	67.31	530.05
LOLF (occ/y)	0.0213	0.0650	0.2187	1.3210
LOLD (h/occ)	0.9201	0.9400	0.9647	1.0552

The results show that as the EV penetration increases, the performance of the static reserve gets worse. When DC strategy is applied, the LOLE index increases from 0.0196 h/y to 1.3940 h/y. Although the magnitude of the index is not big, the ratio between values is around 71 times. In this sense the static reserve evaluation shows that even considering the worst case scenario, the estimate of the LOLE (1.394 h/y), does not jeopardise the generation system adequacy for 2030, in terms of capacity to deal with the load increase imposed by EV. The LOLE index of 0.0848 h/y of the case using VC strategy, in the aggressive scenario, shows that this strategy can maintain the risk indices in the same magnitude order than the scenario with no EV.

Table 6.10: Results for the static reserve evaluation of the PGS 2030 - Valley charging strategy.

	EV penetration levels			
	No EV	Low	Moderate	Aggressive
LOLE (h/y)	0.0196	0.0196	0.0211	0.0848
EENS (MWh/y)	4.40	4.40	4.52	25.72
LOLF (occ/y)	0.0213	0.0213	0.0230	0.1143
LOLD (h/occ)	0.9201	0.9201	0.9173	0.7426

These differences between direct and valley battery charging strategies reflects the impact of the EV charging behaviour in the power systems from the demand perspective. While the DC strategy allows the EV charging throughout the day, increasing the daily peak demand, the VC strategy commits the EV owner to charge its EV during the valley hours, where the conventional demand is, generally, lower.

Operating Reserve Capacity Evaluation - Direct, Valley and Controlled Charging Strategies - HPP Approach - Portuguese Generating System 2030

Tables 6.11, 6.12 and 6.13 present the reliability indices of the operating reserve capacity evaluation of the PGS for 2030. The results on these tables show that the estimates of the reliability indices of the operating reserve capacity evaluation increase considerably if DC strategy is applied. Considering the aggressive EV penetration scenario, the LOLE increases by 8.4 times regarding the scenario with no EV. It means that the estimates of the reliability indices of the operating reserve capacity might increase considerably towards values that may be considered risky by the utilities when using direct charging in the aggressive penetration scenario.

Table 6.11: Results for the ORC evaluation of the PGS 2030 - Direct charging strategy.

	EV penetration levels			
	No EV	Low	Moderate	Aggressive
LOLE (h/y)	1.0570	1.8020	3.2620	8.8490
EENS (MWh/y)	548.31	1040.25	2082.05	7027.04
LOLF (occ/y)	1.2000	2.0330	3.6860	9.4590
LOLD (h/occ)	0.8808	0.8863	0.8849	0.9355

However, if a VC strategy is used, the LOLE increases only by 1.1 times in the EV aggressive scenario (see Table 6.12). This strategy can take advantage of systems with low conventional demand in the valley hours.

Note that in the EV low scenario the use of the VC strategy can maintain the magnitude order of the reliability indices.

Table 6.12: Results for the ORC evaluation of the PGS 2030 - Valley charging strategy.

	EV penetration levels			
	No EV	Low	Moderate	Aggressive
LOLE (h/y)	1.0570	1.0880	1.2080	1.9910
EENS (MWh/y)	548.31	567.46	643.66	1195.01
LOLF (occ/y)	1.2000	1.2440	1.3960	2.4440
LOLD (h/occ)	0.8808	0.8745	0.8653	0.8146

On the other hand, the CC strategy can decrease the LOLE index from 1.0570 h/y to 1.0370 h/y in the EV low scenario. The ability of contributing to the operating reserve of the controlled battery charging strategy is due to the postponement of the EV charging to a later moment, when the conventional demand is lower (usually in the valley hours). This strategy makes possible to maintain a similar performance of the scenario with no EV, mitigating the EV impact on the system adequacy.

Table 6.13: Results for the ORC evaluation of the PGS 2030 - Controlled charging strategy.

	EV penetration levels			
	No EV	Low	Moderate	Aggressive
LOLE (h/y)	1.0570	1.0370	1.0480	1.1400
EENS (MWh/y)	548.31	543.14	558.43	601.09
LOLF (occ/y)	1.2000	1.1780	1.1850	1.3000
LOLD (h/occ)	0.8808	0.8803	0.8843	0.8769

By analysing the performance of the static reserve and operating reserve capacity, it is possible to state that the 2030 configuration of the Portuguese generation system is adequate to accommodate the expected additional load of EV with exception of the EV aggressive scenario using direct battery charging strategy.

Static Reserve Evaluation - Direct and Valley Charging Strategies - HPP Approach - Spanish Generating System 2030

Tables 6.14 and Table 6.15 present the static reserve risk indices of the SGS for 2030. The results demonstrated that the use of DC strategy, in the aggressive scenario, increases the LOLE regarding the scenario with no EV from 0.0012 h/y to 0.1644 h/y. Although, the later means 137 times the scenario with no EV, the LOLE index is still low.

Table 6.14: Results for the static reserve evaluation of the SGS 2030 - Direct charging strategy.

	EV penetration levels			
	No EV	Low	Moderate	Aggressive
LOLE (h/y)	0.0012	0.0061	0.0230	0.1644
EENS (MWh/y)	1.31	7.98	37.16	320.15
LOLF (occ/y)	0.0016	0.0066	0.0210	0.1377
LOLD (h/occ)	0.7500	0.9242	1.0952	1.1938

Regarding the VC strategy, the difference is even smaller than the DC strategy. The VC strategy presents, in the EV-AL scenario, a LOLE index of 0.0447 h/y.

From the static reserve perspective, the configuration of the Spanish generating system is robust enough to support the forecasted EV scenarios for 2030

Table 6.15: Results for the static reserve evaluation of the SGS 2030 - Valley charging strategy.

	EV penetration levels			
	No EV	Low	Moderate	Aggressive
LOLE (h/y)	0.0012	0.0012	0.0019	0.0447
EENS (MWh/y)	1.31	1.31	1.71	80.64
LOLF (occ/y)	0.0016	0.0016	0.0030	0.0666
LOLD (h/occ)	0.7500	0.7500	0.6333	0.6711

independent of the EV battery charging strategy used.

Operating Reserve Capacity Evaluation - Direct, Valley and Controlled Charging Strategies - HPP Approach - Spanish Generating System 2030

The results demonstrate that the estimate of the reliability indices, presented in Tables 6.16, 6.17 and 6.18, increase considerably with the EV penetration level. If DC charging is used in the aggressive scenario, the LOLE increases by 4 times regarding the scenario with no EV. It is still low, highlighting the robustness of the system, from the static reserve perspective.

Table 6.16: Results for the ORC evaluation of the SGS 2030 - Direct charging strategy.

	EV penetration levels			
	No EV	Low	Moderate	Aggressive
LOLE (h/y)	0.2190	0.2640	0.3707	0.9374
EENS (MWh/y)	190.10	267.29	493.76	2000.99
LOLF (occ/y)	0.3417	0.4147	0.5753	1.3490
LOLD (h/occ)	0.6409	0.6366	0.6443	0.6948

At the same EV penetration level, aggressive scenario, the use of VC strategy can increase the LOLE index by 9 times, showing that concentrating the entire EV load in the valley period, may result in a change of the peak consumption from the usual peak hours to the valley hours.

