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New strategies for the massive introduction of electric vehicles in the operation and planning of Smart Power Systems.

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Abstract

In the current context, where global warming is growing progressively, it is fundamental to limit fossil fuels consumption. Hence, transportation is one of the sectors in which several changes are occurring considering the sustainability. The Electric Vehicle appears as a new solution for this gradual change; it does not pollute locally and its energy's balance is very efficient. So, different programs have been proposed for the growth of electric vehicles in the automotive market.

Nevertheless, the change from internal combustion vehicles to electric vehicles generates challenges in several aspects, such as the impact in the electric grid of a massive introduction of electric vehicles: voltage drops, power losses, quality of electricity issues, important investments, among others. Several solutions in operation have been formulated, but most of them do not consider the flexibility of users, which is a significant criterion for the electric vehicle acquisition. Moreover, in several works of the literature, many variables are assumed (state-of-charge, routes, type of battery, etc), which can vary significantly depending on the user, so also the results. Finally, few works have studied the impact of electric vehicles in very complex power systems, as the ones that are isolated from a macrogrid and because of significant penetration of renewable energy sources, such as microgrids.

In this context, this thesis proposes a novel approach to the participation of the electric vehicle users in operation and planning of different electric power systems. This thesis is intended to cover various topics: charging costs decrease, regulation services participation, use of an excess of renewable energy,

and the power generation planning of a microgrid considering the introduction of electric vehicles.

In a first part, an analysis of the electric vehicle and its interaction with power systems is presented. Additionally, the principal works on the topic are summarized.

Based on the analysis of these works, this thesis proposes a new methodology for optimizing the charge of electric vehicles. The participation of a new agent of the electricity market, the electric vehicle aggregator, is proposed. It has the ability to manage the charge of the electric vehicles in a zone with significant size, to coordinate with the grid operator in order to avoid troubles and to minimize charging costs. Furthermore, the different flexibility of electric vehicle users is considered because they will choose an EV customer choice product (CCP) that is adapted to their waiting needs and to the cost they can pay. The methodology has been applied to a case study in the grid of Quito, Ecuador.

The participation in regulation services has been also considered to discuss this participation in Ancillary services. The CCPs from the part before are considered for performing such study but assuming more involvement from the electric vehicle users. The case study of Quito, Ecuador, was also studied.

With the growth of renewable energies, such as solar and wind, the electricity management becomes more complicated. In order to use the excess of renewable energy, an EV charging mechanism for the aggregator is proposed, based on low prices when the renewable energy is in excess.

Finally, a power generation planning for a microgrid is proposed, considering the massive introduction of electric vehicles. The case of the Santa Cruz and Baltra islands, Galapagos, Ecuador are studied to determine its costs and environmental impacts, based on diesel costs sensitivity studies to account for its uncertainty.

Resumen

En el contexto actual, donde el calentamiento climático es cada vez más importante, existe la necesidad de limitar el consumo de combustibles fósiles. De esta manera, el transporte es uno de los sectores en los que más se están generando cambios en cuanto a la sostenibilidad. El vehículo eléctrico aparece como una solución para este cambio paulatino ya que no contamina localmente y su balance energético es muy eficiente. Así, se han propuesto diferentes programas para el crecimiento del vehículo eléctrico en el parque automotor.

Sin embargo, el cambio de vehículos de gasolina por vehículos eléctricos genera desafíos en varios aspectos, como el impacto que ocasiona en la red eléctrica una implantación masiva: caídas de tensión, pérdidas de potencia, problemas con la calidad de la electricidad, inversiones importantes, etc. Se han planteado algunas soluciones en la parte operativa, pero muchas de ellas no han tomado en cuenta la flexibilidad de los usuarios, lo cual es muy importante para la adopción de vehículos eléctricos. De igual manera, en muchas ocasiones, en la literatura se asumen valores para ciertas variables (estado de carga, recorrido, tipo de batería, etc) que pueden cambiar según el comportamiento de cada usuario, lo que modificaría las previsiones realizadas. Finalmente, pocos trabajos han estudiado el impacto de lo vehículos eléctricos en redes eléctricas cuya gestión energética es más complicada debido a su aislamiento de una macrored y con alta penetración de energías renovables, como lo son las microredes. En este marco, esta tesis propone un enfoque novedoso en cuanto a la participación de los usuarios de vehículos eléctricos en la operación y planificación de diferentes sistemas eléctricos de potencia. Esta trata de algunos aspectos principales: disminución de costos de carga, participación en servicios de reg-

ulación, aprovechamiento de energía renovable, así como la planificación de generación de una microred incorporando vehículos eléctricos. En una primera parte, se presenta un análisis del vehículo eléctrico y su interacción en sistemas de potencia. De igual manera, se presentan los trabajos de investigación relacionados sobre la temática.

En base al análisis de dichos trabajos, esta tesis propone una nueva metodología para optimizar la carga de los vehículos eléctricos. Se propone la participación de un nuevo agente del mercado eléctrico, el Agregador de vehículos eléctricos. Tendrá que gestionar la carga de dichos vehículos en una importante zona, coordinar con el operador de la red para evitar fallos y minimizar los costos de carga. De igual manera, se considera la diferente flexibilidad de los usuarios ya qu podrán escoger una tarifa que se adapte a su disponibilidad en espera y pagar el precio por aquello. La metodología ha sido aplicada a un caso de estudio a la red de Quito, Ecuador. Se propone también la participación en servicios de regulación, necesitando esta vez de usuarios que sean más flexibles al dejar su vehículo conectado a la red. Se considera las tarifas de la parte anterior para realizar dicho estudio. De igual manera, se aplicó al caso de estudio de la red de Quito, Ecuador. Con el crecimiento de las energías renovables, como solar y eólica, la gestión de la electricidad se vuelve más compleja. Con vistas a utilizar el exceso de energía renovable, se propone una tarifa de electricidad que permita al agregador de cargar los diferentes vehículos, tomando en cuenta precios bajos en periodos en donde la energía renovable esté en exceso.

Finalmente, se plantea a planificación de generación de una microred que incluya la introducción masiva de vehículos eléctricos. Se aplicó al caso de las islas de Santa Cruz y Baltra, Galápagos, Ecuador, estudiando el impacto en los costos y en el medio ambiente de nueva generación y considerando la variación del precio del diésel debido a su incertidumbre.

Resum

En el context actual, on l'escalfament climàtic és cada vegada més important, hi ha la necessitat de limitar el consum de combustibles fòssils. El transport és un dels sectors en els quals més s'estan generant canvis pel que fa a la sostenibilitat. El vehicle elèctric apareix com una solució per a aquest canvi gradual ja que no contamina localment i el seu balanç energètic és molt eficient. Així, s'han proposat diferents programes per al creixement del vehicle elèctric al parc automotor. No obstant això, el canvi de vehicles de gasolina per vehicles elèctrics generen desafiaments en diversos aspectes, com son l'impacte que ocasiona a la xarxa elèctrica una implantació massiva: caigudes de tensió, pèrdues de potència, problemes amb la qualitat de l'electricitat, inversions importants, disminució de la vida útil dels transformadors, etc. S'han plantejat algunes solucions a la part operativa, però moltes d'elles no han tingut en compte la flexibilitat dels usuaris, la qual cosa és molt important per a l'adopció de vehicles elèctrics. De la mateixa manera, en moltes ocasions, en la literatura s'assumeixen valors per certes variables (estat de càrrega, recorregut, tipus de bateria, etc.) que poden canviar segons el comportament de cada usuari, el que modificaria les previsions realitzades. Finalment indicar que pocs treballs han estudiat l'impacte del que vehicles elèctrics en xarxes elèctriques on la gestió energètica és més complicada a causa del seu aïllament d'una macroxarxa i amb alta penetració d'energies renovables, com ho són les microxarxes. En aquest marc, aquesta tesi proposa un enfocament nou pel que fa a la participació dels usuaris de vehicles elèctrics en l'operació i planificació de diferents sistemes elèctrics de potència. Aquesta tracta alguns aspectes principals: disminució de costos de càrrega, participació en serveis de regulació, aprofitament d'energia renovable, així com la planificació de generació d'una microxarxa incorporant

vehicles elèctrics. En una primera part, es presenta una anàlisi del vehicle elèctric i la seva interacció en sistemes de potència. De la mateixa manera, es presenten els treballs de recerca relacionats sobre la temàtica. En base a l'anàlisi d'aquests treballs, aquesta tesi proposa una nova metodologia per optimitzar la càrrega dels vehicles elèctrics. Es proposa la participació d'un nou agent del mercat elèctric, el Agregador de vehicles elèctrics. Haurà de gestionar la càrrega d'aquests vehicles en una important zona, coordinar amb l'operador de la xarxa per evitar fallades i minimitzar els costos de càrrega. De la mateixa manera es considera la diferent flexibilitat dels usuaris ja que podran escollir una tarifa que s'adapti a la seva disponibilitat en espera i pagar el preu per allò. La metodologia ha estat aplicat a un cas d'estudi a la xarxa de Quito, Equador. Es proposa també la participació en serveis de regulació, necessitant aquest cop d'usuaris que siguin més flexibles en deixar el seu vehicle connectat a la xarxa. Es consideren les tarifes de la part anterior per a realitzar dit estudi. De la mateixa manera, es va aplicar al cas d'estudi de la xarxa de Quito, Equador. Amb el creixement de les energies renovables, com solar i eòlica, la gestió de l'electricitat es torna més complexa. Amb vista a utilitzar l'excés d'energia renovable, es proposa un tarifa d'electricitat que permeti a l'agregador de carregar els diferents vehicles, especialment en períodes on l'energia renovable estigui en excés. Finalment, es planteja la planificació de generació d'una microxarxa que inclogui la introducció massiva de vehicles elèctrics. En concret, es va aplicar al cas de la illes de Santa Cruz i Baltra, Galápagos, Equador, estudiant l'impacte de la nova generació en els costos i en el medi ambient i considerant la variació del preu del dièsel, causa de la seva incertesa.

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List of Acronyms

BEV Battery Electric Vehicle

CCP Customer Choice Product

DER Distributed Energy Resource

DR Demand Response

EES Energy Storage System

EV Electric Vehicle

G2V Grid-to-Vehicle

ICT Information and Communication Technologies

ICV Internal Combustion Vehicle

LC Load Controller

MC Microsource Controller

PCC Point of Common Coupling

PEV Plug-in Electric Vehicle

PHEV Plug-in Hybrid Electric Vehicle

PV Photovoltaic

RES Renewable Energy Source

V2G Vehicle-to-Grid

Nomenclature

Parameters Chapter 4-6

α_P Penalty coefficient (\$/kWh)

α_U Coefficient from the EV aggregator that is paid to the EV users who participate in ancillary services

α_{bd} Battery degradation cost due to discharging (\$/kWh)

ΔT Time interval

ϵ_B Part of EV users participating in blue CCP

ϵ_G Part of EV users participating in green CCP

ϵ_R Part of EV users participating in red CCP

η EV charging efficiency (%)

$\overline{P^{EV}}$ Maximum charge power rate for EVs (kW)

$\overline{P^{res}}$ Maximum residential load (kW)

$\overline{P_k^{EV,tot}}$ Maximum EV Power Constraint at step k (kW)

$\overline{P_{k,i}}$ Maximum authorized power for charging an EV i at step k (kW)

$\overline{SOC^{EV}}$ Maximum state-of-charge for EVs (%)

$\pi^{E,D}$ Market selling price for regulation down (\$/kWh)

$\pi^{E,U}$	Market selling price for regulation up (\$/kWh)
π_k	Cost of electricity at the step k (\$/kWh)
$\underline{E_i^{req}}$	Minimum required energy (kWh)
$\underline{P^{EV}}$	Maximum discharge power rate for EVs (kW)
$\underline{SOC^{EV}}$	Minimum state-of-charge for EVs (%)
Bc_i	Nominal battery capacity of vehicle i (kWh)
C^B	Daily Cost of all blue CCP EV users (\$)
C^G	Daily Cost of all green CCP EV users (\$)
C_p	Penality cost if the aggregator overpass charging pattern (\$)
c_t^D	Hourly regulation price down (\$)
c_t^D	Hourly regulation price up (\$)
c_t^E	Price of electricity at time t (\$)
D	Number of time intervals in a day
E^D	Dispatched energy for regulation down (kWh)
E^U	Dispatched energy for regulation up (kWh)
E_i^{req}	Energy required from EV i (kWh)
FP	Additional power factor
N^B	Number of vehicles participating in blue CCP
N^G	Number of vehicles participating in green CCP
N^R	Number of vehicles participating in red CCP
N_{EV}	Total number of EV users
p^F	Constant value in the EV user price i (\$)
$P^{B,av}$	Average power consumption for blue CCP (kW)
$P^{G,av}$	Average power consumption for green CCP (kW)
$P^{R,av}$	Average power consumption for red CCP (kW)

$P^{x,av}$ Average power consumption for a x CCP (kW)

$P_k^{res,tot}$ Total residential load at step k (kW)

r^D Dispatch ratio for regulation down

r^U Dispatch ratio for regulation up

R_t^D Regulation capacity down available at time t (kW)

R_t^U Regulation capacity up available at time t (kW)

$R_t^{D,B}$ Offered regulation bid down for time t (kW)

$R_t^{U,B}$ Offered regulation bid up for time t (kW)

st_i Starting charging time of EV i

T_d Time delay of starting charging time (h)

Variables Chapter 4-6

ΔE_i Energy variation between each step time of EV i (kWh)

ΔS^B Daily differences for cost for blue CCP (kW)

ΔS^G Daily differences for cost for green CCP (kW)

$\overline{P_k^{EV,O}}$ Operator load constraint at step k (kW)

Π Daily benefits ($)

C^R Daily Cost of all red CCP EV users ($)

$C^{B,eq}$ Daily EV aggregator specific cost for blue CCP users($/MWh)

C^{EV} Total daily costs for charging EVs ($)

$C^{G,eq}$ Daily EV aggregator specific cost for green CCP users ($/MWh)

$C^{x,y}$ Daily Cost of x CCP in scenario y ($)

C_B EV aggregator Costs from battery degradation ($)

C_E EV aggregator Costs from cost of energy ($)

C_H EV aggregator Costs from bi-directional chargers($)

C_P EV aggregator Costs from penalty charge ($)

C_{eq} Daily EV aggregator specific cost (\$/MWh)

$d^{x,y}$ Daily percentage cost difference for x CCP from y scenario to third scenario (\$)

$E^{B,tot}$ Total energy dispatched in a day to all EVs participating in blue CCP (kWh)

$E^{G,tot}$ Total energy dispatched in a day to all EVs participating in green CCP (kWh)

E_P Energy not complied from the EV aggregator (kWh)

$E_{k,i}$ Energy stored in the battery vehicle at the step k (kWh)

P_t^{bas} Power prediction at time t

p_i Price that EV user i has to pay to the EV aggregator (\$)

P_k^B Total power consumed by cars participating in blue CCP at step k (kW)

P_k^G Total power consumed by cars participating in green CCP at step k (kW)

P_k^R Total power consumed by cars participating in red CCP at step k (kW)

P_k^{EV} Total EV load at step k (kW)

$P_t^{EV,d}$ Total power discharged from EVs (kW)

P_t^{EV} Total power supplied to EVs (kW)

$P_{i,t}$ Charging power rate from EV i at time t (kW)

$P_{k,i}$ Load of an EV i at step k (kW)

R Daily revenues (\$)

R_O Revenues from DSO and TSO (\$)

R_U Revenues from user options (\$)

$SOC_{k,i}$ State of charge of vehicle i at step k (%)

T_i^B Duration of charge for vehicle i participating in blue CCP (h)

T_i^G Duration of charge for vehicle i participating in green CCP (h)

T_i^R Duration of charge for vehicle i participating in red CCP (h)

Sets Chapter 4-6

T Set of time intervals in a day

U_i Set of time intervals of a vehicle i that corresponds to charging period

Parameters Chapter 7

ΔT Time between each time interval (h)

$\overline{P_{i,e}^{EV}}$ Maximum EV charging power rate for an EV i and type e (kW)

π_k Specific Electricity cost at time interval k ($/kWh)

Bat Battery capacity of EV type (kWh)

D Number of time intervals in a day

$E^{EV,tot}$ Total energy needed for charging all the EVs in a day (kWh)

E_i^{req} Daily Energy required by EV i (kWh)

IC^{PV} Installed Capacity of PV ($)

IC^{W} Installed Capacity of Wind ($)

k Time Interval

N^B Number of electric buses

N^C Number of electric cars

N^M Number of electric motorcycles

N^{EV} Number of EVs

P_k^D Power of diesel generator at interval k

P_k^L Residential load excluding EV at interval k (kW)

P_k^W Wind generation power at interval k(kW)

$P_k^{exc,tot}$ Excess of power from RES at a step k (kW)

P_k^{loss} Power losses (kW)

P_k^{PV} PV generation power at interval k (kW)

st_i Hour of plug of EV i

U_i Plug duration of EV i (h)

General Indices

e EV type: 1 for motorcycles, 2 for buses, 3 for cars

g Diesel Generator index

i EV user index

k Time step

t Hour Time index

y year

Set Chapter 7

δ_i Set of time intervals of charging duration of an EV i

γ_i Set of time intervals of plug duration of an EV i

τ Set of time intervals in a day

Variables Chapter 7

$\eta_{exc,RES}$ Ratio of excess energy from RES cosnumed by EV (%)

$\overline{P^{tot}}$ Maximum total power generation (kW)

$\overline{P_{DER}}$ Maximum DER power generation (kW)

C Total daily cost ($)

C^{coo} Total daily cost for coordinated charging ($)

C^{un} Total daily cost for uncoordinated charging ($)

C^{coo}_{eq} Specific cost for coordinated charging ($)

C^{un}_{eq} Specific cost for uncoordinated charging ($)

$E_{exc,EV}$ Excess of energy from RES in a day that was used for charging EV (kWh)

$E_{exc,RES}$ Excess of energy from RES in a day (kWh)

P^{EV}_k Total load demanded from EV charging at time interval k (kW)

$P_k^{exc,EV}$ Excess of power from RES at a step k that was consumed for charging EV (kW)

$P_{k,i,e}$ Power consumed by EV i by type e at time interval k (kW)

Parameters Chapter 8

α_{CO_2} Emission factor for CO_2 emissions [Ton/kWh]

Δt Time interval [1 h]

δ_m^{IS} Time horizon for the start cooking time for each meal m

δ_e Time horizon for the charging starting time for each EV type e

$\overline{P_e^{EV}}$ Maximum charging power in slow mode for each EV type e [kW]

BC_e EV battery capacity for each type e [kWh]

CRF Capital Recovery Factor

CT Annualized net present total cost for the planning horizon [$/yr]

D Number of years for planing horizon

ER_e Average energy required from a user for each EV type e [kWh]

ET Total electrical energy served [kWh/yr]

ET_g Total electrical energy served by generator g [kWh/yr]

N_e^{EV} Number of EVs from each type e

N_G Number of Diesel Generators

N_{IS} Number of ISs

r Discount rate [%])

$st_{e,j}$ Starting time of charge of each i EV of type e

Variables Chapter 8

Δ_{CO_2} Carbon dioxyde emissions Difference [%]

Δ_{COE} Levelized Cost of Energy Difference [%]

Δ_{NPC} Net Present Cost Difference [%]

CO_2 Carbon dioxyde emissions [Ton/yr]

COE Levelized Cost of Energy [$/kWh]

NPC Net Present Cost [$]

P_t^{EV} Total EV load at time t [kW]

$P_{e,j,t}$ Charging power of each i EV of type e at time t [kW]

Sets Chapter 8

$\tau_{e,j}$ Time horizon for the charging of each j EV of type e

Chapter 1

Introduction and Objectives

1.1 Introduction

Climate change is one of the issues that have to be faced nowadays. Although with the fracking technology the natural gas reserves have increased, it is expected that fossil fuels are going to be gradually depleted. In this current context, governments are trying to replace these fuels and create an awareness of energy efficiency. Transportation is one of the fields in which governments are working. In particular, several countries have started to promote policies to gradually shift from gasoline vehicles to fully electric vehicles.

This shift from gasoline to electric vehicles generates technical and economic challenges. On the one hand, electric vehicles have low driving range. In addition, a massive deployment of electric vehicles could cause several issues in power systems. At the economic level, electric vehicles are produced in a much lower amount than internal combustion vehicles, their technology is new and still under development, so their price is high.

For these reasons, electricity companies must have systems that can correct any problem in the network caused by the charging of electric vehicles, supported by tariff systems that encourage the use of electric vehicles, especially in the hours when electricity is cheaper.

Electric vehicles are a new technology, so users tend to resist acquiring this type of vehicles. The penetration of these vehicles in the market is still very small, so the electric companies have not focused enough on managing them.

1.2 Justification

Electricity and Transportation are two of the most important concerns worldwide. Gasoline dominated the individual transportation sector for a long time and gasoline is now shifting progressively to electricity. Hence, governments are proposing new policies for a change to electric vehicles (EVs). The most important reasons could be:

- Energy efficiency: actual EVs have a "well-to-wheel" energy efficiency higher than 90%. This value considers energy flow from the grid to the mechanical traction in the wheels.
- Local pollution reduction: internal combustion vehicles emit toxic gases in cities, while EVS do not. Nevertheless, EVs emit toxic gases indirectly because of the electricity production, but even so, the quantity is much smaller due to EV energy efficiency.
- Oil independence: many studies confirm that in a few decades petroleum will be exhausted. So, there is a need to find alternatives for fuels for transportation. Solutions other than EVs are the focus of research, such as hydrogen vehicles. But, EVs seem to be the solution for transportation pollution issues.

However, this change from internal combustion vehicles to EVs create some challenges.
Firstly, in the electricity sector, some provisions have to be carried out concerning the load increase due to EVs. Without good management, this new load could create some problems, such as voltage drops, voltage deviations, power losses, and grid reinforcement issues.
Then, utilities may not be capable to supply the load if there is a lack of information from EV load.
Furthermore, electricity generation was based on fossil fuels, but the trend is changing to renewable energy sources, which are much fewer pollutants. But

renewable energy sources present fluctuations in their generation, which create another challenge for a proper integration in power systems. The EVs offer an opportunity for these issues due to their batteries that can act as a storage source.
Finally, there are challenges for users. EVs are new technology in which some changes have to be adopted by their users, such as charging a battery instead of fueling a vehicle in a gas station, smaller driving range, maintenance, etc. EV users will also be involved in the participation for building a smarter grid. Considering all this, EVs have many implications for power systems operations. Many researchers have proposed different solutions to these issues, which are detailed in Chapter 3. But, most of the solutions do not consider the correct participation of EV users because some parameters of their behavior and flexibility (waiting time, required energy) have not be considered. These parameters are an important concern, because if users do not feel comfortable with EV charging conditions, they will simply not buy EVs.
Governments are also investing in RES in different locations to mitigate environmental problems. However, the introduction of EVs in such systems creates additional challenges, because RES power present fluctuations and uncertainties. The challenge is more significant when the RES and EV integration is in isolated systems. Thus, it is crucial to develop methodologies for the correct operation and planning of EV integration in such systems.

The research described in the present document has been carried out within the Institute for Energy Engineering of Universitat Politècnica de València (UPV), and partially, during five months research stay at the Department of Electrical and Computer Engineering of the University of Waterloo, Canada. The present dissertation builds on the work performed by the author during the last three years at the mentioned institutions, focusing on achieving better management of electric vehicles in different distribution systems.

1.3 Objetives

The main objective of this thesis is to propose different solutions for the integration of electric vehicles in distribution systems of traditional centralized electric grid (macrogrid) and of microgrids.
The specific objectives can be identified as follows:

- To evaluate the existing applications and approaches for EV integration in operation and planning of electric power systems.

- To develop new methodologies, further to EV schedules or charging shift, of EV smart charging that takes into consideration EV users flexibility and network requirements. For this purpose, an EV aggregator is proposed as the suited partner to perform the correct interaction between EVs and the grid. The methodologies will be considered for a typical macrogrid.
- To develop a methodology for EV charging in isolated systems with high penetration of RES. This methodology will take into account different kinds of EVs.
- To develop a power generation planning of a microgrid considering different levels of penetration of EVs.

1.4 Outlines of the Thesis

To reach these different objectives, the thesis is organized as follow:

In chapter 2, the interaction between electric vehicles and Smart Grids is described. The most significant characteristics are studied to identify new strategies for a massive penetration of EVs in a Smart Grid environment.

Then, chapter 3 presents the literature review about Smart Charging methodologies. The issues of massive penetration of EVs in distribution grids is presented. In that way, different methodologies are described depending in the grid system and the participation of the EV aggregator is considered. The limitations of the present methodologies are highlighted.

Based on the analysis accomplished before, in Chapter 4, a new smart charging methodology is presented. It relies on a smart charging technique that allow users to select between three different customer choice products (CCPs) depending on their flexibility. In addition, a sensitivity analysis of some parameters is proposed to address the possible uncertainties that can impact the methodology.