In this case, from the operational reserve perspective, it might be better to mix the EV battery charging strategies between direct and valley charging strategies, instead of accumulating all EV load in the valley hours.

Table 6.17: Results for the ORC evaluation of the SGS 2030 - Valley charging strategy.

	EV penetration levels			
	No EV	Low	Moderate	Aggressive
LOLE (h/y)	0.2190	0.2190	0.7172	1.9950
EENS (MWh/y)	190.10	190.10	685.43	2869.18
LOLF (occ/y)	0.3417	0.3417	5.0410	2.6845
LOLD (h/occ)	0.6409	0.6409	0.1422	0.7431

The CC strategy remains the best one to mitigate the EV impact on the SGS. This strategy allows the EV contribution to the operating reserve, resulting in a LOLE index lower than the scenario with no EV.

Table 6.18: Results for the ORC evaluation of the SGS 2030 - Controlled charging strategy.

	EV penetration levels			
	No EV	Low	Moderate	Aggressive
LOLE (h/y)	0.2190	0.1505	0.1505	0.1456
EENS (MWh/y)	190.10	170.60	170.60	132.90
LOLF (occ/y)	0.3417	0.1850	0.1850	0.1863
LOLD (h/occ)	0.6409	0.8135	0.8135	0.7815

The results have shown that the configuration of the Spanish generating system is adequate to meet the additional forecasted EV load for 2030.

Static Reserve Evaluation - Direct and Valley Charging Strategies - HPP Approach - Greek Generating System 2030

Tables 6.19 and 6.20 present the static reserve indices of the adequacy evaluation of the GGS for 2030. The results show that the LOLE increases expressively as more

EV is integrated in the system. The use of DC strategy, in the EV-AL scenario, results in a LOLE increase of 20 times, in relation to the scenario with no EV, which is about 13.014 h/y.

Table 6.19: Results for the static reserve evaluation of the GGS 2030 - Direct charging strategy.

	EV penetration levels			
	No EV	Low	Moderate	Aggressive
LOLE (h/y)	0.6421	1.4340	3.3670	13.0140
EENS (MWh/y)	346.04	732.52	1753.31	7559.81
LOLF (occ/y)	0.3230	0.7847	1.8540	6.8990
LOLD (h/occ)	1.9879	1.8274	1.8160	1.8863

On the other hand, when VC strategy is applied, the increase is only of 4 times, resulting in a LOLE of 2.668 h/y.

Table 6.20: Results for the static reserve evaluation of the GGS 2030 - Valley charging strategy.

	EV penetration levels			
	No EV	Low	Moderate	Aggressive
LOLE (h/y)	0.6421	0.6566	0.7498	2.6680
EENS (MWh/y)	346.04	354.18	398.35	1403.45
LOLF (occ/y)	0.3230	0.3493	0.5287	3.4760
LOLD (h/occ)	1.9879	1.8797	1.4181	0.7675

The use of DC strategy leads the GGS to a risk system state. Although the increase of the LOLE index, using valley battery charging strategy, is significant, when compared to the case with no EV, the LOLE index is still low. This strategy can maintain the adequacy of the system, from the static reserve perspective.

Operating Reserve Capacity Evaluation - Direct, Valley and Controlled Charging Strategies - HPP Approach - Greek Generating System 2030

The reliability indices of the operating reserve capacity increase as the penetration level of EV increases, if DC and/or VC strategies are used (see Tables 6.21 and 6.22).

The EV penetration level have impacted in the generation adequacy of the Greek system. Even in the low and moderate scenarios the uncontrolled charging strategies are not able to maintain the risk indices in the same level as the simulation performed with no EV in the grid.

Table 6.21: Results for the ORC evaluation of the GGS 2030 - Direct charging strategy.

	EV penetration levels			
	No EV	Low	Moderate	Aggressive
LOLE (h/y)	2.2090	4.2000	8.4880	26.0170
EENS (MWh/y)	1313.08	2895.72	6663.19	24066.34
LOLF (occ/y)	2.3380	3.9190	7.0400	17.7120
LOLD (h/occ)	0.9448	1.0717	1.2056	1.4688

A particularly noteworthy remark is the LOLE obtained using DC strategy in the aggressive scenario. As it is showed in Table 6.21, this value is very high (26.017 h/y) when compared to the scenario with no EV or even with those obtained using CC strategy (see Table 6.23).

The VC strategy is able to acomodate the EV penetration for the EV low and moderate scenarios. The aggressive scenario has reached a LOLE of 9.2060 h/y when a VC strategy is used.

Table 6.22: Results for the ORC evaluation of the GGS 2030 - Valley charging strategy.

	EV penetration levels			
	No EV	Low	Moderate	Aggressive
LOLE (h/y)	2.2090	2.3550	2.7070	9.2060
EENS (MWh/y)	1313.08	1450.92	1851.64	5990.01
LOLF (occ/y)	2.3380	2.5480	3.0490	17.5580
LOLD (h/occ)	0.9448	0.9242	0.8878	0.5243

Table 6.23 presents the reliability indices of the operating reserve capacity evaluation considering the deployment of the CC strategy. The ability of this strategy in contributing to the operating reserve decreased the risk indices of the GGS for 2030.

Table 6.23: Results for the ORC evaluation of the GGS 2030 - Controlled charging strategy.

	EV penetration levels			
	No EV	Low	Moderate	Aggressive
LOLE (h/y)	2.2090	1.6680	1.6680	1.6670
EENS (MWh/y)	1313.08	1166.39	1165.68	1165.48
LOLF (occ/y)	2.3380	1.6300	1.6310	1.6310
LOLD (h/occ)	0.9448	1.0233	1.0226	1.0220

The GGS may take advantage of the use of advanced control strategies for charging EV in the 2030 configuration of the Greek generation system is of the utmost importance in order to maintain the adequacy of the operating reserve capacity in adequate levels.

6.6.2 IEEE Reliability Test System 1996 HW - Uncontrolled Charging EV Models

This section presents the simulations performed using the uncontrolled battery charging strategies. The simulations follow the EV scenarios given in Section 6.3.3. The stopping criteria is a β convergence of 5% for all risk indices or a maximum number of 10,000 sampled years.

The results are presented considering the HPP and NHPP approaches. The battery charging coefficient α of Equation (4.7), which calculates the charging time through the HPP approach, is set to 0.5. In this sense, the charging time assumed in the HPP approach becomes equal to the mean charging time of the NHPP, presented in Equation (4.10). Therefore, the results calculated using both HPP and NHPP approaches can be compared.

Static Reserve Evaluation - Direct and Valley Charging Strategies - HPP Approach - RTS-96 HW

The goal of this section is to demonstrate the impact that EV, approached by the homogeneous Poisson process, might have on the reliability of the static reserve. Figure 6.10, shows the system performance for the EV-LL scenario. The analysis is made throughout the comparison of the risk indices estimated through the reference and the EV penetration scenarios.

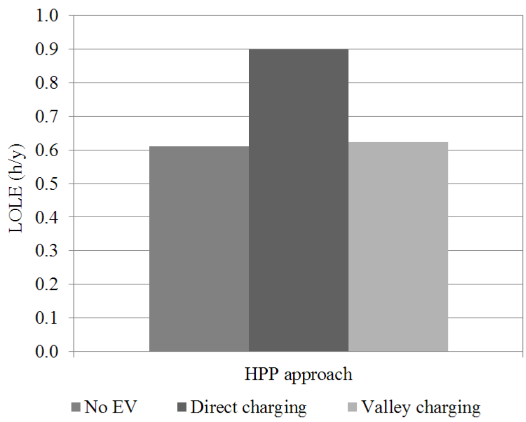

Figure 6.10: Results for the static reserve evaluation - EV-LL - HPP approach.

The LOLE of 0.6115 h/y is the reference case, where no EV load is considered. The addition of EV under DC strategy lead to a LOLE increase to 0.8989 h/y. For such case, this result means the expected number of hours in which the system load level exceeds the available system capacity.

The LOLE of 0.6232 h/y is estimated through the use of a VC strategy. This slight increase, if compared with the case with no EV in the grid, is due to the additional EV load in the valley hours.

Figure 6.11 presents the LOLE index for both uncontrolled battery charging strategies, when an EV-ML scenario is considered. The LOLE index of this case demonstrated that the use of DC strategy can increase the LOLE index to 1.3559 h/y. The deployment of the VC strategy results in an increase 0.6565 h/y.

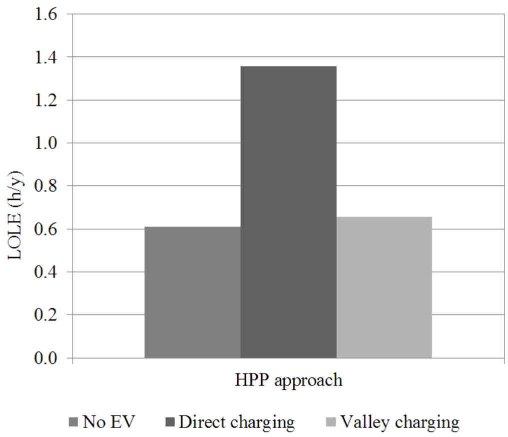

Figure 6.11: Results for the static reserve evaluation - EV-ML - HPP approach.

The EV-AL scenario (see Figure 6.12) shows that the estimated risk index almost double. The direct and valley battery charging strategies led to the LOLE index of 2.6510 h/y and 1.1856 h/y, respectively. Although this scenario has presented a greater impact than the EV-ML and EV-LL scenarios, the estimated risk indices are still low, assuring that the configuration of the generating system is adequate to accept this level of EV according to these battery charging strategies and EV penetration levels.

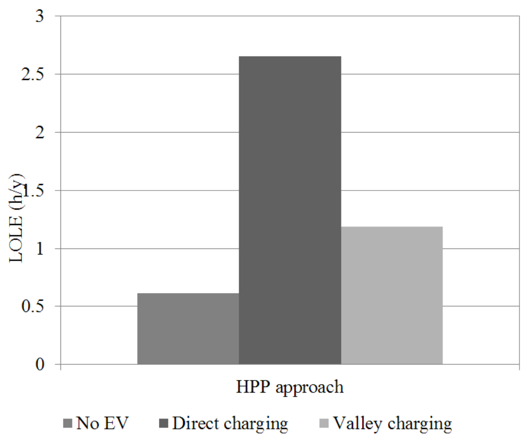

Figure 6.12: Results for the static reserve evaluation - EV-AL - HPP approach.

The difference between the DC and VC strategies is that the conventional load is, generally, bigger during the day. As the DC strategy follows the mobility profile, it is expected that it increases the conventional peak load. Therefore, the DC strategy, in general, has a greater impact on the system adequacy than the VC strategy. A summary of all risk indices is given in Table 6.24.

Table 6.24: General results for the static reserve evaluation - HPP approach.

Charging Strategy	LOLE (h/y)		EENS (MWh/y)		LOLF (occ/y)		LOLD (h/occ)	
	DC	VC	DC	VC	DC	VC	DC	VC
No EV	0.6115		124.08		0.3433		1.7813	
Low	0.8989	0.6232	180.72	124.23	0.5438	0.3860	1.6529	1.6143
Moderate	1.3559	0.6565	279.23	133.40	0.8041	0.3969	1.6863	1.6539
Aggressive	2.6510	1.1856	575.42	374.09	1.4845	0.9428	1.7857	1.2575

From the static perspective and considering the uncontrolled charging models, the VC strategy is the adequate one to maintain the risk indices low, up to a certain level of EV deployment (see Table 6.24), at the same order of the ones estimated in the scenario with no EV.

Operating Reserve Capacity Evaluation - Direct and Valley Charging Strategies - HPP Approach - RTS-96 HW

As a load, the EV also affects the ORC evaluation. The load increase means more synchronised capacity and less available capacity to meet the system requirements and uncertainties. Figure 6.13 presents the risk indices estimated through the ORC evaluation taking the EV-LL scenario into account.

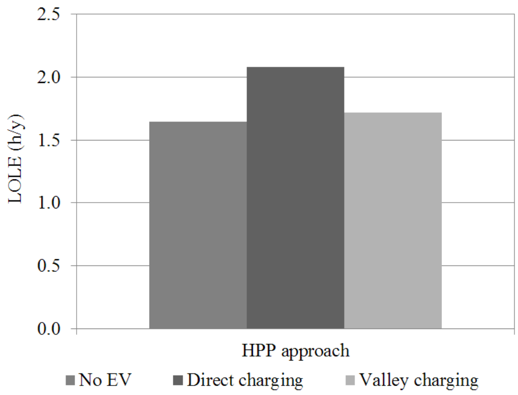

Figure 6.13: Results for the ORC evaluation - EV-LL - HPP approach.

In this case, the LOLE index increased from 1.6463 h/y to 2.0795 h/y when the DC strategy is deployed. On the other hand, the use of the VC strategy was capable to maintain the risk indices almost at the same level of the no EV scenario leading to 1.7161 h/y.

The impact of the EV-ML scenario is presented in Figure 6.14. The DC strategy presented a LOLE index of 2.9135 h/y whilst the VC strategy is 1.7478 h/y. In this case, the valley charging strategy allows the penetration of more vehicles in the system maintaining the risk indices low. Note that almost there are no difference between the LOLE index, considering the VC strategy, of the EV-LL and EV-ML scenarios. This means that if EV owners decide to charge their vehicles during the dawn, the system can accept an increase of EV with almost no impact in the system adequacy.

The impact of the EV-AL scenario on the ORC evaluation is showed in Figure 6.15. From this, one can see the increase in the LOLE index when both direct and valley strategies, are used. From the use of a DC strategy, the estimated LOLE index is 4.8896 h/y whilst the use of a VC strategy produces a LOLE of 2.3239 h/y. In this case, the DC strategy presented a risk index that may compromise the system adequacy to cope with the system uncertainties.