Chapter 5 is devoted to the study of the proposed methodology in the case study of Quito, Ecuador. The methodology is validated and the sensitivity analysis allows understanding the effects of different parameters in the power grid and the EV aggregator costs.

In addition, this new charging methodology may be useful for providing services to the grid, such as Ancillary Services (e.g. secondary regulation) due to the high amount of energy that the EV aggregator manages. Thus, chapter 6 studies the application of the new methodology in ancillary services.

The implementation of EVs will be mainly performed in generation environments where the electricity production comes significantly from RES. Hence, in Chapter 7, a new EV charging mechanism in a grid with high RES penetration is considered. An application case in the island of Santa Cruz, Galapagos, Ecuador is studied.

Although new alternatives for EV energy management are necessary for daily operation, it is also crucial to study the effect of the impact of EVs in microgrid in the long term. Hence, chapter 8 is devoted to a microgrid power generation planning, which includes the massive penetration of EVs. An application case in the island of Santa Cruz, Galapagos, Ecuador is studied.

Chapter 9 summarizes the conclusions of this work and some suggestion for further work are given. The publications in this Ph.D. document are also presented.

Chapter 2

State of the Art - Electric Vehicle Integration in Smart Grids

2.1 Introduction

This chapter presents the different concepts and tools that allow understanding and define the basis of the research presented in this thesis. This chapter starts with a brief presentation of electric vehicles in section 2.2. After that, the ways for charging EVs is discussed in section 2.3. In section 2.4, an overview of Electric Power Systems is presented. The concept of the Smart Grid is discussed in section 2.5 and the concept of Microgrid in section 2.6. The impact of EVs in a Smart Grid is discussed in section2.7. Finally, section 2.8 draw some conclusions of the chapter.

Figure 2.1: Baker Runabout.

2.2 Electric vehicles

2.2.1 Brief History of Electric Vehicles

EVs are considered as the transport of the future, but it is crucial to mention that this kind of vehicle was first developed in the 1830s. The car designed by Baker (Baker Runabout) was one of the most important EV of the 19th century, as shown in Figure 2.1.

At the beginning of the 20th century, internal combustion vehicles dominated the market of vehicles for the following reasons. First, EVs in these years had a battery capacity of 30 Wh/kg in comparison of the 9000 Wh/kg of gasoline. Second, the production cost of batteries was very expensive, and oil was in a period where the price was decreasing. Also, it has to considered that EV batteries in these years had a lifetime of 5 years which was too short. Finally, recharging EV batteries resulted in these years long, and the autonomy was not significant. Because all these facts, internal combustion vehicles are so far the most used vehicles.

At the end of the 20th century, there were growing concerns about climate change, especially regarding carbon dioxide emissions. In that way, the technology of electric motors and batteries have improved, which allowed producing most efficient EVs. EVs, as a clean way of transportation, started another time to have importance.

EV technology actually continues to develop in many terms as battery capacity, motor performance, and costs. In particular, EV is considered as the vehicle of the future thanks to its benefits: energy efficiency, local reduction pollution, and oil independence.

2.2.2 Types of electric vehicles

An electric vehicle is a vehicle that uses at least one electric motor to propel. There are two main kinds of EVs: battery electric vehicle

Hybrid electric vehicle

The Hybrid electric vehicle (HEV) is a vehicle that combines an internal combustion and electric motor. There are two principal arrangements for this vehicle: serie hybrid and parallel hybrid. In the serie hybrid, the vehicle has at least one electric motor supplied either from the battery, from an IC motor, which is a generator unit, or from both. Furthermore, the vehicle propulsion comes entirely from the electric motor. On the other side, in the parallel hybrid, the vehicle can be driven either by the electric motor by the IC motor. It is important to mention that in these two cases, the battery can be recharged by the IC motor while driving. Also, regenerative breaking allows a vehicle to slow down in order to stop and to charge the battery. These arrangements are illustrated in Figure 2.2.

Plug-In Hybrid electric vehicle

Plug-In Hybrid Electric vehicle (PHEV) is a vehicle with the same characteristics as an HEV, but it has a plug to connect to the electric grid in order to charge the battery. The advantage of this vehicle is that it allows a bigger utilization of the electric motor, which improves costs where oil is expensive and reduces gas emissions.

Battery Electric Vehicles (BEV)

Battery electric vehicles are vehicles that use only an electric motor for propulsion. Moreover, the electric motor is powered by a battery, which performance is much more important than hybrid vehicles. Batteries have to be recharged through a plug. Figure 2.3 schematizes this vehicle.

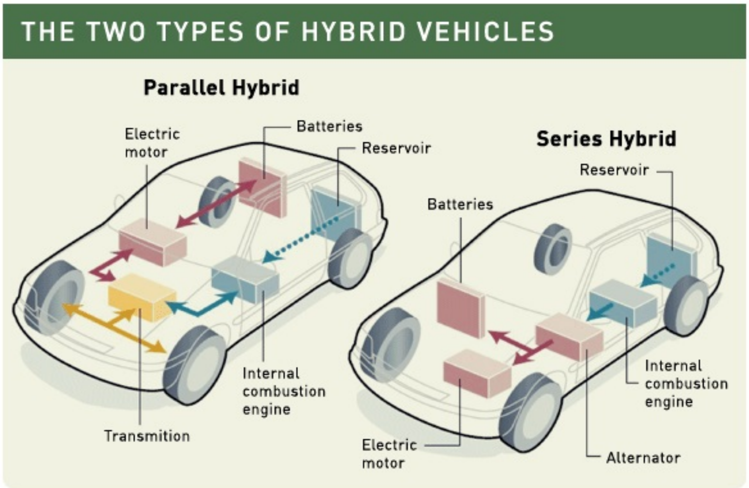


Figure 2.2: Serie and Parallel hybrid vehicles

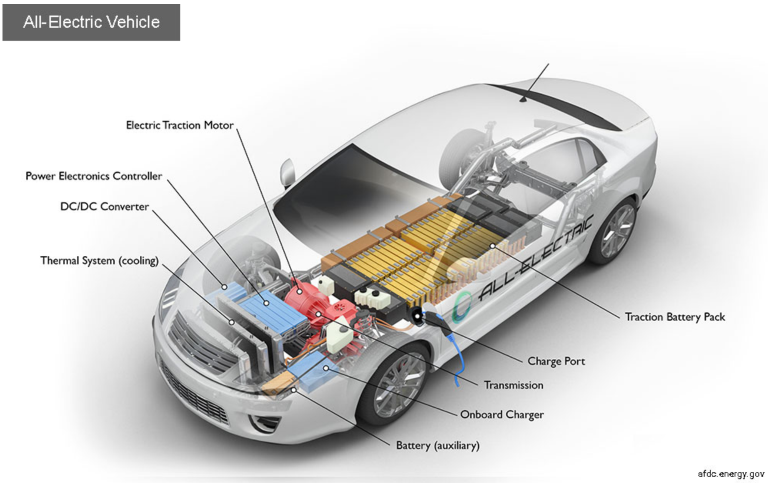


Figure 2.3: Battery Electric Vehicle

2.2.3 Electric vehicle components

Charger

A charger is a device which converts alternative current (AC) from the grid to direct current (DC) that has to charge the battery pack. It also has a control mechanism, which allows communicating between the vehicle to the grid in order to have a correct charging.

Main Battery (Traction Battery Pack)

The battery store the energy that is required to power the electric motor and also the auxiliary electrical systems.

Inverter

The Inverter converts DC current delivered by the battery to AC current which is needed to power the electric motor.

Electric Motor

The electric motor converts the electricity to mechanical energy to the wheels. Nowadays, AC motors are the most used in comparison to DC motors because of their high efficiency.

12 V Battery (auxiliary)

This battery is the same that exists in IC vehicles, it allows to power auxiliary electrical systems. The main battery cannot deliver power directly to the auxiliary systems because the voltage and power are too high, so an intermediate DC-to-DC converter is needed.

DC-to-DC Converter

This converter transform power from the main battery pack to a lower power battery of 12 V that allows to power auxiliary electrical systems.

Auxiliary Electrical Systems

These systems are the same that exists in IC vehicles. They are components related to security, lighting and information systems.

2.2.4 EV models

In Table 2.1, principal EV models are described.

Model	Nissan Leaf	Kia Soul EV
NEDC Authonomy	199 km	212 km
EPA Authonomy	121 km	150 km
Motor Torque	254 N.m	285 N.m
Motor Power	80 kW	81,4 kW
Battery Capacity	24 kWh	27 kWh
Model	BYD e6	Renault Kangoo Z.E.
NEDC Authonomy	212 km	170 km
EPA Authonomy	200 km	113 km
Motor Torque	450 N.m	226 N.m
Motor Power	90 kW	45 kW
Battery Capacity	75 kWh	22 kWh
Model	Renault Twizy	Tesla X
NEDC Authonomy	100 km	500 km
EPA Authonomy	80 km	402 km
Motor Torque	57 N.m	525 N.m
Motor Power	12 kW	375 kW
Battery Capacity	3,1 kWh	75 kWh

Table 2.1: EV Models

2.2.5 Advantages of Electric Vehicles

Some of the advantages of EVs are:

- Reduce the consumption of fossil oils
- Eliminate the emission of greenhouse gas for the vehicle, which is generally in urban areas, and reduces considerably the total greenhouse emission, even if the energy mix generation is pollutant, because the EV has a much higher efficiency than an internal combustion one.
- Improves air quality in the urban areas
- Well-to-wheel efficiency of EVs (around 90%) is much higher than ICVs (about 30%)

2.3 Charging EV

2.3.1 Charging Levels

Technical organizations have different standards for charging levels. Here are resumed three principal charging levels (Yilmaz and Krein 2012):

Level 1 or Slow Charging

This charging is based on a residential voltage from 120 Vac to 230 Vac, a current from 12 A to 20 A and power from 1.4 kW to 1.9 kW, single-phase and the charger is on-board. This charging level is the most recommended by car manufacturers because the battery degradation won't be important.

Level 2 or Quick Charging

This charging is based on a one or three-phase connection. The battery can be charged from 240 V to 400 Vac with a current from 17 A to 80 A and power from 4 kW to 19.2 kW. This charging level is not used a lot, because not all vehicles allow it and because a three-phase connection is needed. It could be used for private or public outlets.

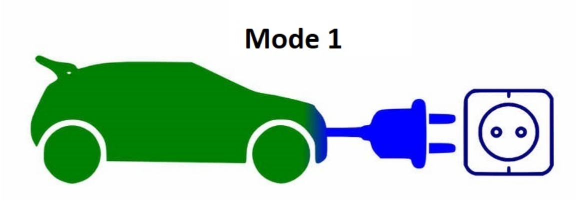


Figure 2.4: Mode 1.

Level 3 or Fast Charging

This charging is suitable for public facilities when users are urged to charge their EV. The charger is off-board. The battery is charged in a voltage from 208 Vdc to 600 Vdc and with a current from 100 A to 125 A. The charging power will be from 50 kW to 100 kW which implies that the battery will be charged quickly. In most cases, the battery is charged 80% in less than 30 minutes. This kind of charging is recommended by manufacturers as urgent charging because the battery degradation is significant.

2.3.2 Charging Modes

The standard IEC 62196-1 indicates the different charging modes for EV. It refers to the capacity of communication between the EV and the grid.

Mode 1

This mode consists of a direct and passive connection of the EV to the grid. It uses a Schuko plug, usually incorporated in the EV, which means there are no extra pin that works as communication.

Mode 2

This mode consists of a EV connection to the grid through a cable with a communicating charge monitoring device. This device sends charging communication through a pin, which is considered the pilot function and verifies the correct connection of the EV to the grid. The mode 2 devices are usually included when purchasing an EV.

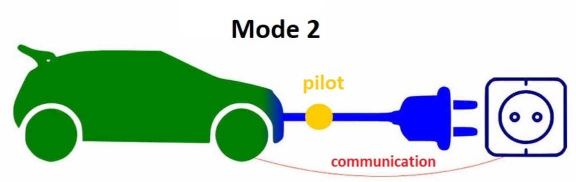


Figure 2.5: Mode 2.

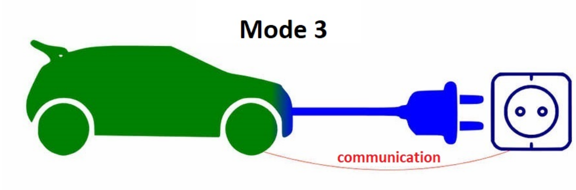


Figure 2.6: Mode 3.

Mode 3

This mode consists of the connection of the EV to a fixed charging station, usually considered as Wallbox, which includes earth and pilot function inside. The communication is higher and the pilot function is also able to modulate the charging power rate, between the ranges of level 2 charging. The charging power rate depends on the frequency of the pilot PWM signal that is emitted to the charger. Note that this modulation is currently able to be done when the charging have not started.

Mode 4

This mode consists of a direct current charging. It only applies to fast charging. The communication between EV and the grid is significant, considering the fact that the charging is in DC and the power could be easily modulated and shifted.

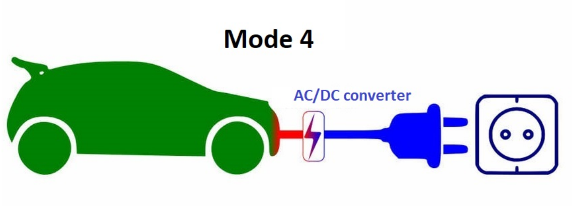


Figure 2.7: Mode 4.

2.3.3 Charging Points

It is possible to differentiate charging points depending on the place where EVs are charged:

Residential

Residential charging consists of EV charging at home. Charging is generally done when users arrive from work in the evening. It is usually done with slow charging and modes 1,2 or 3.

Commercial

Commercial charging consists of EV charging in public places. Charging is done when users spend some time in these places during the day.

Fast charging station

This charging consists of charging EV in specific places in the cites or in the roads when users are urged to charge their EV.

2.3.4 EV batteries

The purpose of the batteries is to store energy. EV batteries are considered the most important components in the EV structure, and there are also in the focus of research because the performance of the batteries is still not satisfying the requirements of car manufacturers. They determine essential characteristics of the EV such as the autonomy and the power which can be delivered to the electric motor (Larminie and Lowry 2003).

The battery performance is determined by essential factors such as: Energy, Power, Lifetime, Safety, and Cost (Rajakaruna, Shahnia, and Ghosh 2015b). During last years, substantial improvements have been performed on these battery factors.

Energy Capacity

The energy storage capacity (kWh) determines the distance that an EV can travel considering the motor power. Furthermore, for a car manufacturer, it is important to consider the size of the battery pack for design and esthetic conditions and the weight for mechanic conditions. For this reason, it is crucial to analyze also factors such as specific energy (kWh/kg), which is the amount of electrical energy stored for every kilogram of battery mass, and energy density (Wh/m^3), which is the amount of electrical energy stored for every cubic meter of battery volume.
Another crucial parameter is the energy efficiency and is defined as the ratio of electrical energy supplied by the battery to the amount of electrical energy needed to charge it.

Power

Battery power (W) is the amount of power that can be transferred from the battery to the motor or to the auxiliary electrical system. For design considerations, the specific power (W/kg) is studied, which is the amount of power obtained per kilogram of battery. Note that specific power is a factor that is independent from specific energy: it is possible to have a battery with very good specific energy but a bad specific power. This means that the EV could have a good autonomy but it cannot drive at high speed.

Lifetime

The Lifetime of the battery depends on different factors. The battery has some needs of temperature conditions, so the design needs to be aware of it for not reducing the lifetime. The higher is the number of charging cycles the lifetime will decrease. Finally, fast charging is necessary, but it reduces battery lifetime.

Safety

The battery technology has to respect current policies in order to avoid possible explosions or electrocution in the utilization of the EVs. By another side, most of the current batteries are based on lithium-ion. The materials needed for elaborating the batteries are quite dangerous, so some precautions have to be taken for the supply.

Battery Technology

The main types of battery technology are Lead-acid, Nickel-metal-hydride, Lithium-ion. Considering all the factors mentioned before, the Lithium-ion technology is the one that is most used nowadays, for its high specific energy (up to 200 Wh/kg). The Specific Power vs Specific Energy curve with the different battery technologies is represented in Figure 2.8, which allows comparing the performance from each type depending on the needs. For example, EVs mostly need energy for a longer autonomy and hybrid mostly need power. Note that Li-ion has the best characteristics of specific power and energy.

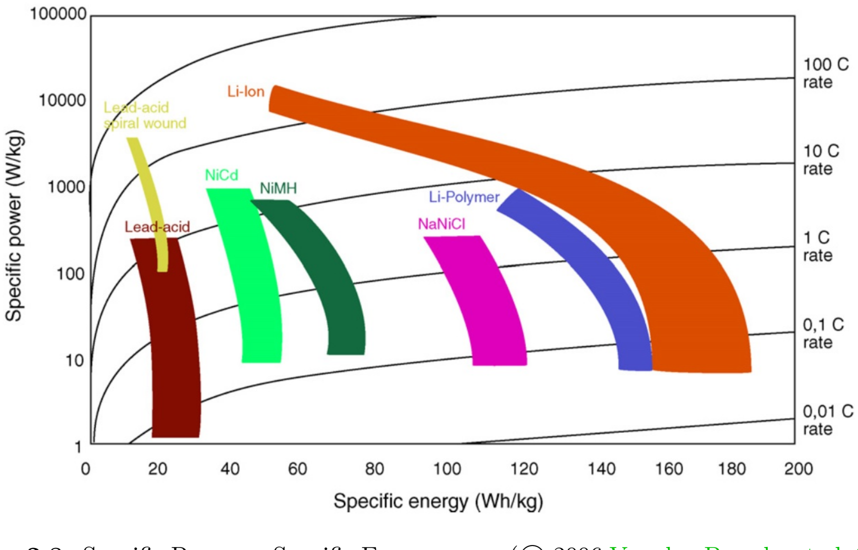


Figure 2.8: Specific Power vs Specific Energy curve (© 2006 Van den Bossche et al. 2006).

Battery Degradation Considerations

The battery degradation is caused commonly by calendar life, which is the lifespan of a battery that left without using, and by cycle life, which is the number of complete charge - discharge cycles a battery can perform before its nominal capacity falls below a certain level (Han, Han, and Sezaki 2012). Moreover, some other factors have to be considered, such as operation temperature, depth of discharge, total energy withdrawn and SOC limits.

2.4 Overview of Electric Power Systems

Energy is one of the fundamental keys of societies and has an important impact on social and economic development of countries. Electricity probably has become the most important source of energy usage. Electricity must appear to be a commodity much like any other on consumers' list of routine expenses. One of the problems of the electricity as a product is that it cannot be stored, so after been generated, it has to be transmitted and distributed to consumers for consumption (Gómez Exposito, Conejo, and Cañizares 2009). Any imbalance between generation and demand could result in problems for the electric power system. This is the reason Electric Power System present complex problems to be solved.

2.4.1 Electric Power Systems Structure

The goal of the electric power system is the Generation, Transmission, and Distribution. From the technical point of view, generation plants produce electricity at high voltages (between 6 and 20 kV). They can be connected to other for electricity exchanges. The electricity generated is transformed to voltages of hundreds of kilovolts (up to 700kV), in order to optimize the transmission of long-distance lines. Then, the electricity is transmitted in smaller quantities from the transmission substations to the distribution substations, where the electricity is another time transformed but to lower voltage levels for customers use (110 to 400V). Finally, the distribution system delivers power to the different customers. Very large consumers can access directly of the energy from the generation plants and large consumers from the distribution substation (Kundur 1994; Gómez Exposito, Conejo, and Cañizares 2009). In Figure 2.9, an electric system configuration and structure scheme is represented. Additionally, in all the systems, conductors have to be large enough in order to minimize electricity losses. In strategic points, voltage regulators and capacitors are installed for compensating voltage drops or losses (Pansini 2007).

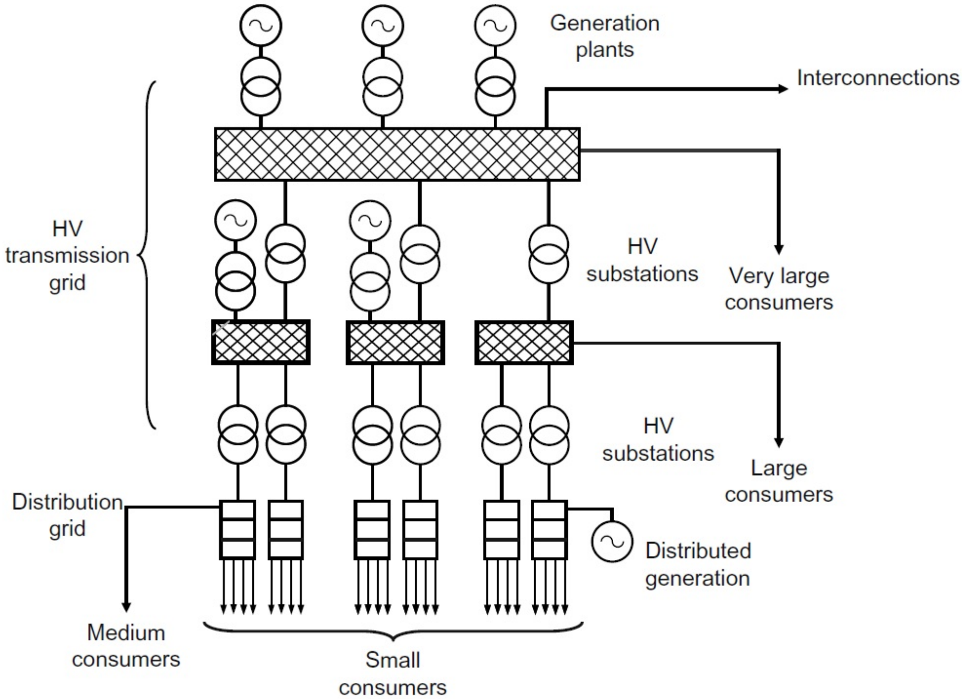


Figure 2.9: Electric power system configuration and structure(© 2009 2006Gómez Exposito, Conejo, and Cañizares 2009).

2.4.2 Service Quality

Load demand could be sensitive to the technical properties of the supply of electricity. The voltage wave has to be perfectly sinusoidal and its magnitude and frequency constant and stable over time in order that all load devices work in good conditions. Consumers become more strict about these conditions for their devices, so service quality is one of the most important topics for electricity service. The factors that influence service quality are listed bellow (Gómez Exposito, Conejo, and Cañizares 2009):

Supply Outages

Supply Outages increase nonlinearity depending on the duration. The causes are different and some of them are faults at power stations, short circuits, overloading and damages of electricity lines.

Voltage Drops

Some equipment as electric motors are very sensitive to voltage drops whose electromagnetic torque depends or the square of the input voltage.

Voltage wave harmonics

They are the result of non-linear electric loads. The voltage waveform becomes complex because the fundamental harmonic in the sine signal is disturbed. The presence of these harmonics result in increase heating in the conductors and equipment, which can damage them.

Flicker

Flicker is due commonly by arc furnaces and electronic devices with thyristors. They cause low-frequency fluctuations in voltage amplitude. The plans for controlling this factor depends on customers and not from the supplier.

Overvoltage

Overvoltage is caused specially by short circuits, faults, lightning, or other events. It can damage consumer devices.

2.4.3 Power System Control

The advantage of electricity as an energy source it that it can be controlled and transported with relative ease and with a high degree of efficiency and reliability. But it is important that a Power System Control exists in order to satisfy next requirements (Kundur 1994):

- Electricity cannot be stored in big quantities, as other sources of energy, so the system must be able to meet load requirements for active and reactive power.

- The power system has to supply the electricity at the minimum cost and with minimum ecological impact.
- The quality of power has to satisfy minimum standards for the factors mentioned before.

2.5 Smart Grid

Growing concerns about global climate change make governments to rethink the energy sector. Electricity is one of the most pollutant because of their traditional generation forms. By other side, the population continue its growth, so do the electricity load, specially in developing countries whose rural population tend to move to urban areas. Renewable Energy Sources (RES) such as wind, solar, and biomass, have been used to address this issue, but their integration in power systems is complex because their electricity generation present uncertainties and fluctuations. All these issues cannot be addressed with the confines of the existing power grid (Farhangi 2010), so the idea o Smart Grid was born.
The definition of the Smart Grid differs depending the source, but it could be considered as an electric grid which interacts with different fields of the engineering: electrical, telecommunications, informatics; in order to have an electric infrastructure with the best efficiency, reliability and security, with important use of distributed energy ressources (DER).

The U.S. Department of Energy mention the principal goals of a SG (U.S. Department of Energy 2010):

- Ensuring the reliability.
- Maintaining its affordability.
- Reinforcing global competitiveness.
- Fully accommodating renewable and traditional energy sources.
- Potentially reducing carbon footprint.
- Introducing advancements and efficiencies yet to be envisioned.

Since 2005, different initiatives for Smart Grid have been developed. The improvements in information and communication technoly (ICT) has offered important opportunities to modernize Power Systems functionalities through an effective control and monitorization (Ekanayake et al. 2012).

Figure 2.10: Smart Grid Scheme (3M).