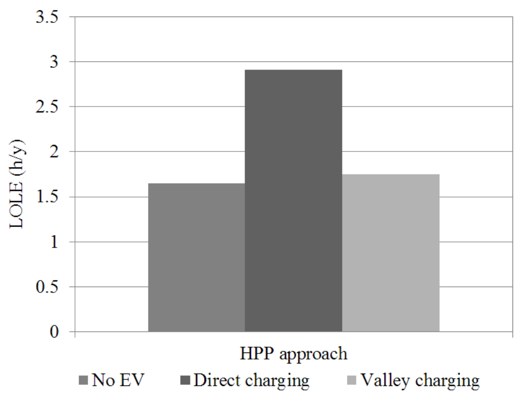

Figure 6.14: Results for the ORC evaluation - EV-ML - HPP approach.

Table 6.25 presents all risk indices calculated during the simulation process. These simulations show that the EV load behaviour, in uncontrolled battery charging modes, mainly depends of the EV penetration level.

From the simulations performed to the HPP approach it is possible to stress the necessity of using the valley battery charging, up to a certain level of EV deployment, in order to keep the risk indices low. For uncontrolled battery charging strategies the number of synchronised generating units increase as the number of EV increase in order to meet this new load. Therefore, the total available reserve to deal with the uncertainties of the system, which are the load

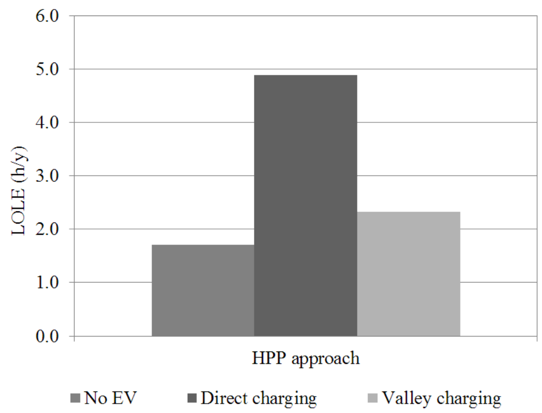

Figure 6.15: Results for the ORC evaluation - EV-AL - HPP approach.

Table 6.25: General results for the ORC evaluation - HPP approach.

Charging Strategy	LOLE (h/y) DC	LOLE (h/y) VC	EENS (MWh/y) DC	EENS (MWh/y) VC	LOLF (occ/y) DC	LOLF (occ/y) VC	LOLD (h/occ) DC	LOLD (h/occ) VC
No EV	1.6463		388.65		1.2300		1.3384	
Low	2.0795	1.7161	649.42	614.40	1.5394	1.0651	1.3508	1.6111
Moderate	2.9135	1.7478	810.84	628.77	2.0704	1.1188	1.4072	1.5621
Aggressive	4.8896	2.3239	1613.14	988.72	3.3381	2.1427	1.4647	1.0845

and wind power forecast errors and the forced outages of the generating units, might not be sufficient.

Static Reserve Evaluation - Direct and Valley Charging Strategies - NHPP Approach - RTS-96 HW

The impact of the EV models, approached by the non-homogeneous Poisson process, is evaluated throughout this section. This approach allows a more detailed representation of the EV mobility, evaluating the system adequacy for each identified EV arrival.

Figure 6.16, presents the LOLE index of the uncontrolled battery charging strategies. The use of a DC strategy results in a LOLE of 0.6522 h/y whilst the LOLE index reached through the use of a VC strategy is 0.6168 h/y.

At this EV penetration level, the difference from the HPP approach may be highlighted when the EV are under direct battery charging. The differences between the approaches are regarding the individual EV arrivals, provided by the NHPP, and the different estimation of the charging time. In the HPP approach it is assumed a fixed charging time whilst in the NHPP approach, the charging time has a uniformly distributed random term in its equation, which produces different charging times for each EV. Even though the mean of the charging time, in the NHPP approach, is the same of the HPP, when α variable is 0.5, the

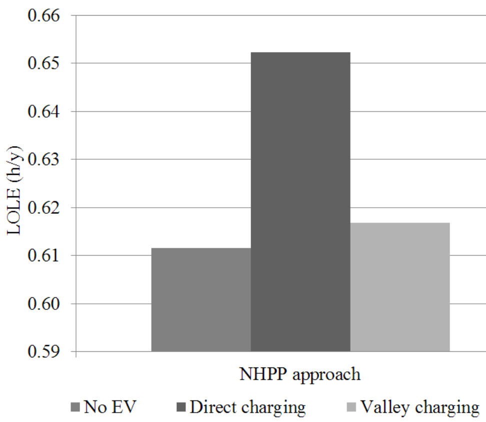

Figure 6.16: Results for the static reserve evaluation - EV-LL - NHPP approach.

chronological sequence of events of the NHPP plus the disaggregation characteristic of the arrivals attenuates the impact of the EV load in the reliability indices. This observation can be confirmed by the results presented through this section.

The simulation using the EV-ML scenario shows slight increase in the LOLE index from both direct and valley battery charging strategies, which are 0.8219 h/y and 0.6300 h/y, respectively (see Figure 6.17). For the same simulation cases, using the HPP approach, the estimates are 1.3559 h/y and 0.6565 h/y. Even considering that the differences between indices are not large, it is possible to note that the HPP results in a greater impact, on the system adequacy, than the NHPP.

A significant increase in the LOLE index, is identified in Figure 6.18, which presents the results of the EV-AL scenario. However, the LOLE index of 2.1815 h/y, when the DC strategy is applied, and of 0.9606 h/y, when the VC strategy is used, are still low. The LOLE indices estimated in the HPP approach are 2.6510 h/y and 1.1856 h/y for both direct and valley charging strategies, respectively.

Table 6.26 presents all risk indices of the performed simulations. Regarding the battery charging strategies, the representation of the EV arrivals, when the NHPP approach is applied, lead to an attenuation of the EV impact in the

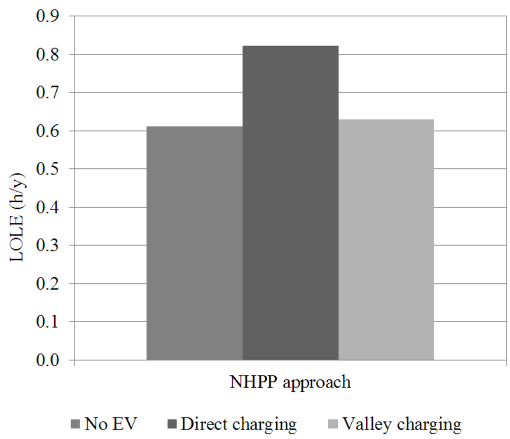

Figure 6.17: Results for the static reserve evaluation - EV-ML - NHPP approach.

system adequacy.

On one hand, the computational effort using the HPP is much lower than the use of the NHPP, however, this subject will be presented later. On the other hand, the NHPP allows the battery charging requirement for each vehicle, providing a more detailed representation of the EV behaviour.