In (Amin and Wollenberg 2005), it was proposed to add intelligence to an electric power transmission system. The idea was to add independent processors in each component and at each substation and power plant, in order to communicate with each others forming a large distributed computing platform. The authors suggested that the Smart Grid was beyond existing protection systems and the central control systems to a fully distributed system. In Figure 2.10 a Smart Grid Scheme is represented.

2.5.1 Smart Grid functionalities

The authors of (Tuballa and Abundo 2016) mention that the following are the Smart grid functionalities:

Realiability, Security and efficiency of the electric grid

Reliability determines the success of the power grid of providing electricity to the end users. The Smart Grid has to prevent fault detection while the power system grows in complexity due to energy mix and load demand.

Deployment and integration of distributed energy resources (DER)

Distributed Energy Sources (DER) are small sources of generation and storage. DER usually use RES for avoiding greenhouse gas emissions. They are considered as an alternative of the traditional electric power system. They usually have a high initial capital costs but it allows in many cases to bring energy to remote communities and mitigating the problems of depleting fossil fuels.

Demand Response

Demand response is a methodology that involves electricity customers for grid operation. The customers have to shift or delay some devices, or may decide to pay higher electricity prices for reducing peaks in the load. Some of the benefits of demand response are customers bill savings, high reliability, market performance, improved choice, system security (Siano 2013). Some of the techniques are presented in (Pallonetto et al. 2016; Nisar and Thomas 2016; Valencia-Salazar et al. 2011; Soares et al. 2017).

Deployment of smart metering

With the improvement of ICT, the purpose of the smart meters is to enable a bidirectional communication, instead of one way, with high precision and speed. The utilities can collect customers load information and analyse this information for a better performance of the grid. The smart meters need high deployment of sensors and communications. One of the limitations of this new technology are the questions about consumer privacy.

Integration of smart devices

Smart devices are devices that can can receive signals and modify their consumption depending on grid conditions. Usually, they are able to shift or decrease their consumption in peak hours. The smart devices are important elements for the implementation of demand response programs.

Energy Storage

Energy storage allow to satisfy load requirements instead of reducing considerably generators conditions. It is an important source for storing excess of renewable energy that is not consumed. It is also a good element for system stability.

Intelligent Control

Optimal control is substantial for the optimal scheduling of energy sources, to maximize power transport, for transient stability and for real and reactive power control.

Interoperability of appliances and equipment

The interoperability of appliances and equipment is necessary for the reliable transport of electricity from generation to consumption.

2.5.2 Technologies required for the Smart Grid and research activities

The principal technologies are listed below. Additionally, EV and microgrid are considered important technologies for Smart Grid but they will presented more in detail.

Information and communication technologies

These technologies will be present in all the components of the Power System (Wissner 2011):

- Generation: the Smart Grid will integrate in a better way RES. The problem is the intermittent feed-in of these power plants. Nowadays, forecasting techniques allow to predict the generation curve of RES, but the models could fail so it is important to have communication between the generators and the utilities for a better performance of the power system. Also, ICT is enable to establish Virtual Power Plants (VPP) which are small generation units that achieve the characteristics of big plants through their combination.

- Transmission and reserve power: transmission companies reserve power to outweigh imbalances between generation and demand. ICT will allow communications between the transmission grid operator and central station much faster.
- Distribution: ICT will allow the good implementation of Demand Response (DR) programs through a fast and possibly automatic communication between customers (or their devices) and the grid. It is possible also to notify real-time pricing (RTP) to customers in order that customers can adapt their electricity consumption behaviour according to it.
- Smart metering: they will have to allow a bidirectional communication between customers and the grid.

ICT technologies for Smart Grid are categorized in three principal categories: LAN in Scada Systems, NAN around the distribution network and HAN in consumers' premises (Ekanayake et al. 2012). In Table 2.2 , communication technologies in different sub-networks are resumed.

Table 2.2: Tecnologies used in different subnetworks.

Sub-network	Communication technologies
HAN	Ethernet, Wireless Ethernet, Power Line Carrier (PLC),(BPL)
NAN	PLC, BPL, Metro Ethernet, Digital Subscriber Line (DSL), EDGE
WAN	Multi Protocol Label Switching (MPLS), WiMax, LTE

All the interaction of the ICT technologies in the Smart Grid is represented in Figure 2.11

The Smart Grid will use different technologies and the data of all the information from Generation, transmission, distribution and smart metering could be vulnerable of cyber attacks. Unauthorized persons could have access to private information about customers for different purpose, which is a problem of customer privacy. It could be possible that unauthorized persons could take the control of some part of the power system and could generate problems to the general grid. It is prime to have Smart Grid plans for the security of the information and control.

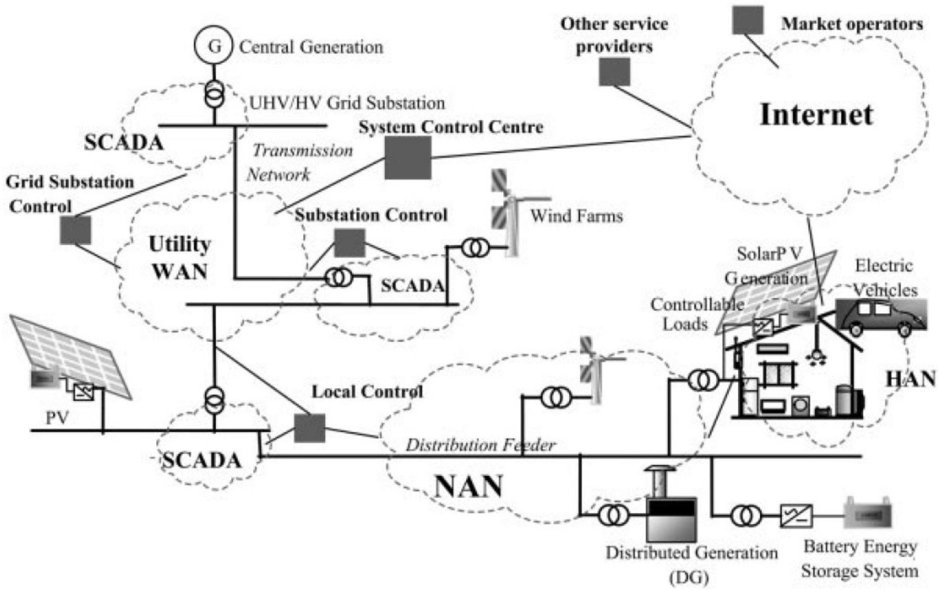


Figure 2.11: ICT in a Smart Grid (© 2012 Ekanayake et al. 2012).

Sensing, Measurement, Control and Automation Technologies

Sensors are essential components for the implementation of Smart Grid technologies. They will enable to monitor each component of the power system and will be massively deployed. Nowadays, one technology that is deployed substantially is Wireless Sensor Network (WSN), which is composed of sensors which data can be transported wirelessly. There are many opportunities in Smart Grid for this technology (Gungor, Lu, and Hancke 2010; Liu 2012; Erol-Kantarci and Mouftah 2011). Other studies involve Distribution Automation Equipment which is the one that allows the operation and control of generation and transmission system.

Power Electronics and Energy Storage

RES present significant variability during electricity generation. It is also considered that some devices will have the capability of modulating their electric profile. These elements create issues for the current power converters. Different techniques are evaluated to perform each requirement of the power system. Even though battery storage present very small energy storage capacity, research in this area is important for improving the stability of power systems and to store the excess of energy from RES.

2.6 Microgrid

The term Microgrid was introduced in the litterature in (Lasseter 2002). It was considered as a solution for the reliable integration of Distributed Energy Sources (DER), including Energy Storage Systems (ESS) and controllable loads. At the present moment, in the literature it exists different definitions of Microgrid, but it can be considered as cluster of loads, Distributed Generation (DG) units and ESSs operated in coordination to reliably supply electricity, connected to the host power system at the distribution level at a single point of connection, the Point of Common Coupling (PCC) (Olivares et al. 2014). Microgrids are small distribution systems, so they avoid complex central coordination and technical problems can be solved easily. In addition, DG reduces the need for new generation and transmission capacity and offers services such as voltage support and demand response (Basak et al. 2012). Furthermore, the microgrid is considered as an important element for the realization of the Smart Grid and it is economically viable due to the improvements in power electronics and power systems control.

A microgrid can work in grid-connected and stand-alone modes. In the grid-connected mode, the deficit generation can be supplied by the main grid and the excess generation produced by the microgrid can be traded with the main grid (Olivares et al. 2014). In the islanded mode, the active and reactive power generated within the microgrid has to be balanced with the microgrid loads, including power transfer of the storage devices, which can actas generators or loads.

Microgrids lies in the opportunity of increasing renewable energy, thereby reducing carbon emissions. The presence os the DER generators close to the load can increase the power quality nd reliability (Hatziargyriou et al. 2007).

There is also isolated microgrids which are microgrids without PCC, and generally corresponds to remote sites.

2.6.1 Microgrid Configuration

Microgrid Architecture

In a basic microgrid architecture, the electrical system is radial with several feeders and loads. This system is connected to the main grid through a separation device, usually a static switch, called point of common coupling (PCC). Each feeder has a circuit breaker (Jiayi, Chuanwen, and Rong 2008) and can be composed of ESSs, DERs and loads. In Fig 2.12, the basic microgrid architecture is presented.

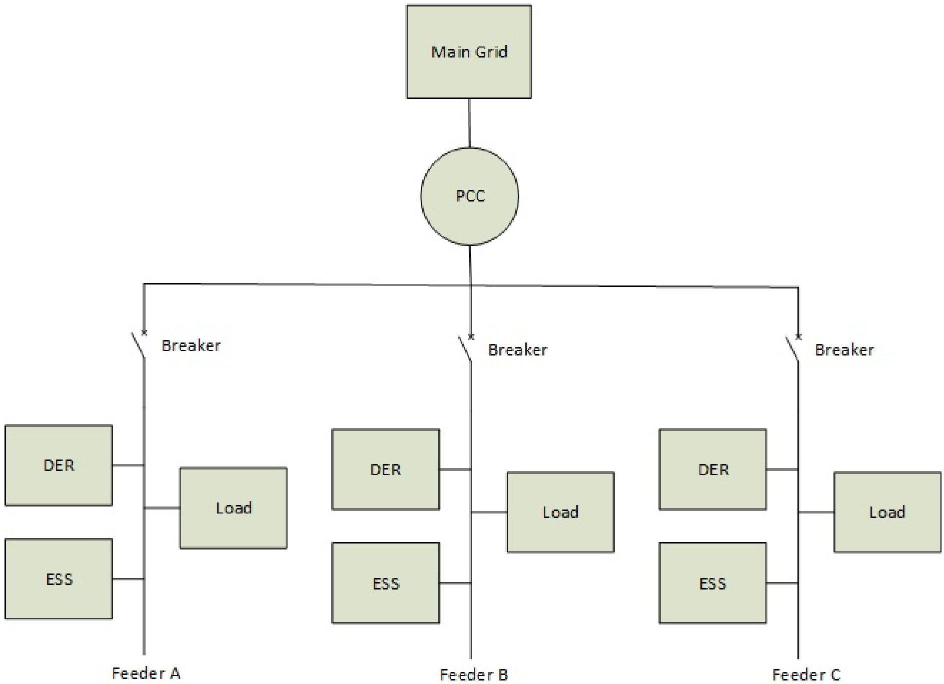


Figure 2.12: Basic Microgrid architecture.

Another architecture is proposed that considers a microgrid central controller. This other architecture has an low voltage network, loads, both controllable and non-controllable micro sources, storage devices, and a hierarchical-type management. It has also a control scheme that monitor and control micro Sources and loads through a communication infrastructure. The head of the hierarchical control system is the MGCC. At a second hierarchical control level, load controllers (LC) and microsource controller (MC) exchange information with the microgrid controller that manages microgrid operation by providing set-points to both load controllers and microsource controller. The amount of data to be exchanged between network controllers is small, since it includes mainly messages containing set-points to LC and MC, information requests sent by the MGCC to LC and MC about active and reactive powers, and voltage levels and messages to control MG switches. The Microgrid architecture with microgrid controller is presented in Figure 2.13.

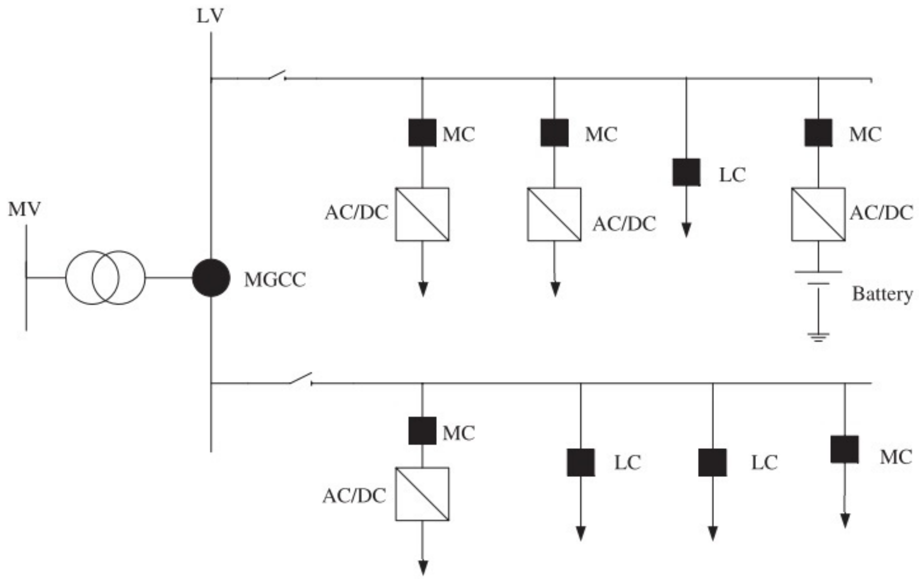


Figure 2.13: Microgrid architecture with microgrid controller (© 2008 Jiayi, Chuanwen, and Rong 2008).

Distributed Generators

The distributed generators in microgrids include well established generation technologies (induction generators, synchronous generators, small-hydro) and new generation technologies (PV, wind, biomass) (Lidula and Rajapakse 2011). Note that well established generation technologies trend to be at its minimum installed capacity because an important goal is the emission reduction. For stability issues and reserves conditions, a minimum well established generation technology might be installed.

Energy Storage Devices

As mentioned before, one of the critical issues of RES is the imbalance between generation and load. The energy storage devices grant in balancing generation and load. This devices are essential for three main reasons (Lidula and Rajapakse 2011):

- They insure the power balance in a microgrid despite load fluctuations and transients as distributed generators with their lower inertia lack the capability in fast responding to these disturbances.
- They provide ride-through capability when there are dynamic variations in intermittent energy sources and allow the distributed generators to operate as dispatchable units.
- They provide the initial energy requirement for a seamless transition between grid-connected to/from islanded operation of microgrids

The most used technologies are batteries, flywheels and super-capacitors.

Microgrid Projects

Several microgrid projects have already been deployed. Some of the principal projects are listed below:

- Bella Coola: it is located in British Columbia, Canada. The Bella Coola Hydrogen Assisted Renewable Power (HARP) System and Micro Grid is a demonstration project that uses a hydrogen energy system (electrolyser and fuel cell) to optimize a run-of-river hydro power generator and to reduce diesel generation. The main power source in Bella Coola is from a run-of-river hydro power generator in Clayton Falls and is supplemented by diesel generators. To optimize the use of the run-of-river generator, the HARP system (Hydrogen Assisted Renewable Power) uses surplus power during non-peak times to create hydrogen through electrolysis, which is then stored as a compressed gas. During peak electrical demand periods, the hydrogen is then used in a fuel cell to generate power that offsets the use of diesel generation, thus reducing GHG emissions associated with the diesel exhaust, as well as reducing diesel fuel consumption. A micro grid controller continuously monitors the various energy outputs and consumption rates, to optimize energy use (*Bella Coola HARP System & Micro Grid*).

- Certs: the project is located near Columbus, Ohio, USA and operated by American Electric Power. Other participants in the CERTS Microgrid Test Bed Demonstration included University of Wisconsin-Madison (PSERC), Sandia National Laboratories, Woodward, Princeton Power Systems, Northern Power Systems, Tecogen, and Lawrence Berkeley National Laboratory. This demonstration was sponsored by the California Energy Commission PIER Electric Transmission Research Program. The testing fully confirmed earlier research that had been conducted initially through analytical simulations, then through laboratory emulations, and finally through factory acceptance testing of individual microgrid components. The islanding and re-sychronization method met all Institute of Electrical and Electronics Engineers 1547 and power quality requirements. The electrical protection system was able to distinguish between normal and faulted operation. The controls were found to be robust under all conditions, including difficult motor starts (*CERTS Microgrid Test Bed*). In Figure 2.14, the CERTS Microgrid Test Bed is shown.

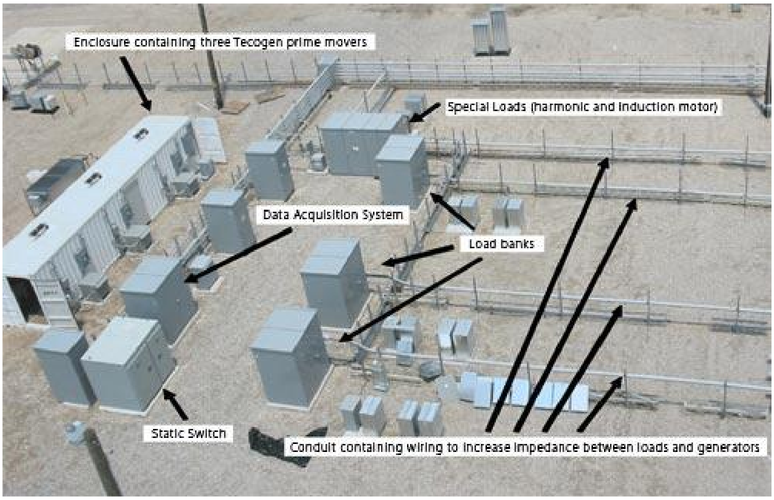


Figure 2.14: CERTS Microgrid Test Bed.

- NEDO: the project is situated in Neemrana Industrial Park of Rajasthan, India. It was built by NEDO, Hitachi, Ltd., Hitachi Systems, Ltd. and ITOCHU Corporation, in cooperation with the Delhi-Mumbai Industrial Corridor Development Corporation Ltd. (DMICDC) under the Japan-India Delhi-Mumbai Industrial Corridor (DMIC) project. In the meantime, 5 MW PV power generation facilities equipped with thin-film PV modules have been installed in the industrial park with power generation performance and other demonstration tests conducted since July 2015 to verify that Japanese thin-film PV modules, having been exposed to India's severe solar radiation, are still able to properly function according to design specifications and provide a stable power supply (*Commencement of Demonstration for Microgrid System Using Photovoltaic (PV) Power Generation in India*). In Figure 2.15, the system configuration at Neemrana Industrial Park in Rajasthan is presented.

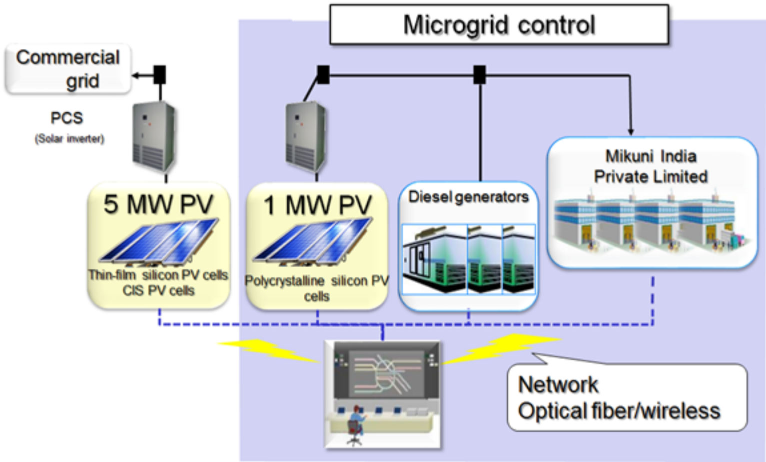


Figure 2.15: NEDO System configuration.

Some of the principal characteristics of the microgrids are summarized in Table 2.3.

Table 2.3: Summarize of Microgrids.

Microgrid	Bella Coola	CERTS	NEDO
Power	Some MWs	About 100 kW	Some MWs
Type of connection	Isolated	PCC	PCC
Energy Type	RES, Fuel, ESS	RES, Fuel, ESS	RES, Fuel, ESS

2.7 Electric Vehicles in Smart Grid

From the point of view of the grid, EVs are a new load that is considered that will grow considerably the next years. Despite EVs could have negative effects in the grid, which will be detailed in the next chapter, they have some of the characteristics of a good player in Smart Grid, when EVs are in big number. First of all, EVs have batteries: in a massive penetration of EVs they could be considered as an important energy storage system that can absorb the excess of RES, become a virtual power plant, control the stability of the system, ancillary services, etc. Then, charging EV could be adapted as a Demand Response program for the EV customers. For this, it is necessary to adapt smart metering for EVs, so the literature presents solutions as "smart chargers".

2.7.1 EV control architectures

It is necessary also to propose smart charging techniques which will allow customers and networks operators to regulate charging profiles for technical and economic benefits (García-Villalobos et al. 2014). The coordination of demand requirements can be performed within different communication and control architectures. It can be considered two main architectural categories: centralized and decentralized, under a possible consideration of a mixed hierarchical architecture (Rajakaruna, Shahnia, and Ghosh 2015a).

Centralized

In centralized architecture, a new electric agent is responsible for managing the charge of all the EVs in an area, called the EV aggregator. In (Guille and Gross 2009), the contribution of a vehicle aggregation is presented that consists of a consolidation of the batteries of the EVs as an appropriate size load and provides interface with the independent system operator or regional transmission organization. Some authors have considered the role of the EV aggregator. Moreover, in (López et al. 2015), an optimization-based model was proposed to perform load shifting where EV aggregators are responsible for load, generation and storage management. Furthermore, the EV aggregator is responsible for EV customers participation in smart charging techniques. This approach has advantages with respect to reliability of charging control and can be integrated easily into existing power system control paradigms. The principal problem of this architecture is the high degree of information needed for allowing accurate planning by the central instance.

Decentralized

In decentralized architecture, the decision-making resides in the EV user, rather than an external entity. It is considered that each EV may have some intelligence for interacting with the grid. The charging coordination works basically based on price based mechanism. This coordination requires more exchange of information, but the number of necessary parameters that need to be communicated is lower because the problem is solved for one unit.

In Figure 2.16, the control architectures are represented

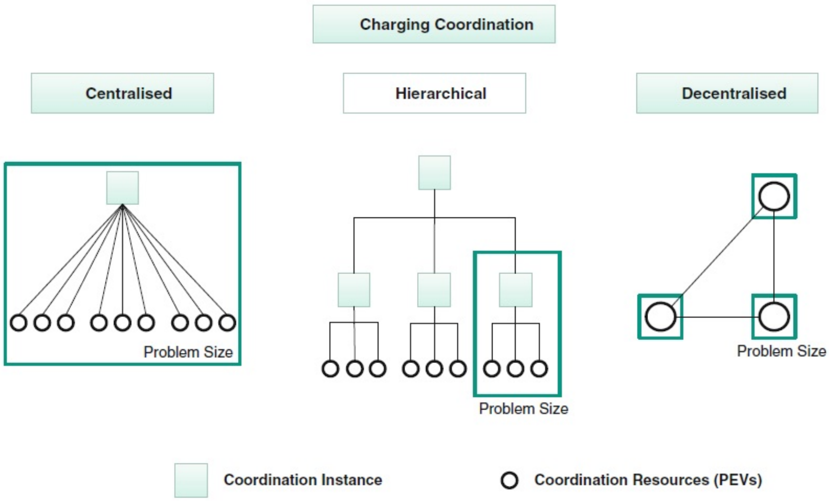


Figure 2.16: EV control architectures (© 2015 Rajakaruna, Shahnia, and Ghosh 2015a).

2.7.2 Vehicle-to-Grid (V2G)

Vehicle-to-grid describes a system in which EV users not only charge their EV from the grid, as unidirectional flow, but allows distributing part of its energy to the grid, as bidirectional flow. This technology allows grid to dispose an additional reserve of generation when the grid has generation issues. The idea of this technology came by the fact that vehicles pass almost all the time parked and if the EVs are plugged, they ca bring such service. Some of the applications of V2G are listed below (Habib, Kamran, and Rashid 2015):

- Active power regulation

- Support reactive power
- Load balancing by valley fillings
- Current harmonics filtering
- Peak load shaving
- Reduce utility operating cost and overall cost of service
- Improve load factors
- Generate revenue
- Reduced emissions
- Tracking of variable renewable energy resources (RES)

For the implementation of this system, the EVs require to have specific chargers that allow bidirectional charging mode. The literature investigates the implementation of such devices. These chargers can use non isolated or isolated circuit configurations. When operating in charge mode, they should draw a sinusoidal current with a defined phase angle to control power and reactive power. In discharge mode, the charger should return current in a similar sinusoidal form. The topologies commonly used are the four-quadrant configuration and the isolated bidirectional dual-active bridge charger (Yilmaz and Krein 2012). In Figure 2.21, these two main configurations are represented.

But, this system is not mature yet and some limitations have to be considered(Habib, Kamran, and Rashid 2015; Tan, Ramachandaramurthy, and Yong 2016):

- Battery degradation: it depends on chemical structure of the battery and a relationship with the square of the current flowing through the battery and its internal resistance. Internal resistance depends also of state of charge (SOC) and working temperature (Han, Han, and Sezaki 2012).
- Electric vehicle load profile: it is necessary to know the load profile of EV users because without this, there could be harmful effects on the grid.
- Impacts of penetration level: if the penetration of EVs in a residential grid is very high, there is not certainty if all the EVs plugged will share part o the energy of their batteries, considering that the EV users will lose part of their flexibility.

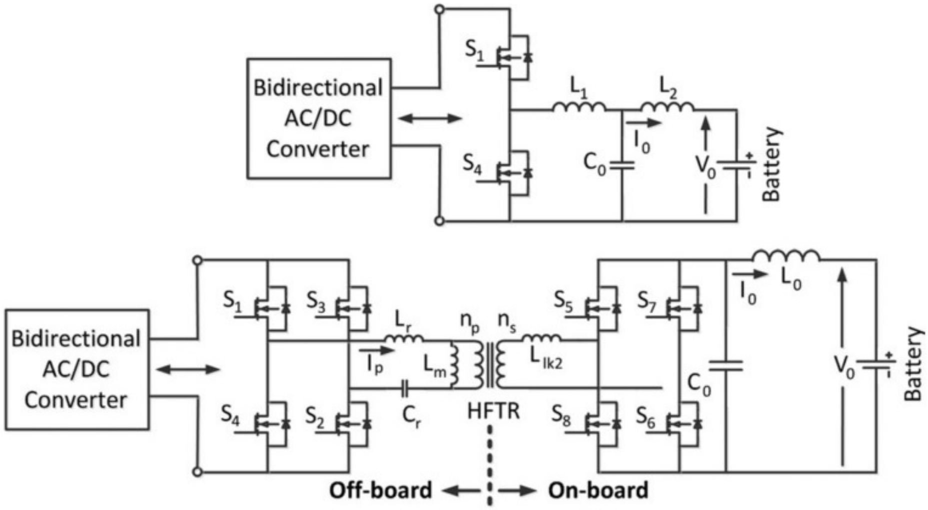


Figure 2.17: Nonisolated bidirectional two-quadrant charger (up) and Isolated bidirectional dual active bridge charger (down) (© 2012 Yilmaz and Krein 2012).

- High investment cost: for adapting V2G technology, it is necessary to install off-board chargers, because the actual ones are just unidirectional. It is important also improvements in software for the correct working of the different flows of the grid. Additionally, charging and discharging the battery several times increase power losses which represents an additional cost of electricity to be considered.

- Lack of willingness to pay for V2G services: EV users could have high inconvenience to pay for V2G contracts. The factors should be Ev users' desire for flexibility in car use, their lack of awareness of how many hours their cars are parked, and their concerns that they may not know how to opt out of some contract terms (Parsons et al. 2014).

2.7.3 Renewable Energy Sources integration with EVs

EVs are a solution for reducing GHG in transportation. But, for a better reduction of GHG, it is necessary that the electricity generation to be less pollutant. For this reason, energy mix tend to be greener with the use of RES such as wind, solar and biomass. Nevertheless, power systems with high RES installed capacity suffer from unpredictable and intermittent supply of the electricity (Mwasilu et al. 2014). In fact, there are issues for balancing the load with the power generation. The balance could be performed by energy storage systems, but they result expensive. Considering a massive penetration of EVs, their batteries could result in energy storage from the point of view of the grid. While parked, the EV batteries could be charged by the excess of RES energy. Therefore there is a clear need to interact between the EV charge and RES generation. For matching generation and consumption, it is necessary the participation of EVs by charging and discharging of batteries (Habib, Kamran, and Rashid 2015).

2.7.4 Companies of Electric Vehicle Solutions

There are several companies that have worked in solutions for the integration of EVs. The most important companies are described in this subsection.

The current solutions have been developed for commercial companies rather than universities or research centers. This is the reason that the company name associated to the proposed solutions is mentioned below.

- Greenlots: it is a global provider of open standards-based technology solutions for electric vehicle (EV) networks and grid management. The company is located in San Francisco and has deployed solutions in 13 countries. Greenlots provide services to utilities, cities, automakers and business. They offer the installation and management of public and fleet charging infrastructure in prime locations. These location refer to residential areas, commercial properties, and public areas. All the charging points form a network that is controlled by the company, through their software and hardware (*Solutions for EV Charging. In 13 countries.*) .
  Greenlots grant users different tools. An application, both for computer and mobile, offers users the possibility to locate nearest charging point, to pay the electricity consumption, check the charging status, get real-time charging updates, and also to remotely turn off/on the EV charging. In addition, users can receive real time electricity prices, so they can continue the EV charging or just stop it if they consider the electricity price

is high (*Greenlots Supports Southern California Edison's Deployment of 80 Level 2 Chargers at Multiple Sites for Demand Response in Workplace Charging*).
From the point of view of utilities, Greenlots offer the possibility to know the charging patterns from different EV users. This data can be processed by the utilities in order to forecast the load and adjust the electric operation. It is also possible to evaluate the impact of EV charging on peak load and the effectiveness of managing the peak through automatic load curtailment. Furthermore, they can evaluate consumer response to a variety of pricing and DR strategies.
Greenlots work also with car automakers, such as BMW and Kia, for increasing the EV penetration levels.

Figure 2.18: Greenlots applications.

- Sema Connect: it is a company located in Bowie, Maryland, USA. The services provided by this company are similar than the ones offered y greenlots: installation and management of charging points. The provide also software application to users and utilities. Although, they have crucial participation with universities. Sema Connect establishes the universities as a hub for innovation and sustainability. As an example, EV case studies in the universities can be used for research (*Get More Out of Your EV Charging Network*). However, their focus is especially EV users than electric utilities, in comparison with Greenlots.

- EVConnect: it is a company located in El Segundo, California, USA. It is a leading provider of electric vehicle (EV) charging solutions for commercial, enterprise, hospitality, university and government facilities. They provide also software for locating charging stations, starting charging re-

Figure 2.19: Sema Charging Station at Johns Hopkins University.

motely, paying through Paypal, and monitoring the charge in real-time (*Smart EV Charging Stations*).

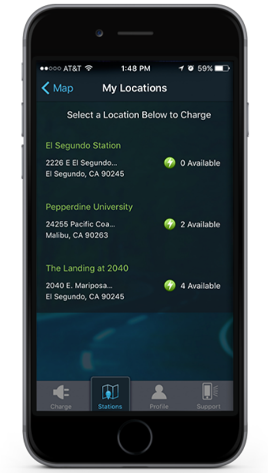


Figure 2.20: EV Connect mobile application.

- WallboxOK: it is a company located in Valencia, Spain. They provide charging points to EV users and they offer different sort of electric vehicle supply equipment, such as the "EV Portable" which is able to charge an EV up to 32kW anywhere or the "UP Wallbox" which is able to charge an EV choosing different charging power rates (*WallboxOk, the supplier of charger you need for your electric car*).

Figure 2.21: EV Portable from WallboxOK.

In brief, these companies offer services to EV users and electric utilities and could probably promote a growing penetration of EVs in the vehicle market. Nevertheless, their services have actually several limitations, which are in the focus of research works. Firstly, EV users could know the electricity prices but they have to check constantly the applications for obtaining a better price and make a decision if they would let or not the EV charging. It may be better that an external agent could bring these services to the users automatically. Then, their energy management is based only in turning off-on the EV charge, which could be improved with charging power rate modulation because it allows to fix the power to a desired power. The services that these companies bring for utilities have also some limitations: utilities receive information of EV charging patterns but they cannot modify them according to the performance of grid operation. For these reasons, several researchers work on new solutions for EV charging.

2.7.5 Electric Vehicle Projects

Several pilot projects have been already deployed and focus on three main aspects: the impact on the grid, the driving and charging behaviour of users, and the technical and economic integration of EVs (García-Villalobos et al. 2014).
The most important deployment projects are summarized:

- Analysis for the implementation of Smart Grids in Ecuador. This project was funded by Inter American Development Bank (IADB) and the Republic of Korea. The project developed a methodology for analyzing all the relative aspects for the Smart Grid implementation in Ecuador, considering the massive introduction of EVs (Álvarez-Bel et al. 2016).

- Grids for Vehicles (G4V). This project was formed by several entities including utilities and research institutions from universities. The objective was to explore an analytical method to evaluate the impact of a large scale introduction of EV and PHEV on the grid infrastructure, proposing a set of recommendations in order to evolve the European grids to smart power systems that can manage a massive EV fleet in whole Europe (*Grid for Vehicles*).

- Mobile energy resources in grids of electricity (MERGE). This project was also formed by European utilities and research institutions, but also by automotive manufacturers consultants and associations. Their goals were similar but they also explored the possible EV integration in Microgrids and VPPs and the possible synergies with the smart metering systems (*Project MERGE*).

- EDISON project. It was funded by the Danish TSO Energinet.dk and the main purpose was to integrate EVs and RES technologies based on ICT open standards. Some of the other purposes included studying the grid impact, charging facilities, tsting battery modules and performing a charge management software. A test system was considered in the island of Bornholm. In Figure 2.22, an Edison Project Scheme is represented (*Edison*).

- SmartV2G project. It is also a European project, whose purpose was to connect EV to the grid by enabling controlled flow of energy and power, considering security conditions. To address this purpose, a charging strategy was developed based on Model Predictive Control (MPC) theory. The advantage of this methodology is the real-time monitoring of the current state of the grid, possible demand side management orders

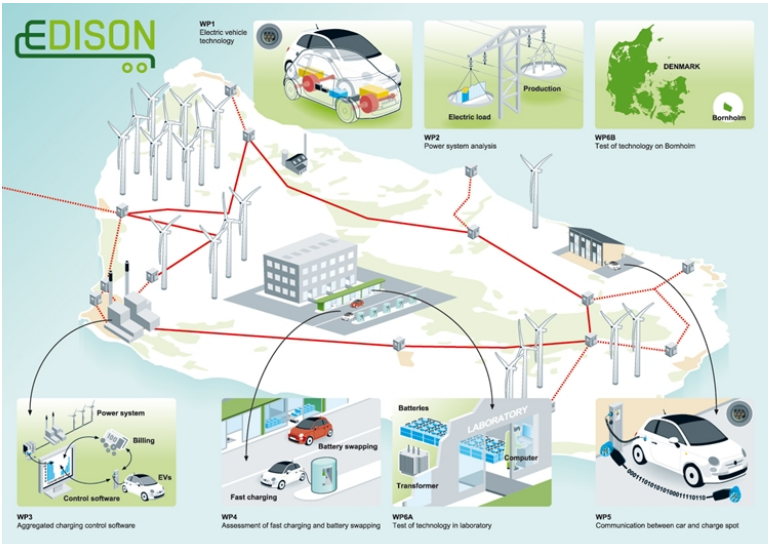


Figure 2.22: Edison Project Scheme (*Edison*).

received in the charging post central controller by DSO or TSO and the PEV users preferences. In Figure 2.23, the SmartV2G Grid Interface is shown (*SmartV2G*).

Figure 2.23: SmartV2G Grid Interface (*SmartV2G*).

- Green eMotion. This project was funded by the European Commision and it prepared in four years the foundation for the mass deployment of Europe-wide electromobility. It is composed by forty-two partners from industry, utilities, EV manufacturers, municipalities, research institutions and universities, and EV technology institutions, that have come together for the purpose of identifying the challenges of Europe-wide emissions-free transportation (*Green eMotion*).

- Mobincity. It is composed by a consortium of 13 partners from 5 European countries. This project aimed to define efficient and optimum charging strategies adapted to user and PEV needs and grid conditions. One major purpose was the development of a complete ICT-based integrated system that is able to interact between driver, his vehicle and all involved infrastructures to optimize the vehicle's charging, discharging and energy saving strategies by offering specific solutions for trip planning, routing and in-car energy management (*SMART MOBILITY IN SMART CITY*).

- EV project. This is a project from USA, considered as the biggest initiative for introducing PEVs and CPs in U.S.A, funded by the U.S.A. Department of Energy and several partners, such as Nissan and Chevrolet. During the project, significant data has been collected to characterize the use of EVs in different regions and climates. The effectiveness of charging infrastructure and possible business models have been evaluated for the implementation of public and commercial charging posts (*The EV Project*).

- Vehicle-to-grid demonstration project. It is a project from USA that aimed to demonstrate the feasibility and practicality of EVs based grid regulation, and to assess the economic value based on real operating data and real market prices for the service being provided (*The Grid-Integrated Vehicle with Vehicle to Grid Technology*).

- Zem2All e-mobility pilot project inaugurated in April 2013 in Malaga city, Spain. It is the largest V2G pilot project. It features 23 CHAdeMO DC fast charging points including 6 bidirectional chargers capable of providing V2G functionalities. The project comprises 200 EVs (Nissan Leafs and Mitsubishi iMiEV) compatible with the CHAdeMO DC-fast charging standard. To be precise, it makes up 229 EV charging points in total. In 2.24, a V2G charger station pilot is shown.

Figure 2.24: Zem2All V2G prototype.

2.8 Conclusion of the Chapter

In this chapter, a review of EVs was presented. An overview of electric power systems and was also performed. Furthermore, the Smart Grid and Microgrid principles were discussed, and the interaction of EVs was exposed.

The different types of EVs up to the date were presented, highlighting the fact that battery EVs are the most promising technology as they not pollute locally. Several components are different from ICVs, so the new users will have to become familiar with them. Furthermore, several standards have been developed to define the EV charging characteristics, such as the modes, points, and levels. The EV battery is considered an essential component, so it is crucial to analyze its several parameters.

EVs use electricity from the power grid to obtain the required energy to operate, so the electric power systems have been analyzed, highlighting the idea of Smart Grid and new supply systems, such as microgrids.

Furthermore, this chapter has studied the most significant current experiences of EV integration in power systems. Thus, the principal companies that offer EV solutions (e.g. EV supply equipment) were described. The deployment of EV solutions will probably encourage more people to buy EVs. However, the present solutions offered are limited by the growing users' needs and power systems requirements. Therefore, governments are considering new solutions for more efficient and better integration of EV users in smart charging programs, through pilot projects that were also analyzed. Most of the works offer guidelines for the research on different topics of EV charging.

However, an EV massive penetration could result in several problems for power systems. These issues and new proposals for smart charging techniques are proposed in the next chapter.

Chapter 3

State of the Art - Charging Strategies and Grid Configurations for the Electric Vehicle adoption

3.1 Introduction

The number of EVs in the vehicle market is currently very small. However, new policies and fuel price increase result in a growing acquisition of EVs in the world. Some integration projects of EVs have been deployed. In addition, some companies have been already working on solutions for EV integration. Nevertheless, a massive introduction of EVs can cause several problems in the power grid, which will be discussed in this chapter. Researchers have focused their work on new charging methodologies for avoiding these problems. By other side, EV has a battery with a considerable amount of energy that may behave as a controllable load in power systems. Therefore, EVs could result in an opportunity for a better performance of the grid. This consideration needs the crucial participation of EV users. Several works have also focused on this participation of EVs in the grid operation, which they are explained in this chapter.

3.2 Issues of EV massive penetration in Distribution Grids

The impact of massive penetration of EVs in Distribution Grids have been studied in the literature. A paper that is becoming a milestone about the impact of EVs in the grid is (Clement-Nyns, Haesen, and Driesen 2010). The authors studied the impact of large penetration of Plug-in Hybrid Electric Vehicles (PHEV) to assess the voltage deviations and the power losses a distribution grid. Some considerations were established for the simulation, such as a battery storage of 11 kWh, a maximum output power of 4 kW, a penetration level of 30 %, that the charges are made at home, a household load typical of Belgium. The IEEE 34-node test feeder was selected for the model, which represents a radial residential grid. In Figure 3.1, it is observed the voltage profile in a node of the distribution grid for a penetration degree of 0%and 30 % during a winter night. It is observed a decrease of the voltage in the presence of PHEVs during the charging period.

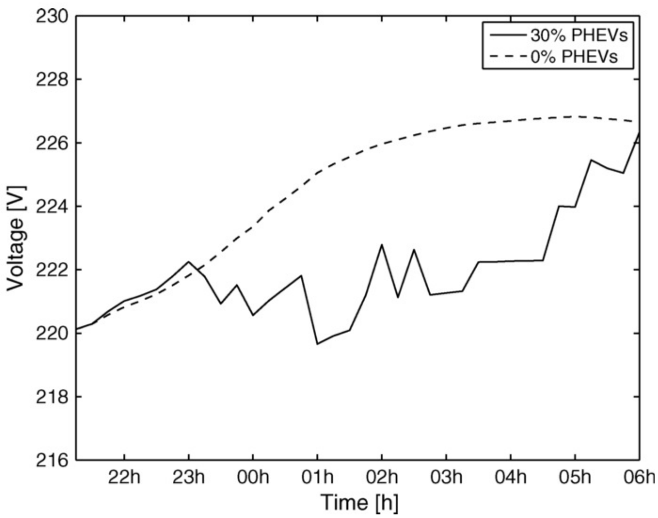


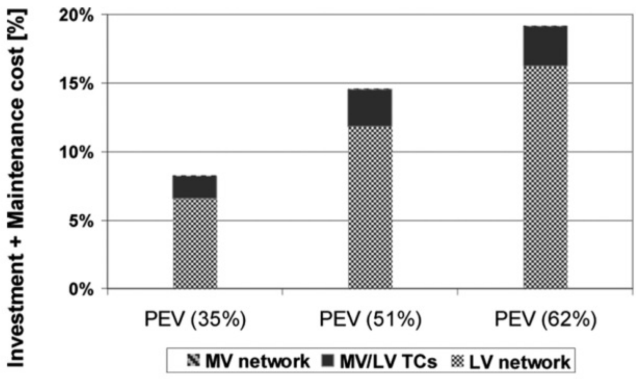
Figure 3.1: Voltage profile in a node of the distribution grid for a penetration degree of 0%and 30 % (© 2010 Clement-Nyns, Haesen, and Driesen 2010).

The authors also demonstrated that an increase of the penetration levels of PHEVs leads to a significant increase of the voltage deviations. As an example, the voltae deviations fr a 30% of PHEV integration between 18h00-21h00 in winter was of 10,3 %.

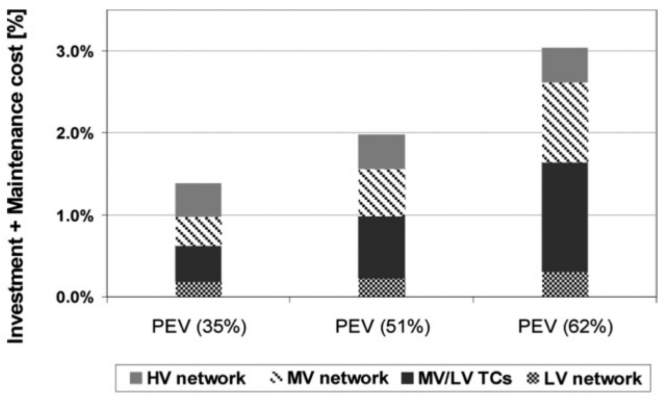
In (Pieltain Fernández et al. 2011), it was studied the impact of EVs in distribution network investments and incremental energy losses. The authors focused their study in large-scale distribution networks. Two different areas were studied: the first one is a residential urban area and the second one is an industrial and residential area. Different models of PHEVs are considered for representing the different peak powers and battery energy capacities. Three scenarios were taken into account with different penetration levels. For the case studies, the incremental investment is expressed as a percentage of the investment cost of the base case distribution network without PEVs taken as reference. The results of the investment costs are represented in Figure 3.2. It shows that PHEV penetration in large urban and industrial areas lead to important investment costs that can reach more than 15 %. Note that the costs of charging points or stations were not considered for this study. Additionally, the power losses in off-peak hours were studied. The results are represented in Figure 3.3. Power Losses can reach more than 40 % for PEV penetration of 62 %.

The impacts of PHEVS on Power Distribution Systems were also studied in (Shafiee, Fotuhi-Firuzabad, and Rastegar 2013). In this study, some variables were studied deeper, such as PHEV owners' behavior during different days, PHEV type, "all electric range", battery capacity, PHEV distribution prediction, PHEV penetration levels. It was also considered the IEEE-34 node test feeder for the simulations. Different case studies were simulated depending on the penetration level of PHEVs. In Figure 3.4, the impacts in the load curve are presented and in Figure 3.5, the impacts in the total loses. The authors demonstrated that an increase of PHEVs in the distribution networks leads to an increase of the distribution load and an important increase of the total power losses. Furthermore, the impact of the peak load was also studied. Figure 3.6 shows the impact of PHEV in peak load. Authors conclude that peak load increases with PHEV level increment. Nevertheless, note that this important increment is due only by the conditions of the users analyzed and the effect could differ from different region because of different behavior.

In (Lucas et al. 2015), the impact of massive EV fast charging was studied in voltage and current harmonics. It was performed four measurements of EV fast charging. The fast charger characteristics was of a current of 63 A and a voltage of 230V. Different low states of charge were studied. In Figure 3.7 it is represented the voltage and current harmonic histogram. The



(a)



(b)

Figure 3.2: Incremental investment and maintenance costs in area A (a) and B (b) (© 2011 Pieltain Fernández et al. 2011).

authors explained that individual harmonics fail to respect IEEE standard limits because of the 11th and 13th orders.

The authors of Turker investigated the Low-Voltage Transformer Loss-of-Life for a high penetration of PHEVs. The EV charging load was simulated through the information of French vehicle fleet characteristics A thermal model was used to estimate the hot-spot temperature. In Figure 3.8, the life duration of a transformer is represented. It shows that with EV increase the life duration of the transformers presents a high deterioration.

Another study, (Qian, Zhou, and Yuan 2015) evaluated also the impact of EVs in the loss of life of transformers. The findings were similar and demonstrated

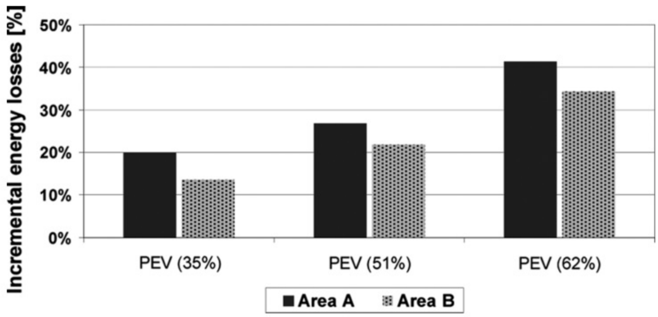


Figure 3.3: Incremental energy losses in off-peak hours (© 2011 Pieltain Fernández et al. 2011).

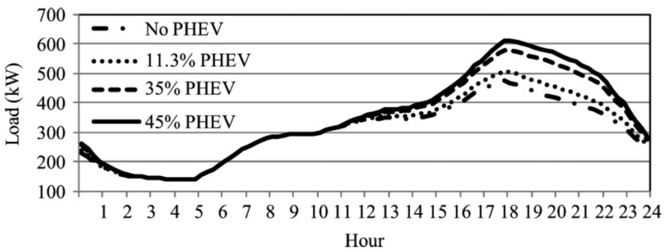


Figure 3.4: Impacts of PHEV charging on total load curve for different PHEV pen- etration levels in summer of 2020 (© 2013 Shafiee, Fotuhi-Firuzabad, and Rastegar 2013).

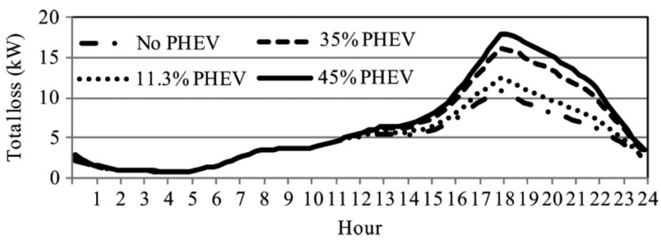


Figure 3.5: Impacts of PHEV charging on total losses for different PHEV penetra- tion levels in summer of 2020 (© 2013 Shafiee, Fotuhi-Firuzabad, and Rastegar 2013).

the degradation of life duration of the transformers because the increase of transformers power load.

The authors of (Putrus et al. 2009) analyzed the impact of EVs in voltage profiles. A typical network model was used for the simulations. Results showed

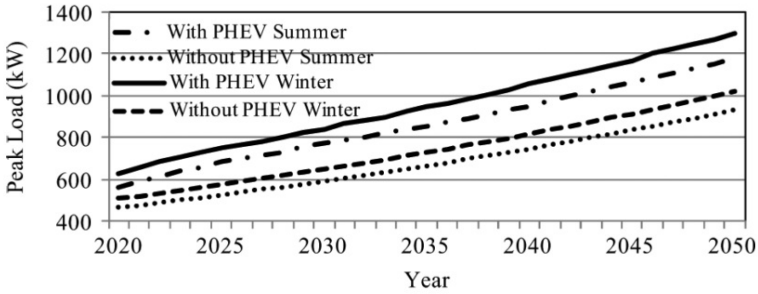


Figure 3.6: Impact of PHEV charging on peak load for long-term investigation during 2020 and 2050 in summer and winter. (© 2011 Pieltain Fernández et al. 2011).