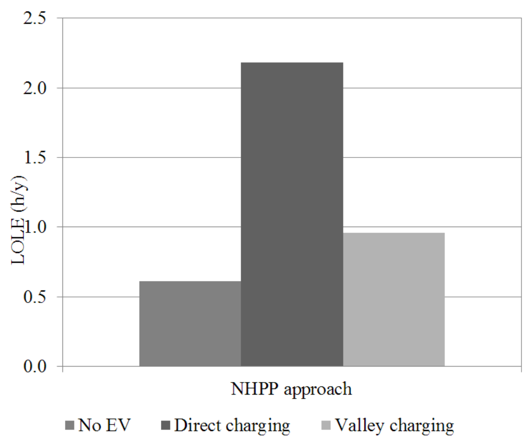

Figure 6.18: Results for the static reserve evaluation - EV-AL - NHPP approach.

Table 6.26: General results for the static reserve evaluation - NHPP approach.

Charging Strategy	LOLE (h/y)		EENS (MWh/y)		LOLF (occ/y)		LOLD (h/occ)	
	DC	VC	DC	VC	DC	VC	DC	VC
No EV	0.6115		124.08		0.3433		1.7813	
Low	0.6522	0.6168	125.54	124.47	0.4047	0.3465	1.6116	1.7801
Moderate	0.8219	0.6300	175.83	127.32	0.6772	0.3774	1.2136	1.6691
Aggressive	2.1815	0.9606	497.57	192.86	1.8551	0.7137	1.1759	1.3459

Operating Reserve Capacity Evaluation - Direct and Valley Charging Strategies - NHPP Approach - RTS-96 HW

The reference case (with no EV in the grid) of the operating reserve capacity evaluation produces a LOLE index of 1.6463 h/y, as showed in Figure 6.19, which presents the results for the EV-LL scenario. Using a DC strategy, the LOLE index reaches 1.8005 h/y. For the same situation, the simulation performed with the HPP approach estimated a LOLE index of 2.0795 h/y. The LOLE index estimated by the use of a VC strategy is 1.6615 h/y using the NHPP approach. The HPP approach estimated a LOLE index of 1.7161 h/y using the same EV scenario.

Figure 6.20 presents the results of the LOLE for the EV-ML scenario. Both direct

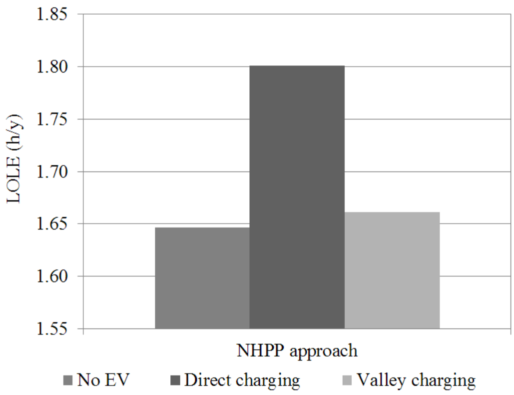

Figure 6.19: Results for the ORC evaluation - EV-LL - NHPP approach.

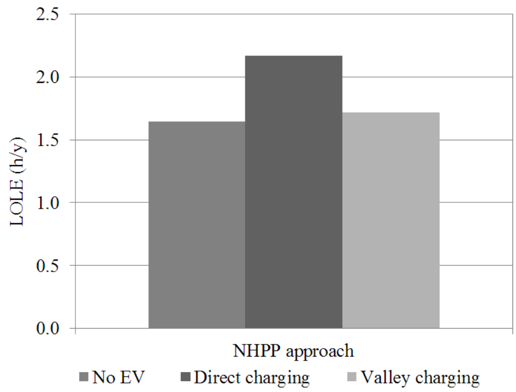

Figure 6.20: Results for the ORC evaluation - EV-ML - NHPP approach.

and valley battery charging strategies increased their LOLE index as consequence of the increased EV load. While the LOLE index, estimated through the NHPP, is 2.1671 h/y and 1.7166 h/y for both direct and valley battery charging strategies, the HPP estimates a LOLE index of 2.9135 h/y and 1.7478 h/y, respectively.

At this EV penetration level, the result differences between both HPP and NHPP approaches are not large. This differences have a slight increase when the EV penetration level increases and the DC strategy is used. Figure 6.21 presents the simulations considering the EV-AL scenario.

The LOLE index estimated through the use of a DC strategy is 3.8674 h/y. The VC strategy estimates a LOLE of 2.3155 h/y. The HPP approach, for the same scenario, estimated a LOLE index of 4.8896 h/y, which may compromise the system adequacy.

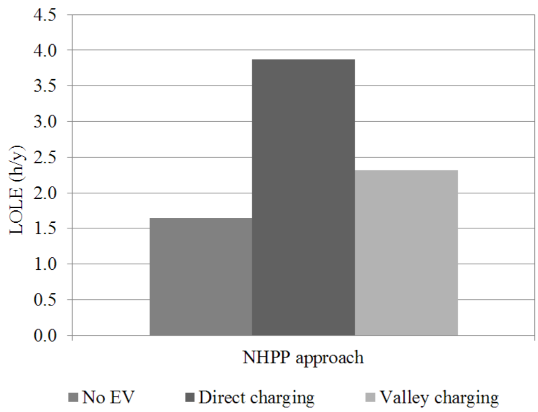

Figure 6.21: Results for the ORC evaluation - EV-AL - NHPP approach.

The LOLE index estimated through the NHPP approach (see Figure 6.21) is also significant. The VC strategy for both HPP and NHPP approaches has kept the risk indices low. Table 6.27 summarises all risk indices of the performed simulations using the NHPP approach.

Next section will present the results for the controlled charging models. The differences between the HPP and NHPP approaches, aforementioned, are also identified in the next simulations. However, the NHPP approach allows the possibility of estimate the SOC of each EV for the V2G strategy, which is not possible through the use of the HPP approach.

Table 6.27: General results for the ORC evaluation - NHPP approach.

Charging Strategy	LOLE (h/y)		EENS (MWh/y)		LOLF (occ/y)		LOLD (h/occ)	
	DC	VC	DC	VC	DC	VC	DC	VC
No EV	1.6463		388.65		1.2300		1.3384	
Low	1.8005	1.6615	483.01	391.91	1.1702	1.2422	1.5385	1.3375
Moderate	2.1671	1.7166	738.07	400.09	1.6550	1.2989	1.3094	1.3216
Aggressive	3.8674	2.3155	1314.37	528.88	4.5306	1.9031	0.8536	1.2167

6.6.3 IEEE Reliability Test System 1996 HW - Controlled Charging Models

The controlled battery charging strategy is able of taking into account the possibility of controlling the charging rate or even postponing the battery charging for another moment, when the ORC is threatened. Therefore, when a failure state occurs in the ORC evaluation, the EV in controlled charging mode might be turned off to be charged later.

The V2G strategy takes into account the possibility of injecting electric energy from the batteries back to the grid, when a deficit of the operating reserve capacity is identified or when the wind variability is greater than an established threshold.