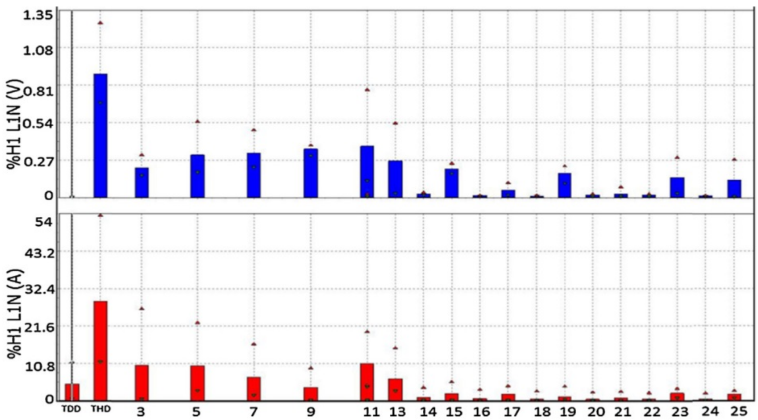


Figure 3.7: Voltage and current harmonic histogram (© 2015 Lucas et al. 2015).

that with 30% penetration of EVs, the voltage levels exceed the minimum voltage levels.

3.3 Smart Charging of EVs in Distribution Grid

As presented in the previous chapter, the Smart charging methodologies could be divided into two main architectures: centralized and decentralized. Thus, the principal works corresponding to these two architectures are presented depending on their primary purposes.

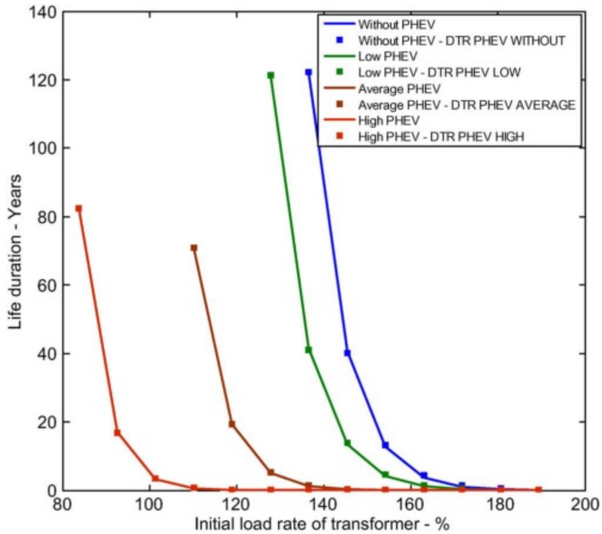


Figure 3.8: Voltage and current harmonic histogram (© 2015 Lucas et al. 2015).

3.3.1 Centralized Architectures

Distribution Losses

The authors of (Sortomme et al. 2011) propose a coordinated charging for PHEVs in order to minimize distribution system losses. Relationships between feeder losses, load factor and load variance are presented. They develop three algorithms with different objective functions and compare the results in load profiles. Authors conclude that minimizing load variance is the most versatile method.

In (Deilami et al. 2011), a Real-Time coordination of PHEVS is presented to minimize power losses and improve voltage profile. A Real-time smart load management control strategy is proposed for the integration of PHEVs, with 5 min intervals. It is also considered a feasible pricing and time zone priority scheme for PEV charging. Results show a decrease of voltage overloads and power peaks compared to uncoordinated charging.

System Costs

The authors of (Valentine, Temple, and Zhang 2011) studied an intelligent PEV charging scheme that significantly reduces power system cost while maintaining reliability compared to the widely discussed valley-fill method of aggregated charging in the early morning. The case study was focused on New York. Different PEV level penetrations were considered.

In (Di Giorgio, Liberati, and Canale 2014), an event driven model predictive control (MPC) framework for managing charging operations of electric vehicles (EV) in a smart grid was presented. The objective is to minimize the cost of energy consumption, while respecting EV drivers' preferences, technical bounds on the control action. The methodology developed an open-loop optimal control problem.

Peak Shaving and Valley Filling

The authors of (Jian, Zheng, and Shao 2017) presented a high efficient valley-filling strategy for centralized coordinated charging of large-scale electric vehicles. The study is set in the scenario of Shenzhen, China for the year of 2035, and the amount of EVs involved is expected to reach 1 million or above at that time. The results demonstrate that the coordinated charging scheme with the pro- posed valley-filling algorithm can greatly alleviate the negative impacts arising from the EV charging loads on power grids.

Frequency Regulation Services

The author of (Han, Soo, and Sezaki 2010) proposes an optimal V2G aggregator for frequency regulation. An optimal energy control for each EV was developed through dynamic programming.

In (Vagropoulos and Bakirtzis 2013), an Optimal Bidding Strategy for Electric Vehicle aggregators in Electricity Markets is proposed. An stochastic optimization is used. Test results demonstrate that the careful consideration of the instructed and uninstructed energy deviations play a key role in the design of the aggregator's bidding strategy.

The authors of (Ke, Wu, and Lu 2017), a real-time power dispatch problem for an EV aggregator is proposed to provide regulation services. The methodology is based on a real-time greedy-index dispatching policy. The authors demonstrate that their methodology present advantages compared to stochastic programming due to the quick resolution in presence of uncertainties.

In (Liu et al. 2016), a supplementary frequency regulation is studied considering the regulation fro the control center and the expected battery SOC from EV users. Similarly, the dispatch uncertainties are considered and both the regulation and the expected charging of EVs are ensured.

The authors of (Sousa et al. 2016) proposed an energy and ancillary services joint management model. The problem considered energy dispatch, regulation down and up, spinning and non-spinning reserves.

In (Le Floch, Kara, and Moura 2016), a novel state-space modeling framework for massive fleets of PEVs was studied, based on aggregation and continuum modeling. The EV aggregator has to manage three possible charging rates (charging, discharging, idle) for ancillary services.

The authors of (DeForest, MacDonald, and Black 2018) provided a V2G fleet demonstration for providing ancillary services in Los Angeles Air Force. The model was based on a MILP optimization for managing the EV charging and day-ahead bidding.

3.3.2 Decentralized Architectures

Distribution Losses

The authors of (Ghiasnezhad Omran and Filizadeh 2017) studied a semi-cooperative decentralized scheduling scheme for PEV charging demand. This scheme is based in two consecutive stages of static and dynamic scheduling. The methodology was applied to an IEEE-13 node radial test feeder and with a laod profile from Manitoba Hydro.

System Costs

In (Xi and Sioshansi 2014), a decentralized charging control is studied that optimizes charging costs of a PE fleet, which is based on a price-based signals. The results of a case study show that it can find a nearl-socially optimal equilibrium.

Valley-Filling and Peak-Shaving

In (Zhang et al. 2014a), an optimal decentralized valley-filling charging strategy for electric vehicles is presented. The power grid indirectly coordinates the charging behaviors of all EVs by implementing a time-power-varying pricing scheme. When the EV owners individually optimize their charge patterns in response to the pricing scheme, the grid automatically achieves a valley-filling charging effect. The methodology was evaluated in a case study of Beijing, China.

The authors of (Zhang et al. 2014b) proposed a charging protocol for PEVs with grid operators updating the cost signal. This protocol is based on the calculation of each PEV optimal charging profile based on the cost signal and communicates it to the grid operators.

In (Fan 2012), a distributed Demand Response algorithm and its Application to PHEV Charging in Smart Grids was proposed. Individual users adapt to the price signals to maximize their benefits while charging their PHEVs.

Chargers

The authors of (Teng et al. 2017) designed a fully decentralized controlled EV charger for mitigating issues on the grid, such as overload. The EV charger measure some parameters that are integrated in a fuzzy logic controller for adjusting the charging current automatically.

Frequency Regulation

The authors of (Luo, Xia, and Chan 2014) proposed a decentralized charging control strategy for plug-in electric vehicles to mitigate wind farm intermittency and enhance frequency regulation. Simulation results verify that the proposed decentralized charging control is capable of neutralizing wind farm power output fluctuations and frequency regulation in a system with high penetration wind power can be greatly enhanced as a result.

These methodologies are useful to minimize charging costs, but users' preferences are not significantly considered, which can create a barrier for users to adopt EVs.

3.4 Smart Charging of EVs in high RES deployment grid

This section presents the techniques proposed in the literature concerning charging techniques for electric vehicles in power systems with a high presence of RES.

The authors of (Ekman 2011) investigated the effects of different EV charging strategies on balance between wind power production and consumption in a future Danish power system. A scenario for 2025 is considered. An algorithm has been implemented that searches for the best hour for the EV charging. Consequently, this work uses a scheduling methodology. However, this work has only considered wind energy.

In (Dallinger and Wietschel 2012), the capability of PEVs to balance intermittent RES in a 2030 case study for Germany was studied. The authors conclude that the consumer reaction on price signals is unclear because the economic incentives from electricity markets are low. But, this work has also just considered wind energy.

In (Saber and Venayagamoorthy 2011), a model for cost and emission reduction, with use of EV and RES, was presented.

The authors of (Soares et al. 2017) presented a stochastic model with uncertainty sources as load demand variability, intermittency of wind and PV generation, EVs stochastic demand and location and market price.

The idea of Electric Vehicles in Microgrids, which generally contain a high level of DER, is also taking importance and different methodologies are studied as (Deckmyn et al. 2017; Guo et al. 2016; Su, Wang, and Roh 2014).

Another vision targets in minimizing electricity costs and CO_2 emissions as done by (Bracco et al. 2015), where they present an overall architecture with a dynamic optimization model. The tests were made at University of Genoa Smart Polygeneration Microgrid, which is composed of different distributed energy resources (DER). However, the scale of the microgrid is very small.

In (Liu et al. 2017), a dual-tariff is proposed for PEV charging coordination to absorb the excess wind energy.

The authors of (Liu et al. 2017) have considered a differentiated-dual tariff scheme for PEV charging coordination in order to absorb wind energy. However, this work has only considered EV charging in a wind generation environment.

In (Soares et al. 2015), a cost allocation model for distribution networks was proposed considering high penetration of distributed energy resources (DER).

3.5 Planning EVs in Distribution Systems

This section presents the different planning models that study the massive introduction of EVs. The planning could be in short or long-term.

The authors of (Bin Humayd and Bhattacharya 2017) presented the long-term distribution planning from the perspective of local distribution companies considering DGs, substations, capacitors and feeders. This framework considered uncontrolled and smart charging of PEVs and the results showed that plan costs are much higher with uncontrolled charging.

In (Aluisio et al. 2017), an optimal operation planning of a V2G-equipped microgrid in the presence of an EV aggregator is studied. The methodology is based on finding the the day-ahead operation plan through a non-linear optimization involving system costs.

The authors of (Alharbi et al. 2017) proposed a novel framework for designing an EV charging facility as a smart energy microhub in distribution systems. New design decisions were determined from the perspectives of the investor and the local distribution company.

In (Xiang et al. 2016), the economic planning of EV charging stations was presented, based on a novel solution for determining the optimal siting and sizing of charging stations. This work considered the interactions between power and transportation industries.

The authors of (Dong, Liu, and Lin 2014) studied also EV charging stations sitting and the impact of te deployment of them on increasing electric miles traveled. This work used a genetic algorithm and it was applied to case study using GPS data.

In (Hajimiragha et al. 2011), an environmental and economic sustainable integration of PHEVs into the electric grid was studied, based on a robust optimization approach, considering crucial planning uncertainties. The model was applied in Ontario, Canada to support the long-term planning horizon 2008-2025.

Although these methodologies are effective for the planning of EVs in power systems, no work has studied the planning of EVs in isolated systems with high penetration of RES.

3.6 Conclusions of the Chapter

In this chapter, the principal issues of a massive penetration of EVs were presented. Principal strategies of EV charging were also explained, considering centralized and decentralized architectures. Then, the Smart Charging of EVs was studied in power systems with high RES deployment. Finally, the planning studies for EV integration in distribution systems was detailed.

As illustrated in the different works, centralized architectures group several EVs as a significant load (or generation), and an EV aggregator will be in charge of managing them; while in decentralized, the decision-making resides in each EV. All the methodologies demonstrate their effectiveness, so it is not possible to say that one architecture is better than the other, but they have to be implemented considering the grid requirements.

Most of the works presented use methods that shift the EV charging or allow charging only in specific conditions (schedules). However, these methods could also discourage users to adopt them, because they would like to have flexibility to charge when they want to (Sadeghianpourhamami et al. 2018) and it could create uncertainty about the autonomy. It is compulsory to find new alternatives considering EV user convenience, like different tariffs depending on the time users could wait. These alternatives should consider technical conditions for charging the EV battery, such as power rate modulation, and a novel mathematical method to consider EV charging during a day-ahead considering some uncertainties such as state of charge (SOC), battery capacity or rated power of battery chargers. Furthermore, the smart charging techniques focus only in one source of RES.

Chapter 4

New Methodology: Smart Charging Using Customer Choice Products (CCPs)

4.1 Introduction

The methodologies presented in the previous chapter have different objectives and could result efficient in the grid performance, but most of them do not offer any advantage for EV users flexibility. The methodologies are specially based on schedules and EV load shifting, which can cause uncertainty in EV users about the daily autonomy of their EVs and disagreement concerning their daily habits. Hence, the methodologies should take into account these EV users flexibility characteristics. On the other hand, some works consider some variables fixed and the same for all EV users, such as state-of-charge (SOC), battery capacity or rated power of battery chargers in their respective models. In addition, few works have focused on the minimization of electricity costs for charging EVs and considering the available power from the power grid. Thus, the aim of this chapter is to present a novel methodology for an EV aggregator through charging power modulation. The EV aggregator will adjust slow charging power in order to fulfill technical constraints imposed by network operators while EVs are charged at the lowest cost. According to that, EV users will consider different power levels of slow charging depending on network conditions and contracts. The desired characteristics of the proposed method are highlighted as follows:

- An interaction should be proposed between the EV aggregator and the Distribution System Operator (DSO) and the Transmission System Operator (TSO). The EV aggregator will be in charge of avoiding technical issues in the electricity network, while the charging costs are optimized, both in the operational planning and in real-time.

- Different users charging patterns should be simulated with real-time information provided by EV chargers when a new EV is plugged such as State of Charge (SOC), time of plug and EV power consumption. This model should be adjusted to any electricity network, independently of the country in which it may be located, and even if the demand conditions, electricity prices, and users behavior is different from the case study presented in this chapter. In this chapter, only G2V will be considered according to the above-mentioned reasons. Nevertheless, this model is easily adaptable to a V2G system, if technical and economic conditions are favorable.

- The charging method consists of modulating the charging power rate, which will be remotely controlled by an EV aggregator taking into account electricity prices and technical constraints. EV users would have the possibility of selecting a charging customer choice product (CCP) (before starting the charging process) depending on their time flexibility, and this will avoid some typical management problems such as unexpected interruptions of the charging process or waiting for a long time before driving.

- Different sensitivity analyses are performed for each crucial parameter in EV Smart Charging technique in order to quantify the technical and economic variations

- Results of the sensitivity analysis are useful for performing an optimal planning of an EV aggregator in distribution systems

- The sensitivity analysis propose practical information for the decision making of the EV aggregator Business Model

The chapter is organized as follows: in section 4.2, the new methodology is presented. In section 4.3, the problem formulation is discussed. Then, in section 4.4, the parameters for the sensitivity analysis are studied. Finally, in section 4.5 the work is concluded with some remarks.

4.2 New Methodology

4.2.1 EV aggregator for System Operation

DSO and TSO may have troubles in the future due to the presence of EVs uncoordinated Charging. Additionally, residential load patterns could have important changes from one day to another. DSO and TSO have to manage all these problems using all the available resources. The EV aggregator becomes a necessary partner that provides technical services to the DSO and TSO. The EV aggregator will act as an intermediate agent among operators, who will probably use market mechanisms to get the necessary resources and EVs consumers.

This agent will provide flexible demand packages that can be offered to grid managers and other interested agents. This flexible potential will be provided by the EV users with charging power modulation facilities. As mentioned before, the flexibility in the demand response will be only obtained through charging load modulation and not with grid injection. The aggregator will offer its services to TSO and DSO for grid operations and possibly to other electricity partners in order to optimize their buying energy portfolio.

In a future scenario, TSO and DSO will probably have, in their operation area and besides the EV aggregators, Demand Response aggregators, that will manage flexible load from residential, commercial and industrial customers. In this paper, this load will be considered as a non-flexible load, and the TSO and DSO will interact with this new EV aggregator and with other aggregators in order to solve daily technical problems as peak or valley loads. This EV aggregator will compensate this non-flexible load with the EV charging load when, flexible. Consequently, the EV aggregator will modulate the EV charging curve in order not to exceed the maximum available power for EV charging at any moment of the day (see Figure 5.3) determined by network operating requirements (Distribution and Transmission). The aggregator will be economically benefitted in case it complies (not overpass) this "Maximum EV Load Profile".

It is assumed in the proposed methodology that the EV aggregator will be provided by system operators with this profile as well as the associated economic conditions.

Figure 1 represents the scheme of the methodology.

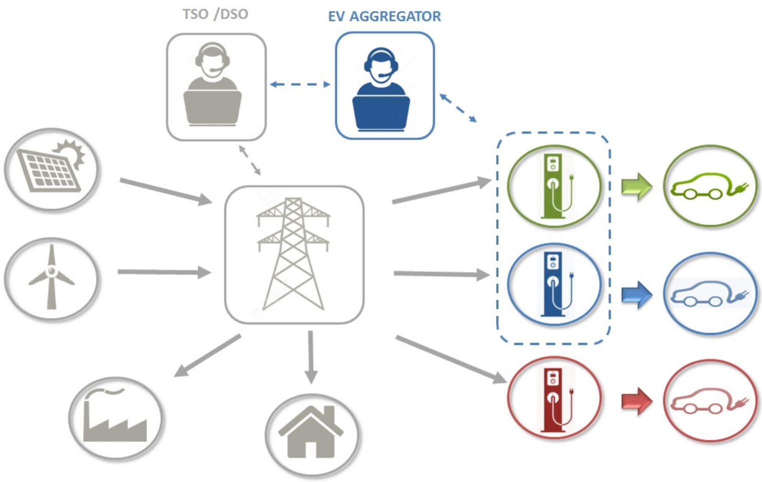


Figure 4.1: Scheme methodology.

4.2.2 EV Users options

In some cases of demand response programs, people may have some resistance to adopt these programs because they suffer disconnections when they need to use their machines in peak hours. The case of the EV owners could be the same: when a common user connects his vehicle to the grid, he will expect to have at least a minimum of his battery charged after a time to drive some distance. Some solutions in the literature propose EV schedules (Sharma et al. 2014; Sheikhi et al. 2013; Deilami et al. 2011; Lausenhammer, Engel, and Green 2016; Ghiasnezhad Omran and Filizadeh 2017; Wu, Aliprantis, and Ying 2012) or EV load shifting (Qian, Zhou, and Yuan 2015; López et al. 2015; Lopes, Joel Soares, and Rocha Almeida 2011), it could result in a problem: a common EV user would like to charge its vehicle arriving home and have it charged after a moment, but these schedules could discourage these users to adopt it. It is clear that for the aggregator it is better to charge the EV when price is the cheapest, but it is not in accordance with user preferences.

It is assumed that the aggregator will use charging power modulation as (Sortomme et al. 2011; Clement-Nyns, Haesen, and Driesen 2010), but in this case between 0 kW and 7.2 kW. It is disregarded 22 kW charging, because not all vehicles accept this power and because is a three-phase connection, and the others mono phase. The aggregator will have to manage parking lots or residential vehicles that have slow charging chargers.

In this chapter's methodology, customer choice products (CCPs) are proposed for charging the users' EVs. They are defined as different electricity pricing for charging the EVs, which will be coordinated by the EV aggregator. They differ from a tariff because it is the EV aggregator which fix the pricing and not the electricity regulator. For the methodology, three CCPs are selected, but this number could be modified depending on users and grid conditions. The CCPs are associated with an average charging power corresponding to the total duration of charging. In this case, the EV user must select one before starting the charging process. The number of CCPs and their characteristics (average charging power rate, etc.) could be modified according to user's preferences from countries where they are applied. For this methodology, it is considered that there will be installed smart chargers that allow EV users to set the final charge level. The Smart Chargers are in research development. It is expected that they will have a screen for showing different information to users such as energy delivered, remaining time, charging power rate. It will be able to communicate this information to the utilities and to the EV aggregator. The EV aggregator will be able to have decisions concerning the charging of the EVs in the area, so a remote controlling is also needed. When an EV user performs this process, the duration for each CCP will be calculated and showed in the display as well as the associated average electricity price. After that, the EV user will be able to select one of them according to his needs, but he must consider that if he stops the charging process before ending the selected charging period, there is no guarantee to achieve the selected charge level. The CCPs proposed are defined as: green, blue and red.

Charging Prices

- Green CCP: it is the cheapest CCP.
- Blue: it is the intermediate CCP considering prices
- Red: it is the most expensive CCP

The EV aggregator has to fix the prices depending on the conditions imposed by DSO and TSO. It is expected that the prices have to vary depending on the period on the day. The different prices of the three CCPs have to be presented in the screen of the smart charging before starting the charging. It means that for a same CCP, the end-price the EV user has to pay differs depending on the period of the day. This will encourage EV users to charge when prices are lower. As mentioned, it is not possible to disconnect during the charging process, because there is no warranty that a minimum amount of energy has be delivered to the EV battery. So, it is important to considered that the user has to consider effectively the CCP depending on the time he can wait.

When an EV i is plugged the EV aggregator calculates the corresponding price to pay that is defined:

$$p_i = \frac{D}{24}\sum_{k=1}^{k=D} \pi_k . P_{k,i} + p^F, \forall k \in U_i \tag{4.1}$$

The EV user has to pay the variable electricity price and a constant value p^F that corresponds to the benefits of the EV aggregator, which corresponds to its benefits for the service provided. Note that the price is calculated for each time horizon U_i, which is different for all users.

Charging Duration

The charging duration from each CCP is defined:

$$T_i^G = \frac{E_i^{req}}{P^{G,av}} \tag{4.2}$$

$$T_i^B = \frac{E_i^{req}}{P^{B,av}} \tag{4.3}$$

$$T_i^R = \frac{E_i^{req}}{P^{R,av}} \tag{4.4}$$

It represents the time that each user has to wait until its EV battery is charged depending on the CCP he selects and the energy the battery requires. Before starting the charge, EV will have to select the CCP it prefers depending on the price he has to pay. It is considering that a smart device will show the energy needed for its battery, the energy that he requires and the time needed from each CCP. Several researchers are working about these smart devices, but this is not the topic of this methodology. Note that the duration could be finished before the indicated duration. The EV aggregator determines these parameters depending on its experience on EV users' behavior. When several users purchase EVs, the EV aggregator has to analyse the duration that an EV user can wait to have its EV charged, and the different starting charging hours. With this information, it has to define the different average charging power rates that will define the duration of the different CCPs. As an example, considering that $P^{G,av}$=1.5 kW, $P^{B,av}$=2.5 kW, $P^{R,av}$=7.2 kW, the table summarizes 4.1 the different duration times considering different energy required from users E_{req}:

Table 4.1: Charging Duration from each CCP depending on energy required.

$E_{req}(kWh)$	$T^G(h)$	T^B (h)	T^R (h)
2	1.3	0.8	0.3
4	2.7	1.6	0.6
6	4.0	2.4	0.8
8	5.3	3.2	1.1
10	6.7	4.0	1.4
12	8.0	4.8	1.7
14	9.3	5.6	1.9
16	10.7	6.4	2.2
18	12.0	7.2	2.5
20	13.3	8.0	2.8
22	14.7	8.8	3.1
24	16.0	9.6	3.3

- Green and Blue CCP: the user is committed to let the EV aggregator modulate its charging power rate, depending on electricity markets conditions. It means that when the electricity is more expensive, charging power could be zero, but when the electricity is cheaper, it could be to the maximum power rate that is 7.2 kW. If user unplug its EV before the determined time, he does it at his own risk because there is not guarantee a minimal charging before the end of the time determined.

- Red CCP: the user can charge constantly at the maximum charging power that is established in 7,2 kW. This CCP is designed for users that need car ready as soon as possible and are willing to pay this high price for that. These users will prefer to charge at work or at home in order not to charge in a fast charging station.

4.2.3 EV Users Requirements

EV users have different behavior, so it's difficult to predict the EV daily curve load. This behavior depends on different parameters such as start charging time, end charging time, charging power rate, battery vehicle type, state of charge (SOC). In order to face these uncertainties, the aggregator model needs to know the different data of the EVs charging. For that purpose, it is important that the EV owners, or parking lots, who participate in the program install smart meters to communicate this data with the aggregator, such as the one is presented in (Nandan et al. 2015). In this paper, this data is assumed to be obtained in real time.

In a day, it is considered D discrete time intervals (15 minutes). The set of time intervals are defined:

$$T = \{1, 2, \ldots\ldots, D\} \tag{4.5}$$

For each vehicle i, it is considered a plug time Ui ∈ T, which is the set of sample times between starting charging time and the time that the charge is complete.

The power consumed by all vehicles managed by the aggregator at each step time k P_k^{EV} is, the sum of the power consumed by EV users of green CCP P_k^G, blue CCP P_k^B and red CCP P_k^R:

$$P_k^{EV} = P_k^G + P_k^B + P_k^R, \forall k \in T \tag{4.6}$$

Also, each whole EV CCP load is calculated as, for x ∈ {green, blue, red}:

$$P_k^x = \sum_{i=1}^{N_x} P_{x,k,i} \tag{4.7}$$

Thus:

$$P_k^{EV} = \sum_{i=1}^{N_G} P_{k,i}^G + \sum_{i=1}^{N_B} P_{k,i}^B + \sum_{i=1}^{N_R} P_{k,i}^R, \forall k \in T \tag{4.8}$$

The energy stored in a EV battery i will depend on the last value and on the power delivered $P_i[k]$ on each step time ΔT. It is calculated as:

$$E_{k+1,i} = E_{k,i} + \eta . P_{k,i} . \Delta T = E_{k,i} + \Delta E_i \tag{4.9}$$

The total energy dispatched in a day to all EVs participating in an x CCP is defined as:

$$E^{x,tot} = \sum_{k=1}^{D} P_k^x . \Delta T \tag{4.10}$$

The total energy dispatched in a day to all EVs is defined as:

$$E^{EV,tot} = \sum_{k=1}^{k=D} (P_k^G + P_k^B + P_k^R) . \Delta T \tag{4.11}$$

The SOC (%) also depends ont he last value and on the difference of energy ΔE_i and the capacity of the battery Bc_i. It is calculated:

$$SOC_{k+1,i} = SOC_{k,i} + \frac{\Delta E_i}{Bc_i} \tag{4.12}$$

4.2.4 EV Aggregator Benefits

The daily benefits depends on total revenue R and costs C_{VAR}, as defined as:

$$\Pi = R - C_{VAR} \tag{4.13}$$

From all the duration of the EV charging, users have to pay to the EV aggregator the average of the electricity price during this period, plus a constant amount defined by EV aggregator contract. The sum of the payments from all users are defined as the Revenues from users options R_U.

Additionally, DSO and TSO may fix a daily constant payment to EV aggregator by its services. This revenue for the EV aggregator is defined as Revenues from DSO and TSO R_O.

In this way, total daily revenues R are defined as the sum of the two revenues mentioned above:

$$R = R_U + R_O \tag{4.14}$$

The EV aggregator has to pay for market price electricity that it supplies to their customers (EV users). Additionally, the EV aggregator has a compromise to respect DSO and TSO conditions. In case it is not possible, for example for excess demand of EV users, the EV aggregator has to pay a penalty cost, that is assumed as 5 times more the price of kWh as (Ministerio de Economía 2000).

In this way, the EV aggregator costs can be defined as:

$$C_{VAR} = C_p + \sum_{k=1}^{k=D} \pi_k.(P_k^G + P_k^B + P_k^R) \tag{4.15}$$

The EV aggregator cost per energy delivered to an x CCP users is defined as:

$$C^{x,eq} = \frac{C^x}{E^{x,tot}} \tag{4.16}$$

The specific cost equation is defined as:

$$C_{eq} = \frac{C^{VAR}}{E^{EV,tot}} \tag{4.17}$$

4.2.5 Additional Model Inputs

- Minimum required energy per charge: it is the minimum amount of energy that the EV aggregator requests from each user for charging the EV battery.
- Time delay: it is an additional time that an EV user has to wait before starting the charging process to obtain better electricity prices. For the first analysis, this parameters will be assumed to be zero. Then, this parameter will be studied in the sensitivity analysis.

4.3 Problem formulation

The interest for the EV aggregator is to maximize its benefits. The problem consists in minimizing economic costs.

Let's suppose $\mathbf{P}_k^G$, $\mathbf{P}_k^B$, and $\mathbf{P}_k^R$ the vectors of decision variables for green, blue and red CCPs, at a step k they are defined based on the number of EV users they have.

$$\mathbf{P}_k^G = \begin{bmatrix} P_{k,1}^G \\ P_{k,2}^G \\ ... \\ P_{k,N^G}^G \end{bmatrix}$$

$$\mathbf{P}_k^B = \begin{bmatrix} P_{k,1}^B \\ P_{k,2}^B \\ ... \\ P_{k,N^B}^B \end{bmatrix}$$

$$\mathbf{P}_k^R = \begin{bmatrix} P_{k,1}^R \\ P_{k,2}^R \\ ... \\ P_{k,N^R}^R \end{bmatrix}$$

In this way, the problem is formulated as:

$$min\ C_{VAR} = min(C_p + \sum_{k=1}^{D} \pi[k].(\mathbf{P}_k^G + \mathbf{P}_k^B + \mathbf{P}_k^R) \tag{4.18}$$

The proposed methodology focus on the study of the daily costs associated with EV aggregator's activities; while the annual benefits will be analyzed in future work. The problem depends on the next constraint:

- Minimum and Maximum Power: The charging power rate from each user will vary from zero to a maximum value in slow charging, which is 7.2 kW, depending on grid conditions. This constraint is defined as:

$$0 < P^{k,i} < \overline{P_{k,i}}\ \forall k \in T \tag{4.19}$$

- When a user plug its EV i to the charger, he selects the energy he requires for its EV E_i^{req} (depending if he wants to fully charge or to partly charge his battery). It is assumed that the charger will indicate the SOC. The EV aggregator has to dispatch all this energy needed. For this, he has to select a CCP, and he will receive the information about the charging duration as specified in equations (4.1), (4.2), (4.3). It is necessary that the user let its EV plugged this time U_i More than one charging could be considered for a user, for example at work and at home, but in every case users have to specify the energy he needs. This constraint is defined as:

$$E_i^{req} = \sum_{k=1}^{D} P_{k,i}.\Delta T \ \forall k \in U_i \tag{4.20}$$

- Operator charging pattern: total charging power from all EV users will not have to exceed limits imposed by the DSO and TSO. This constraint is defined by generation, transmission and distribution conditions. In case that the problem has no solution, the EV aggregator will have to pay a penalty to the DSO and TSO and not disconnect EV. This is in order to respect EV users preferences. This condition is defined as:

$$0 < P_k^G + P_k^B + P_k^R < \overline{P_k^{EV,O}} \ \forall k \in T \tag{4.21}$$

This problem can be solved by a linear optimization.

4.3.1 Implementation

- At the end of the previous day to the day in which the charging process is going to be scheduled, the EV aggregator receives from the electricity market the predictions for the next day of the electricity price. Additionally, information as power CCPs could be updated by the EV aggregator, if the options change.

- At the start of the new day, it has to be considered EV charging that was not completed the ending day. This is a result available from the optimization performed for this day.

- At the beginning of every 15 minutes step, the EV aggregator has to receive real time information of new cars plugged in. This will be done through smart meters installed in the customer facility, where the EV users will have the information of the costs from the different CCPs in real-time. If new cars are connected for loading, each smart meter has to send the associated information to the EV aggregator: State of Charge and CCP selected. The EV aggregator will combine this information with the information about the actual and short term EV status, resulting from the last optimization periods to calculate the maximum constraint for this period that can be defined either by the maximum EV total power required or by the operator, according to equations (4.13) and (4.15).

- After the maximum constraints are computed, an optimization process is performed to obtain a charging profile for each EV taking into account the calculated charging period U_i and the total power needed. As a result, it will also be known the moment when an EV will be totally charged. The optimization is performed for each EV connected in a specific moment and not for the sum all of them. The optimization process will determine the new charging according to both the network constraints and the committed charging in previous steps.
- This process will be repeated every 15 minutes until the end of the day ahead. The optimization will consider that the EV charging will continue in the next day if charging start late in the day ahead, but this charging pattern has to be considered as mentioned at the beginning of the new day.

4.4 Sensibility Analysis and Determination of Parameters Evaluated

4.4.1 Sensitivity Analysis

In smart charging methodology, some parameters should be assumed and fixed considering local user preferences, such as minimum required energy, the time delay of the starting charging time, number of users from each CCP and average charging power rates. Also, user behaviors differ depending on the country so that the EV aggregator might adjust its conditions modifying these parameters. So, a variation of these parameters could lead to essential changes in the EV aggregator benefits or the grid conditions. Furthermore, before implementing smart charging techniques, the EV aggregator has to fix the price for each CCP depending on user behavior; for example, a lot of EV users could prefer to use red CCP if the price difference with the other CCPs is not significant, which could create the studied problems in the grid. So, in this case, the fixed term in the red CCP may increase to promote the other CCPs. Finally, in this thesis, three CCPs are proposed, but this number could increase if the analysis of the different parameters leads to additional results that could benefit the EV aggregator. For these reasons, an evaluation of different parameter variations on the model has to be performed.

In a mathematical model, some input variables can determine one or different output variables through a function f. In many cases, this variable could be very difficult (not linear for example), so it is not easy to know the impact of the inputs in the outputs (Jacques 2011). Sensitivity Analysis is defined as a method that studies how the uncertainties in the model inputs affect the model's response (Campolongo, Saltelli, and Cariboni 2011). It describes the relative input in determining the output variability. The function considered for the model is no linear and it is determined by a mathematical code, so there is the interest of making a sensitivity analysis. In this case, the variables studied are: minimum required energy, time delay of the starting charging time, share of green CCP users, average charging power rate of green and blue CCP. As mentioned before, the variations of the variables from red CCP will not be studied because it is a CCP that allows users to charge the EV at maximum power. In each case, the EV load and the different costs will be studied as represented in Figure 4.2.

For each parameter under study, the EV load profile was simulated for each scenario in order to have a technical view of the crucial periods on the day. Also, a Monte Carlo simulation of the specific costs were performed to analyze through a regression analysis the impact of the variation of each parameter. The EV users behavior could change importantly (starting charging time, energy required from each user) so the model presents some uncertainties. Therefore, a significant amount of simulations was done. Because of the complexity and the computation time 100 simulations of Monte Carlo were performed for each scenario. The regression of the specific cost was performed with the mean of each scenario and without considering anomalous values.

In Figure 4.3, an example of a box and whisker plot for the case of the Minimum Required Energy is represented where it is possible to observe the variation of the upper and lower values and means depending on each scenario. This plot allows deleting anomalous values and making the most precise regression curve with the mean values for each variation.

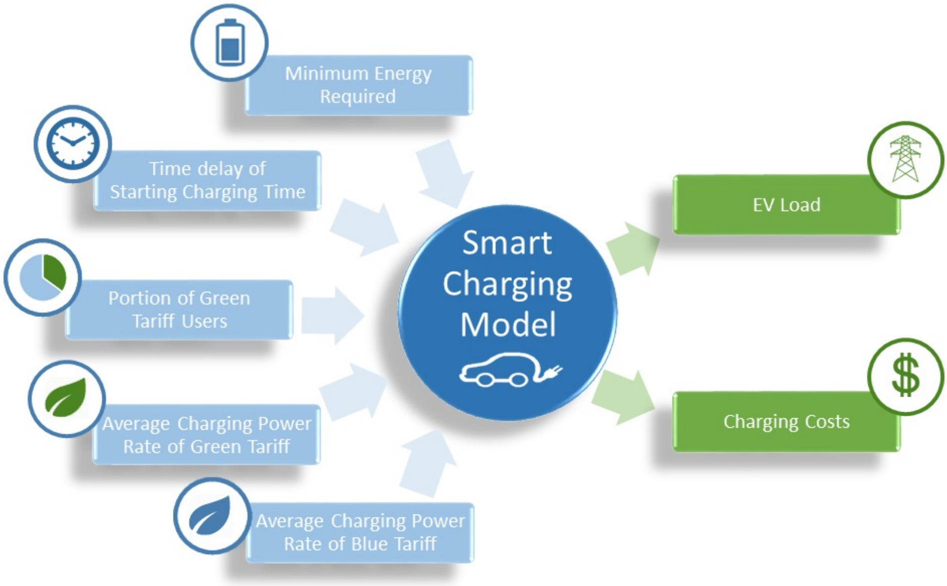


Figure 4.2: Sensitivity Analysis Scheme

The range of study of different parameters was selected considering some aspects of users' behavior and the information provided in (Álvarez-Bel et al. 2016; Sadeghianpourhamami et al. 2018; Grahn et al. 2013).

4.4.2 Minimum Required Energy per charge

The objective is to quantify how the EV aggregator specific costs per kWh decrease. In the reference scenario, the minimum energy for each user needed was established in 4 kWh. But, if EV users charge their EV at this minimum energy, the duration of charging T_x^i will be short. The methodology could not have a proper performance with a short time, especially if the electricity price variation is not significant. In this way, a sensitivity analysis is performed considering a variation of 0.5 kWh for the minimum energy required. For the sensitivity analysis, the lower bound for minimum required energy was considered at 4 kWh. The upper bound is established at 9 kWh, which is envisaged the highest value that users can feel confident not having a problem with the battery the next day.

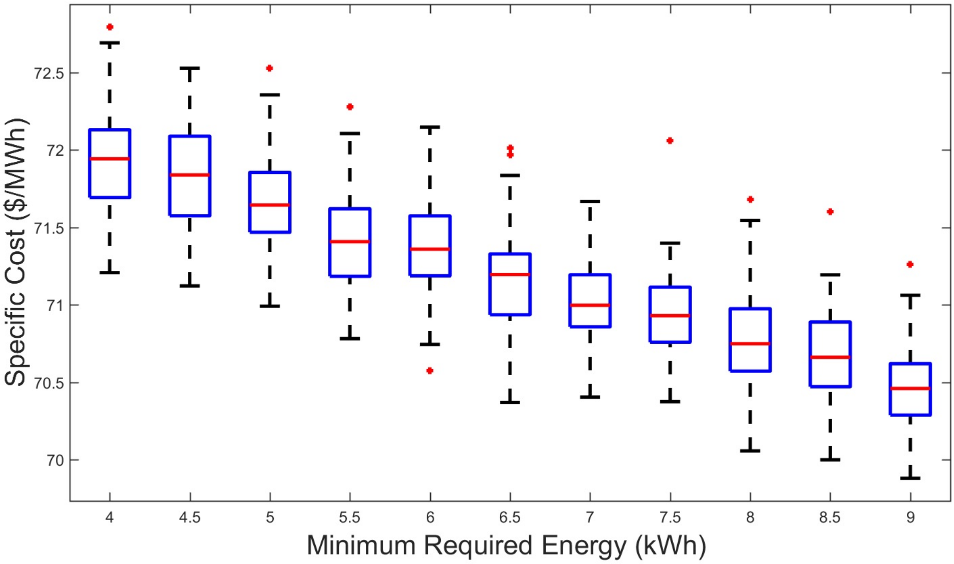


Figure 4.3: Box Diagrams of the specific cost from each case.

4.4.3 Time delay of the starting charging time

Due to high prices of electricity between 4 PM and 9 PM and the fact that people generally will not disconnect their EV during the night, it is considered that EV aggregator can benefit of reduced charging costs if a delay of the starting charging time exists. The sensitivity analysis starts with no delay and continues with an increment of 30 minutes until 5 hours. The value of 5 hours is selected because it is considered an extreme delay which users can wait.

4.4.4 Portion of green CCP users

The objective is to quantify which impact has a variation of green CCP users in relation to total users. In the reference scenario, users of green CCP were established in 60%. For the sensitivity analysis, it will be considered a share from 0% to 100%, with increments of 10 % in order to have an idea of all the range of share of green CCP users. For this analysis, it will be assumed that blue CCP users will be the double in number than red CCP users.

4.4.5 Average Charging Power Rate of Green and Blue CCP

The implications of average charging power rate of green CCP and blue CCP are investigated. In the reference scenario it was considered that average power consumption of an EV participating in green CCP was 1.5 kW and for blue CCP, 2.5 kW.

For the sensitivity analysis, the selected lower and upper bounds of the average charging power rate of green CCP are 0.5 kW and 3.0 kW respectively, which are the third and two times the value of this parameter of the reference scenario (1.5kW). Note that the objective is to analyze the effects of the variations of this parameter, because if the average charging power rate for the green CCP is close to 3 kW, the blue has to be higher.

For the sensitivity analysis, the selected lower and upper bounds of the average charging power rate of blue CCP are 1.25 kW and 5.0 kW respectively, which are the half and two times the value of this parameter of the reference scenario (2.5kW). As the case of the Green CCP, if charging power rate of Blue CCP is too low, the Green one has to be lower then. The criterion for choosing these values was that they correspond to the limits of time that EV users can wait for having their EV charged and interacting with the grid.

In this case, only the load demand from each CCP is studied, because the number of vehicles considered is not so high in order to have a variation of the power consumption of other EV users CCP due to Operator Constraint. But, the costs of the corresponding CCP and the total costs are evaluated.

4.5 Conclusion

In this chapter, a novel methodology for an EV aggregator is presented. It is proposed that the EV aggregator will have to optimize power delivered to the EV battery through charging power rate modulation in slow charging. The novelty lies in consideration of three different CCPs that will be suitable depending on EV user preferences. The EV aggregator will also consider technical specifications as a maximum charging pattern given by the DSO and TSO.

This chapter explains also some parameters to be studied in a sensitivity analysis for an EV aggregator. The parameters under consideration are: minimum required energy, time delay of the starting charging time, share of green CCP users and average charging power rate for green and blue CCP. The sensitivity analysis has to study the effect of these parameters on the daily EV Load and the charging costs. This analysis is appropriate for the EV Aggregator to fix these parameters depending on CCP prices.

The methodology discussed in this chapter has been applied to a real case, in Quito-Ecuador, in the next chapter, testing its effectiveness and the effects of the variations of the parameters under study.

Chapter 5

Case Study: Distribution System of Quito-Ecuador

5.1 Introduction

In previous chapter, the new methodology of EV Smart Charging managed by an EV aggregator was presented. A case study is presented that illustrates this novel methodology for an EV aggregator. In this chapter, this methodology is applied to the Distribution System of Quito-Ecuador. This case study was selected according to the Ecuadorean government willingness to introduce EVs in the automobile market (Vera, Clairand, and Álvarez-Bel 2017). Furthermore, Quito is one of the selected zones from the government to be a pilot for the introduction of the EVs. The goal of the case study is to demonstrate the technical and economic improvements in the EV charging process for different scenarios. The variables that are used in this optimization problem are described in this section. The area of Quito selected for the study is called Cristianía. It is an industrial and commercial area. Electricity is distributed by Empresa Eléctrica Quito (EEQ) in Quito, which belongs to the Ecuadorian public company CELEC EP. A distribution feeder of the EEQ has been selected to evaluate the proposed methodology. This feeder was chosen because it presents some overloading in some periods of the day, so it is suitable to evaluate the management of a new significant load. This chapter starts with a description of the case study in section 5.2. After that, the results and discussions of the proposed methodology are presented in section 5.3. The sensitivity analysis of the selected parameters is studied in section 5.4. Finally, section 5.5 is devoted to conclusions of the chapter.

5.2 Case study characteristics

5.2.1 Charging scenarios

Three scenarios will be considered, considering type of charging:

1. Uncoordinated charging at maximum power: users start charging immediately their EV when plugged in. It is also considered for this scenario that all users start charging their EV at maximum power which corresponds to 7,2 kW.

2. Uncoordinated charging at average power: users start also charging immediately their EV when plugged in. For this scenario, it is considered that users are grouped into different CCPs. It is considered a charging power rate for each CCP, which will be constant during all charging time. In this case, in eq. 14, the term $P^i[k]$ is constant for each step time and becomes for an EV i:

$$E_i^{req} = \sum_{k=1}^{D} P_{k,i}.\Delta T = P_{x,av}.\sum_{k=1}^{D} \Delta T = P_{x,av}.\Delta T.D \qquad (5.1)$$

Without a presence of an EV aggregator, the EV owner will have to plug its EV of a supply equipment, which will limit the charging power rate. This technique is often used by distribution companies to mitigate the effects of high power demand from EVs. EV users will charge their EV at a constant power corresponding to the value of the average charging power rate from each CCP. So far, EVs supply equipment allow to fix a constant charging power, such as (*WallboxOk, the supplier of charger you need for your electric car*).

3. Proposed Smart Charging with charging power rate modulation: the number of users from each CCP are the same that previous case, but charging power rate from each user will vary between zero to 7,2 kW, in order to optimize power delivered depending on grid conditions. Nevertheless, the energy required will be delivered to EV users and in the same time established that

previous scenario. This means that in these two last scenarios, it will be same average charging power, depending on CCP selected.

In each scenario, an additional study will be done, considering different EV penetration. Each scenario will consider EV penetration levels of 50%, 75% and 100%.

5.2.2 EV input variables

Number of EVs of each CCP

In a previous work (Álvarez-Bel et al. 2016), it was concluded that the number of vehicles of this zone was nearly 1000. This value is assumed as the total number of vehicles.

For the evaluation of the case study, the portions of the green, blue and red CCPs are assumed respectively as 60%, 30% and 10% in this study. In next section, the sensitivity analysis of these values is performed. The Table 1 describes the number of vehicle for each penetration level of EV.

Table 5.1: Number of vehicles from each CCP depending on penetration level.

Penetration Level	N^G	N^B	N^R
50%	300	150	50
75%	450	225	75
100%	600	300	100

Starting charging time

From studies about road traffic in Quito, and working conditions starting charging time is considered by the following way (Vega and Para 2014; INEC 2014):

- A 20% of EV users who participate in the program plug their EV at work between 07h00 and 10h30.
- A 40 % of EV users who participate in the program plug their EV at home, after returning from work between 16h00 and 21h00.

- The rest of EV users who participate in the program plug their EV in different periods of the day (shops, home, work, etc).

In order to create starting charging time profiles, random numbers according to these schedules are generated. For each vehicle, a starting hour st^i is assigned, where i $\in \mathbb{N}$. The histogram corresponding to the starting charging time of 500 EV users in a day are represented in Figure 5.1.

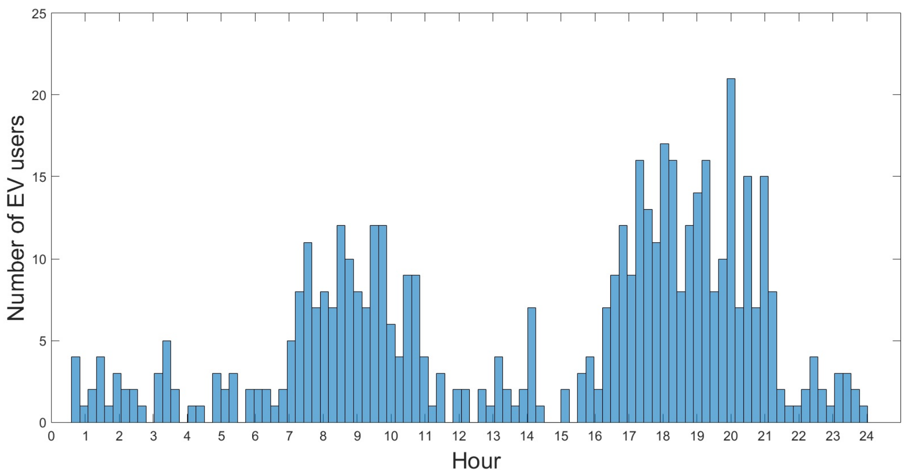


Figure 5.1: Histogram of the starting charging time of EV users in a day in the selected zone in Quito.

Daily energy needed from each EV

It is expected that different types of EVs (brands and models) will soon be seen on roads all over Ecuador. Some of them are Nissan Leaf, BYD e5, BYD e6 and Kia Soul EV. These EVs have different battery capacities from 24 kWh to 75 kWh of Nissan Leaf and BYD e6 respectively. For that reason, it is more valuable to consider in the calculation the daily energy demanded by each EV user than the battery capacities of each EV . According to several studies, it is considered that near half of the people drive less than 50 km a day. In (Clairand and Vera 2014), it is verified that in ideal circumstances of traffic EV drivers do 8,19 km/kWh in Quito, which means 0,122 kWh/km. Considering a system energy efficiency of η=0.85%, it is concluded that 0,144 kWh of grid electricity will be consumed per kilometer driven. This is confirmed by the studies of range autonomy in (Rajakaruna, Shahnia, and Ghosh 2015a). A frequency curve about electricity consumption for 100 km is shown in (Asamer et al.