In one hand, the mobilisation of the EV can lead to the increase of the operating reserve by injecting the electric energy stored in their batteries. On the other hand, the use of V2G might mitigate the wind power variation.

The simulation parameters are the ones presented in the reference case (Section 6.5.1). The stopping criterion is β convergence of 5% or 10,000 sampled years.

Operating Reserve Capacity Evaluation - Controlled Charging Strategy - HPP Approach - RTS-96 HW

Figure 6.22, presents the effect of the controlled battery charging strategy through the LOLE index using the HPP approach. The LOLE index of 1.2943 h/y shows the effective contribution of the battery charging postponement for the operating reserve, once the reference of this index is 1.6463 h/y.

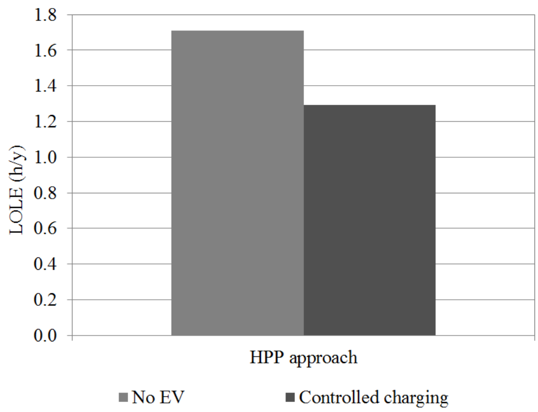

Figure 6.22: Results for the ORC evaluation - EV-AL - HPP approach - Controlled strategy.

Table 6.28 presents all risk indices calculated in this simulation. From that it is possible to confirm the EV contribution to the operating reserve capacity. Assuming an aggregation entity that is able to send a signal to the EV/charging point, in order to postpone the battery charging, the generating units synchronised to meet the EV load will meet the system uncertainties.

If the capacity of these generating units is enough to meet the system uncertainties that exceed the operating reserve level, then the system failure state is solved.

Table 6.28: General results for the ORC evaluation - HPP approach - Controlled strategy.

	LOLE (h/y)	EENS (MWh/y)	LOLF (occ/y)	LOLD (h/occ)
Charging Strategy	CC	CC	CC	CC
No EV	1.6463	388.65	1.2300	1.3384
Aggressive	1.2943	453.07	0.8347	1.5506

Operating Reserve Capacity Evaluation - Controlled Charging Strategy - NHPP Approach - RTS-96 HW

This case performs the evaluation of the reliability indices using the NHPP approach. The estimated LOLE index is 1.5839 h/y, which shows the improvement of the system adequacy under a deployment of the controlled charging strategy. Figure 6.23 presents this effect.

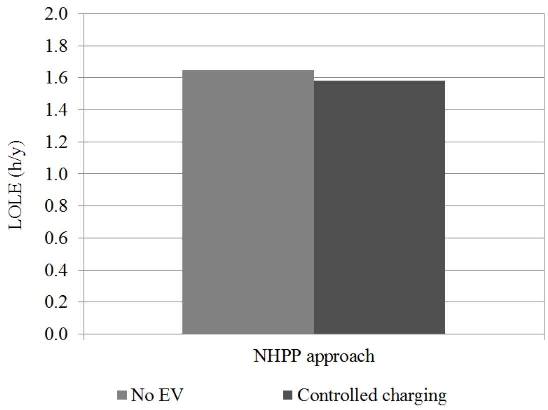

Figure 6.23: Results for the ORC evaluation - EV-AL - NHPP approach - Controlled strategy.

Compared to the HPP case, whose result presented a LOLE index of 1.2943 h/y, the use of the NHPP approach may attenuate this effect. As mentioned before, the detailed representation of the EV arrivals may mitigate this impact. Table 6.29 presents the estimated risk indices for this simulation.

Table 6.29: General results for the ORC evaluation - NHPP approach - Controlled strategy.

Charging Strategy	LOLE (h/y)	EENS (MWh/y)	LOLF (occ/y)	LOLD (h/occ)
	CC	CC	CC	CC
No EV	1.6463	388.65	1.2300	1.3384
Aggressive	1.5839	383.91	1.1721	1.3512

Operating Reserve Capacity Evaluation - V2G Charging Strategy - NHPP Approach - RTS-96 HW

The main advantage of the NHPP approach is the possibility of monitoring the battery SOC of each EV. Therefore, the next simulations will present the results provided by this model under two different operational strategies: to provide an additional support to the operating reserve capacity and to compensate the wind power variation.

V2G - Operating Reserve Capacity Support

Table 6.30 presents the conventional reliability indices related to the evaluation of the RTS-96 HW. The LOLE index of the case with no EV is decreased from 1.6463 h/y to 1.0236 h/y, when the V2G strategy is applied. Comparing to the previous case, which considers the CC strategy, the LOLE index reached through the use of V2G decreases from 1.5839 h/y to 1.0236 h/y. This difference is regarding the increase of the system capacity. This surplus of capacity is then used to deal with the system uncertainties.

Table 6.30: General results for the ORC evaluation - NHPP approach - V2G strategy.

Charging Strategy	LOLE (h/y)	EENS (MWh/y)	LOLF (occ/y)	LOLD (h/occ)
	V2G	V2G	V2G	V2G
No EV	1.6463	388.65	1.2300	1.3384
Aggressive	1.0236	232.69	0.7973	1.2838

At the same moment that the vehicles are injecting electric energy back to the grid, they leave the battery charging mode. Therefore, the availability of the generating capacity is greater than the case that uses CC strategy. The presented results show the effective EV contribution to the operating reserve capacity regarding the use of controlled charging strategies.

V2G - Wind Power Variability Compensation

The V2G model was also tested through a different operational strategy. The possibility of charging/discharging vehicle batteries was used to compensate the wind power forecast error or, in other words, the wind power variation. This situation is analogue to the storage stationary battery systems, presented in Chapter 5, which are able to mitigate the impact of the wind power variation. The goal of this simulation is to verify if the V2G strategy is able to decrease the wind power variation by the injection of electrical energy in the grid, in terms of capacity. The following electrical parameters for each battery were used in this simulation. A minimum and maximum battery SOC of 30% and 80%, respectively. The maximum charge and discharge rates are 3 kWh/h and 9 kWh/h and, the charging/discharging efficiency is 97.5%.

Figure 6.24 presents the average SOC representation of a sampled day and the wind power forecast error with and without applying the V2G strategy. Different of the stationary SBS, the EV have a distributed aspect. This operational strategy may be applied in modern power systems, as smart grids. In this sense, the EV mobilisation may compensate the RES variation improving their performances.

Note that the "WFE - after" presents a decrease in its variability due to the V2G strategy. In this environment, suitable forecasting methods are important to

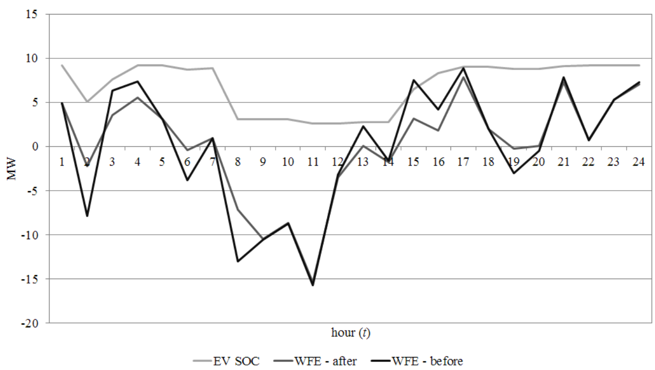

Figure 6.24: Charge/Discharge cycle of the EV batteries - V2G strategy.

provide enough information to the decision makers, as the system operators, in order to mobilise the EV to support this type of operational strategy.

6.7 Computational Burden

The performance of the HPP and NHPP approaches is presented in Table 6.31, considering the IEEE RTS 1996 HW. The desktop computer description used is an Intel Core i7-2600 CPU 3.4 GHz and 8 GB of RAM.

Table 6.31: Elapsed CPU Time - RTS-96 HW Simulation Cases.

	No EV	**Low**		**Moderate**		**Aggressive**		
		DC	**VC**	**DC**	**VC**	**DC**	**VC**	**CC**
HPP	$\approx$ 2 h	$\approx$ 1 h	$\approx$ 2 h	$\approx$ 45 min.	$\approx$ 2 h	$\approx$ 30 min.	$\approx$ 40 min.	$\approx$ 1 h
NHPP	$\approx$ 10.5 h	$\approx$ 10 h	$\approx$ 10.5 h	$\approx$ 9.5 h	$\approx$ 10.5 h	$\approx$ 5.5 h	$\approx$ 9.5 h	$\approx$ 4.5 h

In this sense, the main differences between the HPP and NHPP approaches lie on the clustered and individual monitoring of the EV arrivals. The NHPP approach generates a much greater number of EV arrivals than the HPP approach, increasing the computational effort.

6.8 Final Remarks

This chapter has presented several simulations of test and real systems in order to demonstrate the EV impact on the security of supply. The evaluation is made through the reliability indices analysis provided by the SMCS process.

For such task, three EV scenarios were used regarding their penetration level in the electric systems: low, moderate and aggressive. The test system was assessed by the use of different proposed EV scenarios and battery charging strategies.

From the uncontrolled charging models, the use of the valley hours to charge EV batteries has been a good strategy to keep the reliability indices on the same level as the case with no EV in the grid. However, the impact on the system adequacy, regarding the uncontrolled battery charging strategies, increases as the EV deployment increase. In order to effectively alleviate the EV impact on the system adequacy, the controlled battery models should be applied. They have demonstrated the best system performance to mitigate the EV impact and to provide ancillary services to the power systems.

Regarding the real system assessments, only the HPP approach was considered. The PGS, SGS and GGS have shown that the system configurations are robust enough, from the static reserve perspective, to receive a massive EV penetration scenario without system reinforcement, excepting by some cases where uncontrolled charging strategies were considered. The controlled charging strategy has demonstrated the most suitable one to mitigate the EV impact on the system adequacy. These results point out that under adequate control schemes, more vehicles can be included in the power systems without compromising the system adequacy.

Regarding the used approaches to model the EV load, the results have shown that there are no large differences between the estimated risk indices using both HPP and NHPP approaches. Therefore, from the computational effort perspective, the use of the HPP may is more adequate to achieve the reliability indices to measure the system adequacy using the DC, VC and CC strategies. However, the detailed representation of the EV arrivals provided by the NHPP approach makes it possible to monitor the individual charging requirement and battery SOC of the EV. This feature allowed the development of a V2G strategy considering a more realistic behaviour of the vehicles.

Chapter 7

Conclusions and Future Work

This dissertation has presented the developments carried out within the objectives' framework proposed in Chapter 1. The main conclusions, contributions and the identification of some research topics for future work are presented throughout this chapter.

7.1 Conclusions

A stochastic methodology for developing EV models has been proposed, in order to evaluate their impact on the adequacy of the security of supply in systems with high integration level of RES. The conclusions are divided in proposed modelling methodology, EV charging strategies and real system analysis.

The main conclusions regarding the developed methodologies are:

- The proposed EV models based on the HPP estimate the number of EV arrivals, which proceed to battery charging, in order to calculate the EV load taking into account its mobility behaviour. This approach aggregates the counted arrivals in an hourly basis promoting less computational effort and, consequently, faster results. However, the fixed battery charging requirement, assumed in this approach, has produced a slight different estimates of the reliability indices when compared to the NHPP approach.

- The proposed EV models based on the NHPP estimate the individual EV arrivals addressing the arrival time on the problem. For each EV arrival is estimated a battery charging time, which is calculated based on an uniform distribution, in order to represent different battery charging requirement for each vehicle. The disaggregated EV arrivals and the way how the battery charging time is estimated are the main differences between both HPP and NHPP approaches. These differences led to an attenuation of the EV impact on the reliability indices when the NHPP is applied. Moreover, the NHPP algorithm clearly requires more computational effort increasing the simulation time on account of the EV penetration level increases. On the other hand, the NHPP allows the V2G modelling, once it is possible to monitor the individual arrival and departure times of the vehicles.

The proposed EV models are able to assess the impact of different types of battery charging schemes. In Chapter 6, it was demonstrated the effect of these strategies on the adequacy of different generating systems. The main conclusions regarding the modelled battery charging strategies are:

- Direct Charging – This strategy, in fact, is the absence of a charging strategy. The use of such battery charging strategy in the simulations has demonstrated an increase in the daily peak demand, mainly because this strategy follows the population mobility. Therefore, considering the increase of the peak demand, the generation capacity should be increased in order to meet this additional load.

- Valley Charging – This strategy consists of charging the EV batteries only in the valley period. Up to a certain level of EV integration, the valley battery charging has presented good performances. From the static and operating reserves perspectives, the reliability indices were kept low, close to the ones calculated without EV deployment. Although it does not comprise an intelligent procedure, the valley hours is an appropriate period to charge the EV batteries due to the low conventional demand. On the other hand, above a certain level of EV deployment, this strategy might move the peak hour from the evening to the beginning of the dawn, as showed in Chapter 6, compromising the system.

- Controlled Charging – This strategy consists of an opportunity to provide active demand side management through an aggregation entity, which will be responsible to manage the EV charging. The main idea is to postpone the EV charging or decrease its charging rate to increase the operating reserve capacity through the release of the generating units scheduled to meet the EV load. The results have shown, through the reliability indices analyses, that this strategy can maintain the system adequacy, allowing the increase of the EV penetration level and/or postponing the system reinforcement. Assuming that most of the EV owners follow this strategy, it was showed that the reliability indices might be better than the ones calculated to a scenario without EV, since the battery charging postponement effectively contributes to increase the available operating reserve capacity.