2016). For this study, it is assumed that different levels of energy are going to follow the pattern of this probability curve, but considering last average value. Moreover, it is established, that EV users must charge at least 4 kWh in order to participate in this EV aggregator program. It is considered that the more suitable curve is Weibull density probability, from where random values will be selected (Yang, Zhai, and Huang 2012). This curve is defined as:

$$f(x;a,b,c) = \frac{b}{a}.(\frac{x+c}{a})^{b-1}.e^{-(\frac{x+c}{a})^{b}} \tag{5.2}$$

The charging needs may vary from 4 kWh to 28 kWh, but with more values between 6 and 10 kWh, that can be normal values of energy required (Sierra 2016). This curve allows to have different values of energy required by user, that differs importantly. It was also mentioned that models as BYD e6 have a battery capacity of 60 kWh, but the case of users that have this EVs and charge more than 28 kWh are ignored. Note also that these parameters are selected with the conditions of the case of behavior of people from Quito, but this curve could differ importantly in other parts. So, the values for the parameters selected are: a=7,5;b=1,5;c=4. Density probability curve is obtained in Figure 5.2. Note that the integral of this curve is equal to 1.

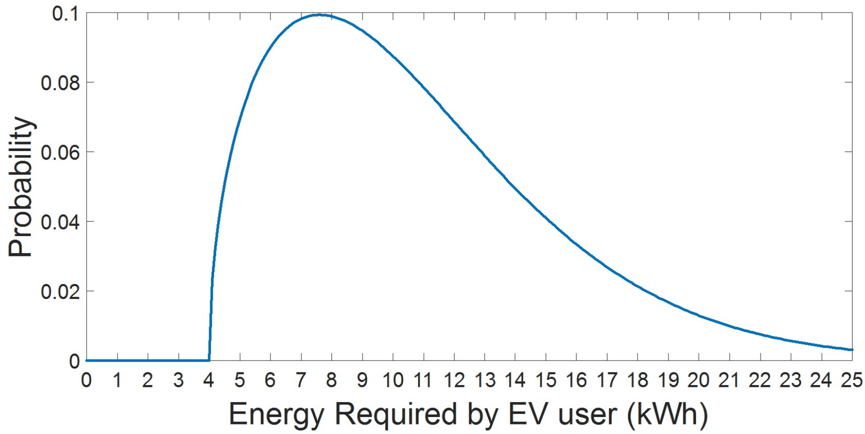


Figure 5.2: Probability Density Curve of Energy required by EV user.

It is considered that EV users consumed energy is a random number from this distribution.

From this way, each set of time intervals U_i that correspond to charging period of an EV i is defined by:

$$U_i = [st_i; st_i + \frac{E^{req}}{P^{av}}] \tag{5.3}$$

5.2.3 CCPs Average Charging Power

Each user have to select a CCP depending on the average charging power defined as in Table 2: As mentioned before, slow charging can vary from zero to 7,2 kW. Red CCP is selected as the maximum value, and for the other two CCPs, small values are selected in order to have a good time to optimize These values were selected for the case study:

Table 5.2: Average power for each CCP.

CCP	Green	Blue	Red
$P_{x,av}$ (kW)	1.5	2.5	7.2

These values were selected in order to have intermediate values in the range of slow charging power rates that are 0-7.2 kW.

Actually, EV users who select red CCP will have its charging power rate constant and established at its maximum value. There will not be an optimization for this case. Users assume the price for this condition.

5.2.4 Total maximum charging power constraint

Total EV maximum charging power constraint is defined as the sum of all the vehicles charging at maximum power.

$$\overline{P_k^{tot}} = \sum_{i=1}^{N^x} \overline{P_{k,i}} \tag{5.4}$$

In this way, EV maximum power constraint curve is observed in Figure 5.3, for a penetration of 100% EVs.

5.2.5 Maximum charging power pattern

The function of this constraint can be defined as:

$$\overline{P_k^{EV,O}} = FP - P_k^{res,tot} \tag{5.5}$$

It is assumed FP=$\overline{P^{res}}$*1.05.

A critical power is considered that is 5% higher than the maximum value of the residential load. This consideration was done because the feeder has reactive energy compensation, and the limit of the transformer can be determined by this active power.

In this way, the obtained curve is also observed in Figure 5.3.

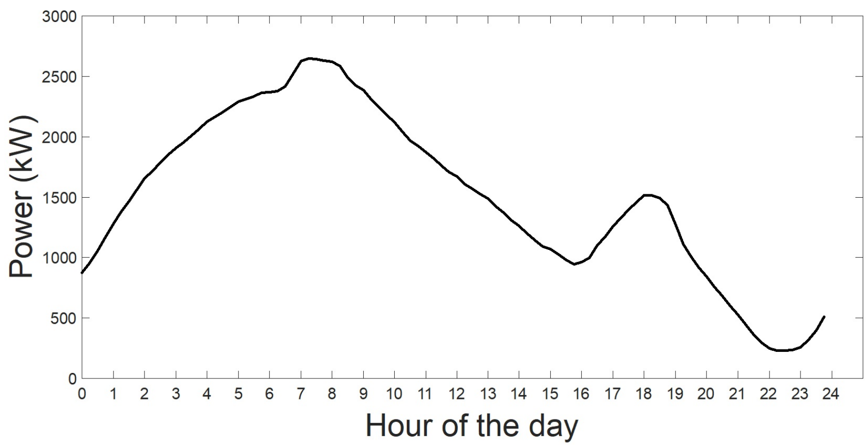


Figure 5.3: Power Constraint.

Note that the two curves are the two that don't have to be exceeded.

5.2.6 Electricity Price curve

In Ecuador, the electricity sector is vertically integrated so there is no electricity wholesale market. There is a tariff for each type of customer. These tariff rates are not linked to the real costs of electricity generation, transmission and distribution in real time. In this way, in previous work (Álvarez-Bel et al. 2016), the authors proposed a method to calculate the electricity prices based on above mentioned costs of generation, transmission and distribution.

The electricity price curve of the selected workday in Ecuador is represented in Figure 5.4. The currency is the U.S. dollar since is the currency of Ecuador. As can be observed in Figure 5.4, this curve has been selected because it is a critical case where the electricity price curve is relatively flat, reducing the potential economic savings, and the cheapest period overlaps the strongest network operator's constraints.

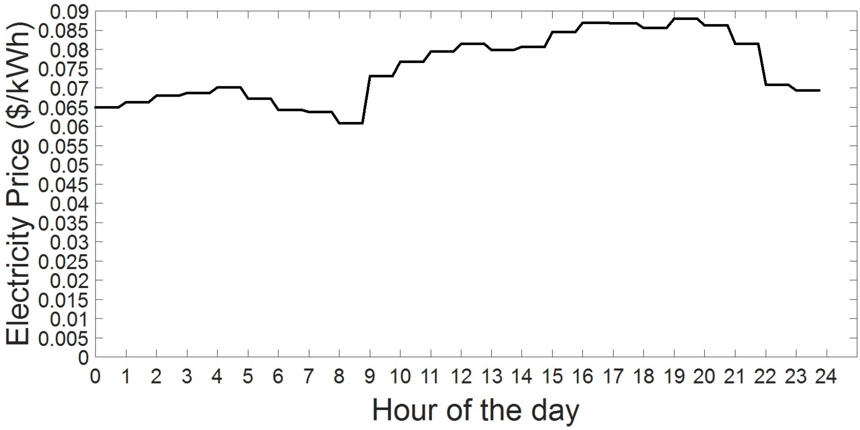


Figure 5.4: Proposed Electricity Price of the 9th of June 2014.

5.2.7 Model Simulation

For the simulation, Matlab 2016 software was used, with an Intel Core I7 computer with 16 GB of RAM. For the optimization problem, "Optimization toolbox" was used with linprog function, because as mentioned before, the optimization problem is linear. In this way, based on the electricity prices that the EV aggregator receives and the different EV users parameters, any day could be simulated.

5.3 Results and discussion

5.3.1 Charging profile of an EV user

In Figure 5.5, it is presented the simulation of an example of an EV user that was selected according to assumptions. This user starts the charging at 2h45 PM and has an EV energy required of 11.67 kWh. The three charging scenarios are represented for the same user. For the case of the scenario 3, it is considered that the EV user has selected the green CCP. It is observed that for scenario 1, the EV battery is charged quickly because the charging starts at maximum power. For scenario 2, it takes much longer. Finally, for scenario 3, it is noted different variations of the charging power rate, which corresponds to the commands from the optimization methodology. Thus, for scenario 3, a peak is observed between hours 15 and 16, which means that in this period, the electricity is cheap and the operator has enough power availability.

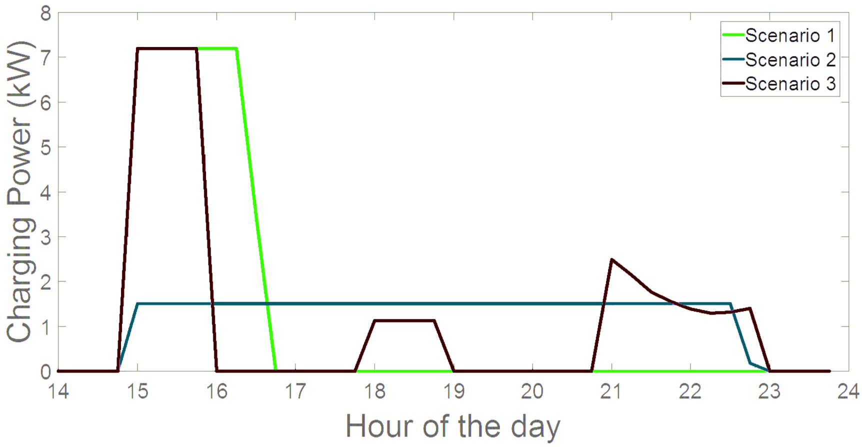


Figure 5.5: Charging profile of an EV user.

5.3.2 Uncoordinated Charging: Scenarios 1 and 2

For the first scenario, EV load is shown in Figure 5.6, considering different EV penetration levels. The increase of EV penetration leads to a significant increase of the peak loads. It is also observed that the EV load is substantial in the hours of the evening, which could create overloading problems because the operator has not enough power available for satisfying this load. Furthermore, the EV load is important in time periods when the electricity is expensive. Observe also that there is a dip of the EV load during hours 2-6. This can be explained because there is not several EVs that are connecting in the grid and the EVs that were previously charging at the beginning of the night finish their charging. Moreover, the peak during hours 10-12 corresponds to the hour where several EV users connect their EV. For the second scenario, EV load is shown in Figure 5.7, also considering different EV penetration levels. In particular, the increase of EV penetration leads to a significant increase of the peak loads. Note that those peaks correspond also to periods when the operator has not enough power available. Observe also that there is a dip of the EV load during hours 6-7. Similar to Scenario 1, it can be explained because there are not several EVs that are connecting in the grid and the EVs that were previously charging at the beginning of the night finish their charging. The dip is delayed than Scenario 1, because the charging of the EVs are longer. Moreover, the peak during hours 10-12 corresponds to the hour where several EV users connect their EV, but the peak is smaller than Scenario 1, because the power demanded is lower.

Then, it is seen that scenario 2 curve has lower peak loads than scenario 1, which is normal because of the difference of charging power rate used. Nevertheless, as mentioned before, it is not a really good solution to make the users charge their EV at minimum charging power rate.

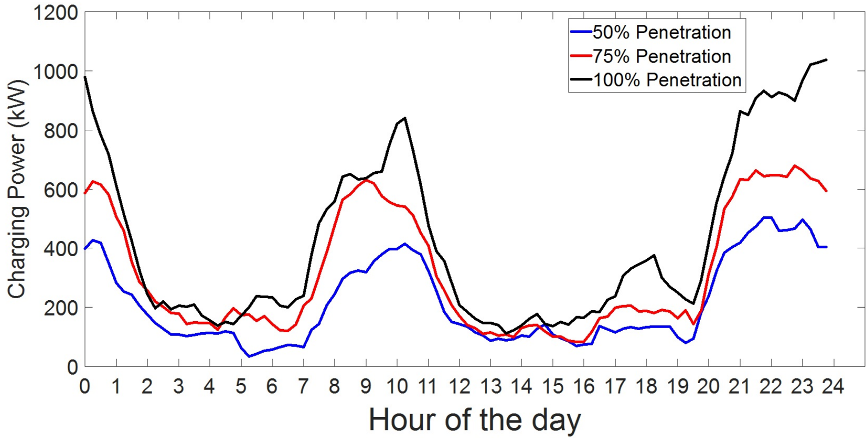


Figure 5.6: Scenario 1: EV Load with different EV penetration levels.

5.3.3 Smart charging with power modulation: Scenario 3

In Figure 5.8, the curves for EV charging in scenario 3 for different EV penetration levels is represented. Charging load presents a high peak between hours 8 and 9, which corresponds to the time when people charge their EV at work and when the electricity is less expensive during these hours. This peak may not create problems for the grid because the operator constraint shows that the energy availability is high enough, which means that the residential load is very small and so the EV load could flatten the total load curve. Moreover, between 19h and 21h, Optimized EV charging load is under the minimum of Operator

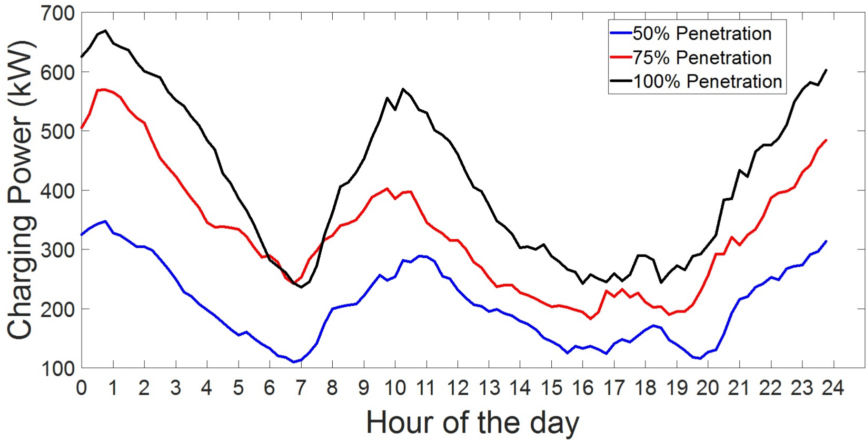


Figure 5.7: Scenario 2: EV Load with different EV penetration levels.

constraint, which means that electric technical constraint are respected. This was not observed in the previous scenarios with uncoordinated charging. So, the benefits of this methodology in technical and economical conditions are demonstrated.

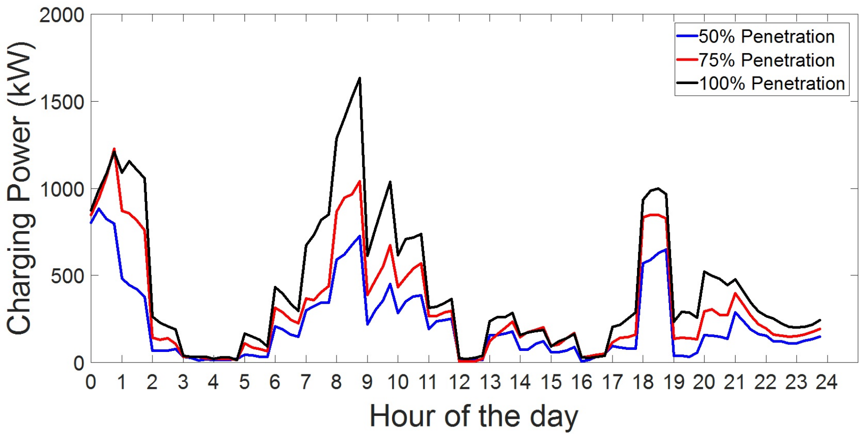


Figure 5.8: Scenario 3: EV Load with different EV penetration levels.

In Figure 5.9 EV smart charging is compared to the first two scenarios. It should be noted that the EV load curve in scenario 3 (smart charging) presents high variations in comparison to th curves of the two other scenarios, but it allows to flatten the total load, which may decrease total load variance and so the distribution losses according to (Sortomme et al. 2011).

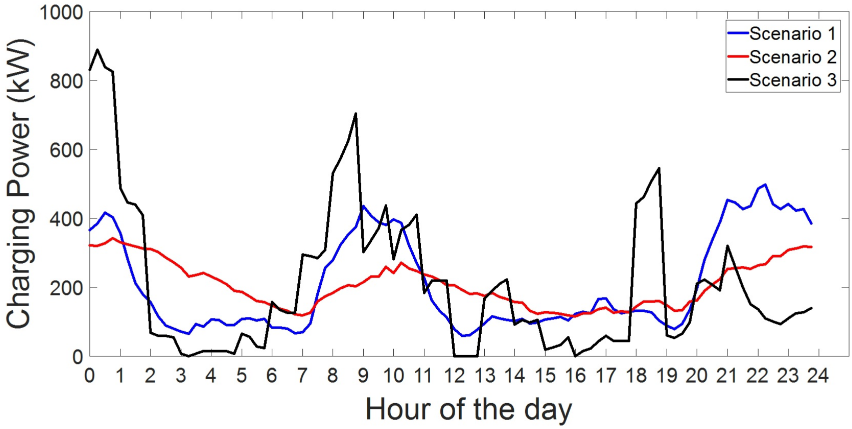


Figure 5.9: EV Load comparison of the three scenarios with 50 % EV penetration.

5.3.4 CCP load analysis

In Figure 5.10, the EV load corresponding to each CCP for the assumptions considered is represented.

Green CCP is the one that presents the most critical variations in a day. Note that a high peak is observed at midnight, which corresponds to a time where the electricity is cheap. The red CCP presents a similar pattern hat the total EV load of the uncoordinated scenarios, which could result negative for the grid as demonstrated if the number of users who select this CCP is high.

5.3.5 EV Aggregator costs by scenario

In Table 5.3, daily costs of the aggregator from each scenario are resumed for the day selected. Is it observed the more the EV penetration grows, the more uncoordinated charging grows. Also, two kind of uncoordinated charging have similar daily costs, which shows the importance of having a smart charging.

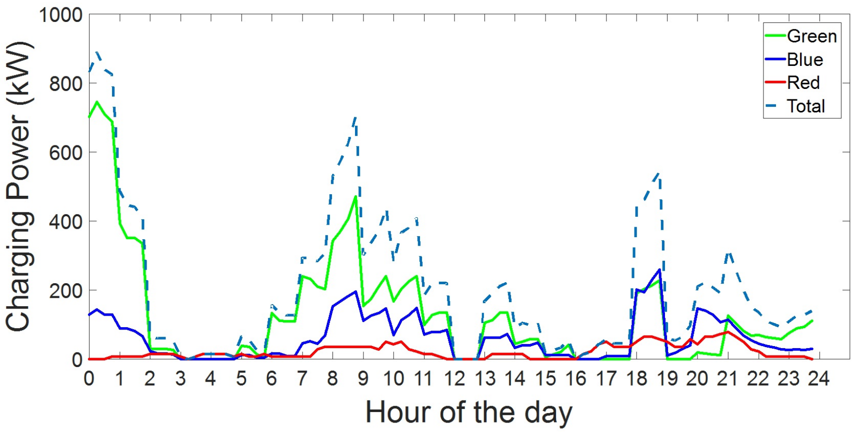


Figure 5.10: EV load by CCP with 50% EV penetration.

5.3.6 Week saving

To evaluate the methodology in a longer horizon and with different input parameters (e.g. electricity price), simulations were implemented for a week. The data of the EEQ from the Monday June 9th 2014, to the Friday June 13th 2014 was used. For this analysis, the operator penalty was considered. Note that the electricity price curve differs from one day to another.

To evaluate the effectiveness of the methodology, a daily difference cost percentage was defined for green CCP, between first and third scenario:

$$\Delta S^{G}_{1-3} = \frac{C^{G,S1} - C^{G,S3}}{C^{G,1}} \tag{5.6}$$

Figure 5.11 represents the percentage cost difference of a week of the green CCP for different EV penetration levels.

A difference cost percentage was defined for blue CCP, between first and third scenario:

$$\Delta S^{B}_{1-3} = \frac{C^{B,S1} - C^{B,S3}}{C^{B,1}} \tag{5.7}$$

Figure 5.12 represents the percentage cost difference of a week of the green CCP for different EV penetration levels.

Table 5.3: EV aggregator Costs by CCP and by scenario.

Scenario	EV P. (%)	C^G($)	C^B($)	C^R ($)	C^{EV}($)
1	50	241.2	117.79	39.33	398.32
1	75	483.19	282.53	59.93	825.65
1	100	894.16	472.17	76.60	1442.93
2	50	326.12	154.62	39.33	520.08
2	75	578.54	299.69	59.93	938.16
2	100	894.54	479.81	76.60	1450.95
3	50	213.51	111.75	39.33	364.67
3	75	321.03	184.55	59.93	565.51
3	100	427.23	254.78	76.60	758.61

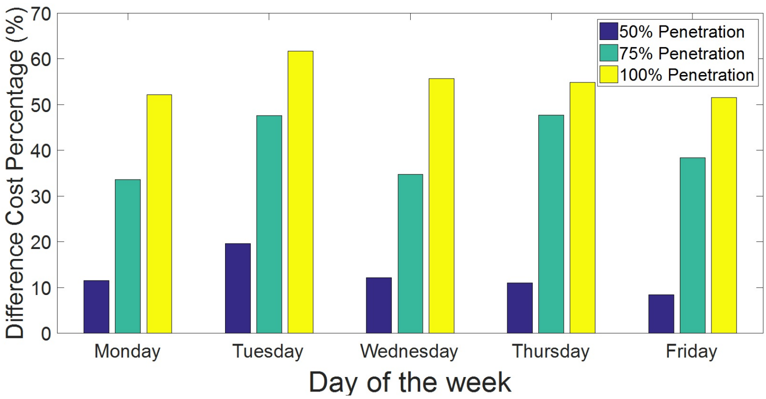


Figure 5.11: Percentage cost difference between scenario 1 and 3 for green CCP.

A daily difference cost percentage was defined for green CCP, between second and third scenario:

$$\Delta S^G_{2-3} = \frac{C^{G,S2} - C^{G,S3}}{C^{G,2}} \tag{5.8}$$

Figure 5.13 represents the percentage cost difference of a week of the green CCP for different EV penetration levels.

A difference cost percentage was defined for blue CCP, between second and third scenario:

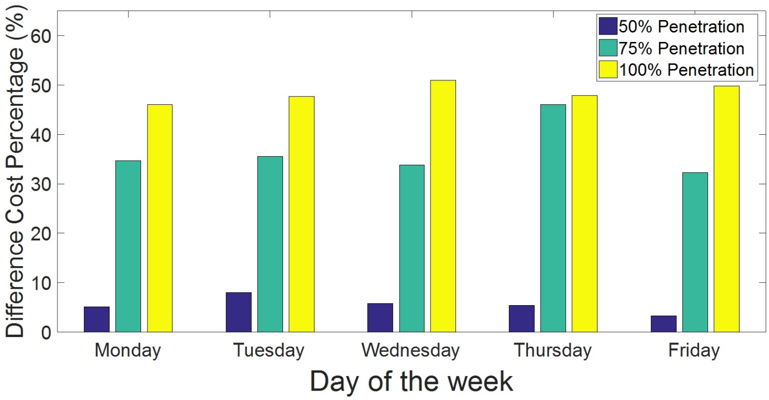


Figure 5.12: Percentage cost difference between scenario 1 and 3 for blue CCP.

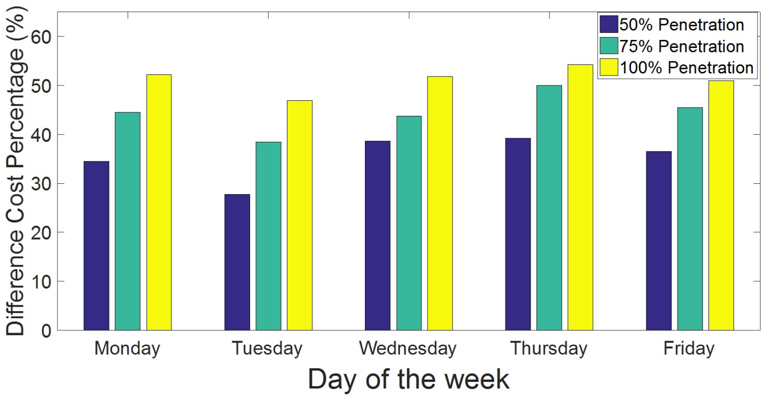


Figure 5.13: Percentage cost difference between scenario 2 and 3 for green CCP.

$$\Delta S^B_{2-3} = \frac{C^{B,S2} - C^{B,S3}}{C^{B,2}} \tag{5.9}$$

Figure 5.14 represents the percentage cost difference of a week of the green CCP for different EV penetration levels.

Comparing to the two first scenarios, the smart charging always has more economic savings, also with 50% EV penetration where there is not penalty cost because the operator constraint is not overpassed by uncoordinated charging.