- V2G Charging – The results have shown the improvement on the reliability indices through the electric energy injection from a set of EV to the grid, increasing the available capacity of the operating reserve. In this sense, the aggregation entity is essential for the success of such strategy in order to mobilise the EV to provide the electric energy needed. This thesis also researched the possibility of EV to compensate the variation of the wind power. The results have demonstrated the decrease of the wind power variation, when a set of EV is mobilised to inject the stored electrical energy back to the grid.

The conclusions, regarding the real system studies, are described as follows:

- Portuguese Generating System – From the static reserve perspective, the performance of the PGS configuration for 2030 has demonstrated the robustness of this system. From the operating reserve capacity perspective, the performance of the EV models under the aggressive scenario has shown that the use of direct charging strategy impacts the adequacy of the PGS with significant reliability indices, which may compromise the system configuration for 2030. However, the valley or controlled charging strategies are able to maintain the reliability indices at the same level of the no EV scenario. Therefore, it is desirable the use of these strategies in order to mitigate the EV impact on the system adequacy and postpone the necessity of increasing the generating capacity of the PGS for 2030 to accept a higher EV penetration level.

- Spanish Generating System – The SGS configuration, from the static reserve assessment, did not show significant reliability indices. Therefore, the adequacy evaluation of the security of supply has demonstrated the robustness of this system. From the operating reserve capacity perspective, the SGS configuration is also flexible enough to keep the system robustness, even with the integration of EV in the system. The obtained reliability indices are not significant, however, during the ORC evaluation an interest result was identified. The performance of the aggressive scenario adopting the valley charging strategy has presented a LOLE index of 1.9950 h/y whilst the performance adopting the direct strategy has presented a LOLE index of 0.9374 h/y. Although the estimated low risk indices, this behaviour change means that the valley charging strategy might affect the ordinary peak demand, moving it to the beginning of the dawn.

- Greek Generating System – The GGS configuration for 2030 has presented the highest reliability values from the static reserve perspective when the EV are integrated in the system. The direct charging strategy has demonstrated significant impact even under the moderate scenario in both static and operating reserve evaluations. From the static perspective, the performance of the EV penetration scenarios through the valley charging strategy allowed to keep the reliability indices low. However, the performance of the operating reserve capacity evaluation has shown a significant increase of the reliability indices. The moderate and aggressive scenarios have demonstrated reliability indices that point out to a need for revision of the GGS configuration for 2030.

In a general way, the EV deployment, under controlled charging strategies, will not require the necessity of increasing the generating capacity for the years to come. In this sense, it is essential to invest on the standardization and implementation of communication infrastructures and an aggregation entity that allows the management of the controlled charging strategies. Otherwise, a massive integration of EV will increase the total system demand compromising the adequacy of the security of supply.

7.2 Main Contributions

The main contribution of this thesis is to allow the evaluation of the EV impact on the adequacy of the security of supply through the static and operating reserve assessments. The other contributions of this thesis are divided as follows: the development of the HPP approach, the development of the NHPP approach, the modelling of the EV battery charging strategies and the studies using four different generating systems, which allows taking conclusions about the different battery charging models behaviour.

- The proposed EV models based on the HPP enabled to address the EV load in the same time basis of the conventional demand using a fixed charging time for the set of vehicles in charging mode. This characteristic impacts on the system adequacy, producing slight different risk indices if compared to the ones estimated through the NHPP. However, this approach has a lower computational effort reaching the result convergence much faster than the NHPP.

- The proposed EV models based on the NHPP evaluates the EV arrivals individually, addressing the arrival time and a random charging time for each vehicle. The methodology allows evaluating the battery SOC for each vehicle supporting the development of the V2G model. The more detailed representation is both the advantage and disadvantage of such approach. On one hand the simulations have taken long time to reach the stopping criteria, because of the increase in the number of system evaluations. On the other hand, the variable battery charging for each vehicle may represent a more realistic situation.

The developed HPP and NHPP approaches can be extended to components that have similar behaviour to be addressed in the adequacy evaluation of the security of supply.

The modelling of the battery charging strategies is another contribution of this thesis. The uncontrolled charging models represent the situation where no aggregation entity exists. The controlled charging models allows to evaluate the EV contribution to the system. The increase in the operating reserve capacity through the use of controlled battery charging strategies increases the system flexibility. These strategies have demonstrated good results in order to maintain the risk indices low in systems with large EV deployment and high level of wind power, such as Portugal and the RTS 96 HW. The V2G charging strategy was implemented under two approaches. Firstly, the EV contribution for operating reserve capacity was taken into account. This scheme has demonstrated the decrease of risk indices allowing to integrate more EV. Secondly, the EV contribution to compensate the wind power variation. The different results have shown that the V2G strategy can decrease the wind power variation produced by the generating systems. This scheme may allow to integrate more wind power sources in a more reliable way. The proposed methodologies presented the inclusion of the EV charging strategies in the Sequential Monte Carlo Simulation method, which has demonstrated the possibility of performing two different stochastic processes in the same simulation framework (Markovian and Poisson processes), representing at the same time the state transitions of the electrical components and the EV arrivals.

The performed studies using four different generating systems allowed to take conclusions about the EV models and the impact of each battery charging strategy on the system adequacy. These studies also allow to verify the behaviour of the operating reserve capacity with and without EV in the system. The results presented good performances of the controlled and V2G charging strategy regarding the EV contribution to the operating reserve capacity. Although both CC and V2G strategies are capable of decreasing the risk indices, the V2G has demonstrated even better results.

7.3 Future Work

The following topics, related to the proposed methodology, were identified to be explored in future researches:

- *Improvement of the HPP assumptions*: the HPP approach has been developed under the assumption that the clustered EV have the same and fixed battery charging requirement. The development of new assumptions may lead to an decrease in the result difference when compared to the NHPP approach. For instance, the random battery capacity requirement used in the NHPP approach could be addressed in the HPP approach.

- *Improvement of the NHPP algorithm*: the NHPP approach is suitable to represent the EV arrivals dependent of the arrival time. However, the SMCS method visits all accepted EV arrivals and departures estimated through the NHPP, which has led to an huge increase in the number of evaluations. This approach might be improved by using different techniques as the ones presented in Section 2.3.4 in order to spent less computational time during the simulations.

- *Improvement of the V2G strategy*: this strategy can be improved through the enhancement of the battery SOC model, which currently is estimated by sampling its value for each vehicle. The use of statistical data could improve the mobility representation of the model.

- *Usage of the EV models*: the current studies were based on the adequacy evaluation of the generating systems, which does not comprise the electrical network. The proposed EV models can be used in the adequacy of the power systems at transmission and distribution levels in order to determine the EV impact on the level of network congestion, for instance.

- *Communication infrastructure impact on the reliability of the power systems*: the current methodology does not account for the communication failures that may happen during the transmission of signals between the aggregation entity and the vehicles/charger point. The development of a communication model may enhance and complete the EV models proposed in this thesis.

The topic related to the EV mobility behaviour was also identified to be further explored. Different assumptions can be made assuming, for instance, specific periods to provide V2G service for the system. This type of assumption may increase the representative analysis of the proposed controlled EV models. Other issue is related to the use of different mobility patterns. An extensive study for different mobility patterns may identify a more generalised benefits of using the different EV models.

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