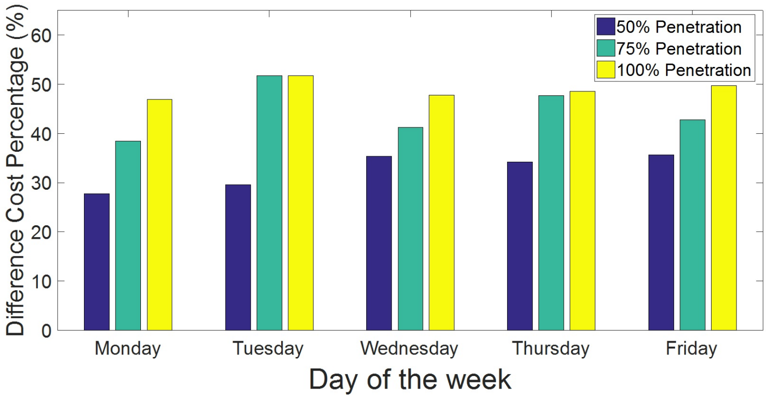


Figure 5.14: Percentage cost difference between scenario 2 and 3 for blue CCP.

By other side, green CCP presents more savings than the blue CCP, especially with low EV penetration level, the reason why it is important to consider strategies to incentive EV users to adopt it.

The savings from scenario 1 and 2 are quite similar, which shows that EV aggregator savings does not depend on a constant power rate, but on its modulation throw the day.

Finally, with the increase of EV penetration, savings of smart charging increase. This is because uncoordinated charging overpass during long periods the operator constraint and the penalty costs become essential.

The effectiveness of the proposed methodology compared to the uncoordinated has been demonstrated. It has also been proved that the model respond adequately to different input data. However, several assumed input data been used in the model so far. There will be significant deviations from these assumed values. To evaluate the impact of these different inputs in the charging costs and in the EV load, the results of the sensitivity analysis are presented next.

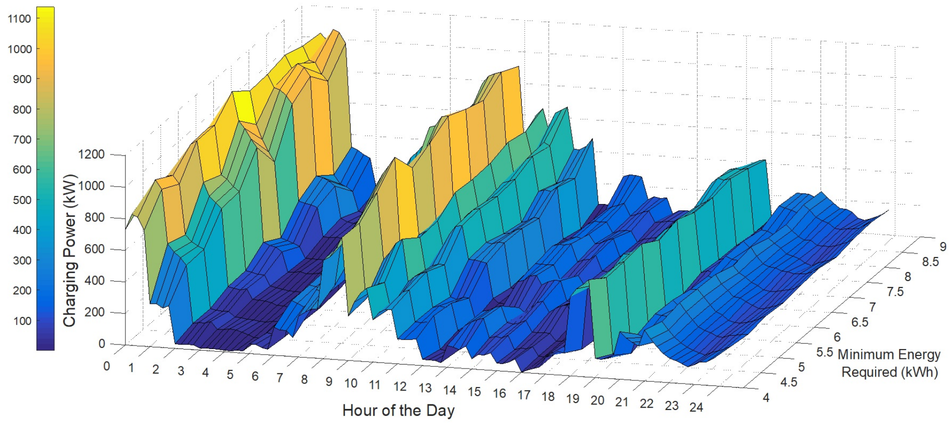


Figure 5.15: EV Load considering different Strategies for Minimum Required Energy.

5.4 Sensitivity Analysis Results for the Case Study

5.4.1 Analysis of Variation of Minimum Required Energy

In Figure 5.15, curves of Analysis of Variation of Minimum Required Energy are represented. It is observed that total energy dispatched to EV $E_{EV,tot}$ grows with the increase of minimum energy required. With the rise of the minimum required energy, the EV load grows considerably during hours 0-3 and 8-9. In these hours, the electricity is at its cheapest. EV load stays stable in hours 16-23 when the electricity is the most expensive. This means that despite the growth of the minimum required energy, EV aggregator does not dispatch power to the EV at time periods when the electricity is expensive, and take advantage of a bigger duration T_x^i to charge the EVs in time periods when electricity is cheaper. Note also that during hours 4-6, the EV Load remains at a minimum level in all cases, because these hours are one of the last of the evening and the electricity price is quite high comparing to the other hours in the evening.

In Table 5.4, the mean values of Scenario results are presented. As expected, an increase in minimum required energy leads to increase in total costs and in total energy dispatched to EV $E_{EV,tot}$. But, the EV aggregator cost per energy delivered decreased from 71.93 \$/MWh ($\underline{E_i^{req}}$=4kWh) to 70.47 \$/MWh ($\underline{E_i^{req}}$=9kWh), which represents a decrease of 2.03%.

Table 5.4: Summary of mean values corresponding to different Strategies for Minimum Required Energy.

$\underline{E_i^{req}}$ (kWh)	C_{VAR} (\$)	$E^{EV,tot}$ (kWh)	C_{eq} (\$/MWh)
4	371.1	5,158.8	71.93
4.5	387.7	5,397.4	71.83
5	406.5	5,671.6	71.67
5.5	422.4	5,914.7	71.42
6	440.5	6,174.0	71.35
6.5	455.8	6,404.8	71.16
7	473.0	6,660.3	71.02
7.5	490.8	6,920.4	70.93
8	507.9	7,175.8	70.78
8.5	524.2	7,415.8	70.68
9	540.0	7,663.0	70.47

In Figure 5.16, it is represented the regression curve with the mean points of each scenario. The next regression function is obtained:

$$C_{eq}(\underline{E_i^{req}}) = -0.288\underline{E_i^{req}} + 73.08 \tag{5.10}$$

In conclusion, increase in minimum required energy has the effect of decreasing costs per energy delivered. Nevertheless, note that the variation between the upper and lower values is not very important.

5.4.2 Analysis of the Time Delay of the starting charging time

Figure 8.4 shows EV charging power in a day depending on Time Delay of the charging starting time scenarios. It is observed peaks in hour 18-19 for the scenarios with small time delay. These peaks are not more observed in scenarios with significant time delay. EV users plug their EV some hours before the hour 18-19, which has the cheapest electricity costs during hours 16 to 21, so the EV aggregator tries to charge the more during this hour. With a delay of the starting charging time in the night, it is observed that the EV aggregator can benefit of cheaper electricity prices later in the night, and also at the first hours of the morning. This is why the peaks of these hours grow

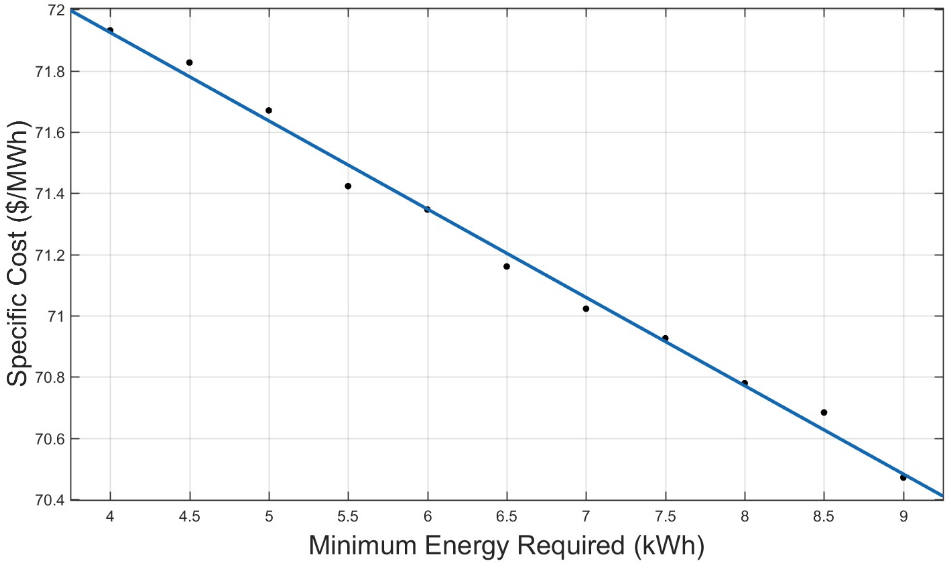


Figure 5.16: Regression Curve and mean points for Minimum Required Energy.

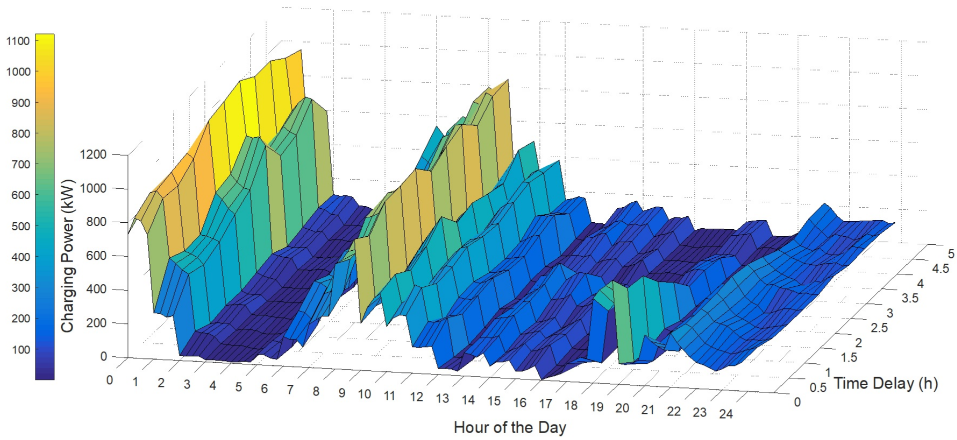


Figure 5.17: EV Load considering different Strategies for Time Delay of the charging starting time.

with the increase of the time delay. Nevertheless, after 3.5 hours of delay, these mentioned peaks do not grow any more.

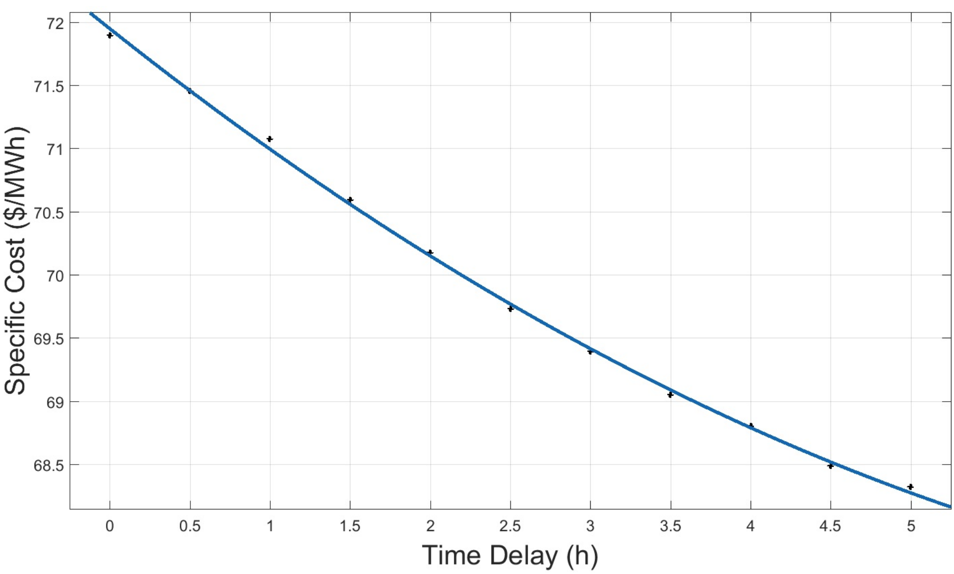


Figure 5.18: Regression Curve and mean points for Time Delay.

Table 5.5 presents the mean costs and energy dispatched for each scenario. The EV aggregator cost per energy delivered decreased from 71.93 \$/MWh (T_d=0h) to 68.33 \$/MWh (T_d=5h), which represents a decrease of 5 %.

In Figure 5.18, it is represented the regression curve with the mean points of each scenario. The next regression function is obtained:

$$C_{eq}(T_d) = 0.55T_d^2 - T_d + 71.95 \tag{5.11}$$

A delay in the charging starting time leads to a decrease of a day-ahead EV aggregator costs per energy delivered, this is due because of the cheaper electricity costs later in the evening. Note that the effect is more important between T_d=0h and T_d=3h (variation of 3.51 %), than between T_d=3h and T_d=5h (variation of 1.54 %). This is due by the fact that a bigger delay than 3 h does not worth for the methodology, because the EV aggregator can not find cheaper electricity prices in the night.

Table 5.5: Summary of mean values corresponding to different Strategies of Time Delay.

T_d (h)	C_{VAR} ($)	$E_{EV,tot}$ (kWh)	C_{eq} ($/MWh)
0	371.1	5,158.8	71.93
0.5	370.2	5,181.4	71.46
1	366.8	5,161.3	71.08
1.5	364.1	5,157.6	70.60
2	362.4	5,163.4	70.18
2.5	360.2	5,166.1	69.73
3	359.2	5,176.9	69.40
3.5	355.8	5,152.1	69.05
4	354.8	5,156.3	68.81
4.5	353.1	5,155.9	68.49
5	353.3	5,170.7	68.33

5.4.3 Analysis of Variation of share of Green CCP

Results of Portion Variation of Green CCP users are shown in Figure 5.19. It can be observed that an increase of the share of EV users adopting green CCP leads to an increase of load when the electricity is the cheapest (hours 0-3 and 7-9), and a decrease of load when the electricity is the more expensive (hours 16 to 22). The duration of the green CCP is longer than blue o red CCP, which allows to the EV aggregator to benefit of better electricity prices later in the evening, but the time is not enough for having the majority of EVs charging in the cheapest period of the day.

In Table 5.6, mean of results of scenarios are resumed. The EV aggregator cost per energy delivered decreased from 74.94 $/MWh ($\epsilon_G$=0%) to 70.02 $/MWh ($\epsilon_G$=100%), which represents a decrease of 7.03 %.

In Figure 5.20, it is represented the regression curve with the mean points of each scenario. The next regression function is obtained:

$$C_{eq}(\epsilon_G) = -0.05\epsilon_G + 74.9 \tag{5.12}$$

An increase of the share of green CCP EV users leads to a decrease of C_{VAR}.

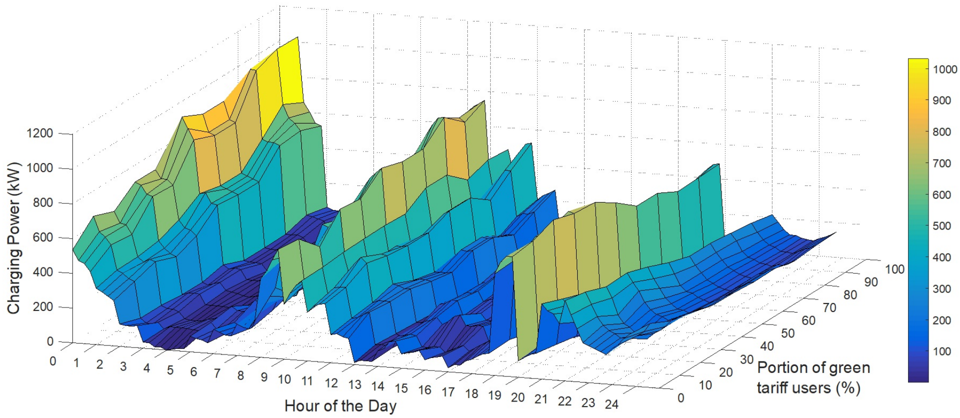


Figure 5.19: EV Load considering different Strategies for Variation of share of Green CCP.

Table 5.6: Summary of mean values corresponding to different Strategies for Variation of Green CCP share.

ϵ_G (%)	ϵ_B(%)	ϵ_R (%)	N^G	N^B	N^R	C_{VAR} (\$)	$E^{EV,tot}$ (kWh)	C_{eq} (\$/MWh)
0	75	25	0	375	125	384.5	5,161.7	74.94
10	67.5	22.5	50	337	113	383.3	5,178.3	74.45
20	60	20	100	300	100	379.5	5,163.5	73.94
30	52.5	17.5	150	262	88	378.4	5,180.6	73.46
40	45	15	200	225	75	374.9	5,167.8	72.97
50	37.5	12.5	250	187	63	372.4	5,169.1	72.47
60	30	10	300	150	50	371.1	5,158.8	71.93
70	22.5	7.5	350	112	38	368.1	5,181.0	71.46
80	15	5	400	75	25	364.9	5,170.3	70.99
90	7.5	2.5	450	37	13	361.9	5,169.2	70.43
100	0	0	500	0	0	359.3	5,162.0	70.02

5.4.4 Analysis of Variation of Average Charging Power Rate of Green CCP

The simulations of Variation of Average Charging Power rate of green CCP are shown in Figure 5.21. A peak between hours 7-9 is recorded with small values of $P_{G,av}$, another between hours 0-2 for medium values of $P_{G,av}$, and

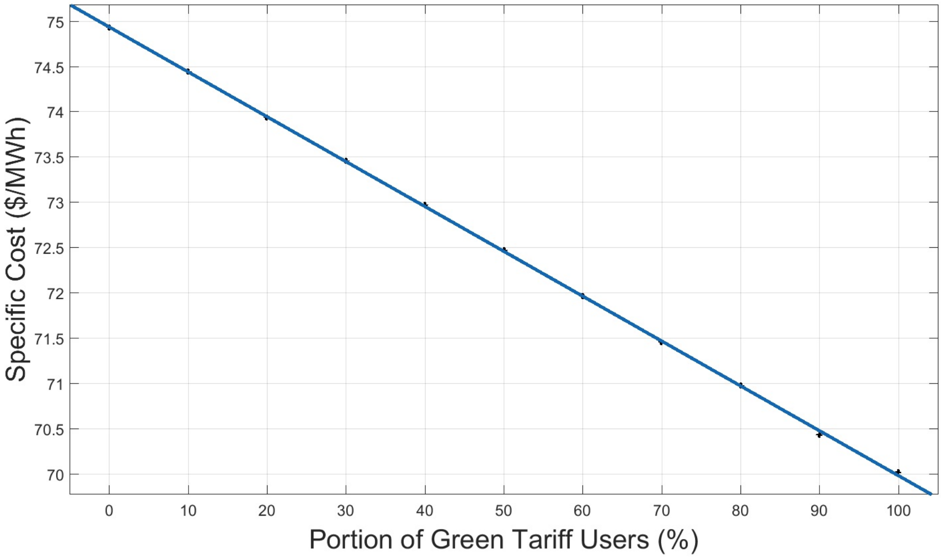


Figure 5.20: Regression Curve and mean points for Portion of Green CCP Users.

another at hours 18-19 for higher values of $P_{G,av}$. This is due by the fact that the EV load is significant in the cheapest hours corresponding to the duration that the EV aggregator has to charge the EVs. A smaller $P_{G,av}$ indicates that the EV aggregator benefits of a larger period to charge the EVs. If the period is larger, the EV aggregator could benefit of better prices. For example, in the first scenarios there is a peak between hours 7-9 because the period to charge is long and in these hours the electricity is at it cheapest, so it could charge the EVs at a maximum power. But, if $P_{G,av}$ grows, the period for charging decreases and the EV aggregator could not more benefit to charge the EVs in hours 7-9 and has to charge the EVs at maximum power during other cheaper periods. These new cheapest periods become hours 0-2 for medium values of $P_{G,av}$ and hours 18-19 for higher values of $P_{G,av}$.

Table 5.7 shows the means of results for the Variation of Average Charging Power rate of green CCP. The EV aggregator cost per energy delivered of green CCP increased from 62.68 \$/MWh ($P_{G,av}$=0.5 kW) to 75.18 \$/MWh ($P_{G,av}$=3.0 kW), which represents an increment of 19.94 %. The total EV aggregator cost per energy delivered increased from 68.11 \$/MWh ($P_{G,av}$=0.5 kW) to 75.10 \$/MWh ($P_{G,av}$=3.0 kW), which represents an increment of 10.26 %.

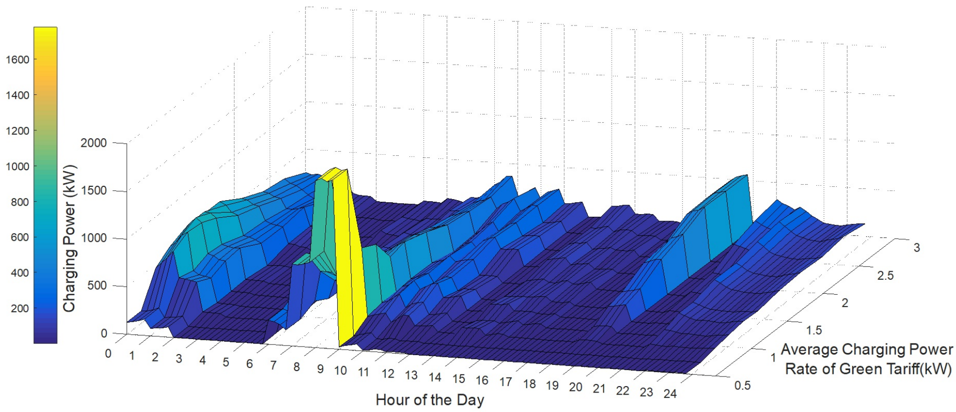


Figure 5.21: EV Load considering different Strategies for Variation of Average Charging Power Rate of Green CCP.

Table 5.7: Summary of mean values corresponding to different Strategies for Variation of Average Charging Power Rate of Green CCP.

$P^{G,av}$ (kW)	C^{G} (\$)	C_{VAR} (\$)	$E^{G,tot}$ (kWh)	$E^{EV,tot}$ (kWh)	$C^{G,eq}$ (\$/MWh)	C^{eq} (\$/MWh)
0.5	194.6	356.2	3,105.2	5,229.1	62.68	68.11
0.7	199.3	358.7	3,108.6	5,206.5	64.13	68.89
0.9	203.4	362.3	3,096.6	5,195.8	65.68	69.74
1.1	207.9	364.6	3,094.7	5,168.2	67.18	70.55
1.3	212.0	367.9	3,097.7	5,162.8	68.45	71.26
1.5	215.6	371.1	3,096.1	5,158.8	69.64	71.93
1.8	220.2	375.7	3,098.6	5,164.9	71.08	72.75
2.1	224.7	379.6	3,099.3	5,159.7	72.50	73.57
2.4	228.0	382.4	3,097.7	5,154.2	73.60	74.20
2.7	230.5	385.3	3,094.7	5,158.1	74.48	74.69
3	232.4	386.5	3,091.1	5,146.8	75.18	75.10

In Figure 5.22, it is represented the regression curve with the mean points of each scenario. The next regression function is obtained:

$$C^{eq}(P_{G,av}) = -0.687P_{G,av}^2 + 5.27P_{G,av} + 65.63 \tag{5.13}$$

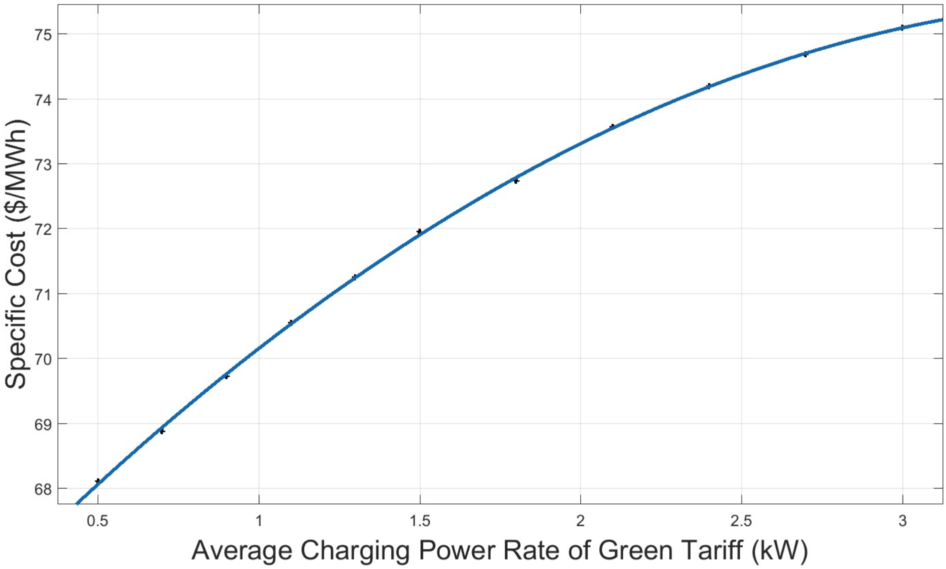


Figure 5.22: Regression Curve and mean points for Average Charging Power Rate of Green CCP.

The increase of average charging power for green CCP leads to a increase of EV aggregator costs. Note that this variation is important.

5.4.5 Analysis of Variation of Average Charging Power Rate of Blue CCP

The results are graphically illustrated in Figure 5.23. A peak between hours 7-9 is recorded with small values of $P_{B,av}$. It is a similar finding that the case of variation of Average Charging Power Rate of Green CCP. But, with the increase of $P_{B,av}$, it is noted that the load become quite random during all day. Load decreases also during the cheapest periods. The management of EV loads loses its interest because of the limited charging duration. In addition, several user tests could not be performed during the simulations optimizations. It can be explained by the fact that maximum constraint imposed by the operator limits the charging load. This means that the EV aggregator will have to pay the penalty cost C_p.

In table 5.8, means of EV aggregator expenses are presented for each scenario. The EV aggregator cost per energy delivered of blue CCP increased from 67.76

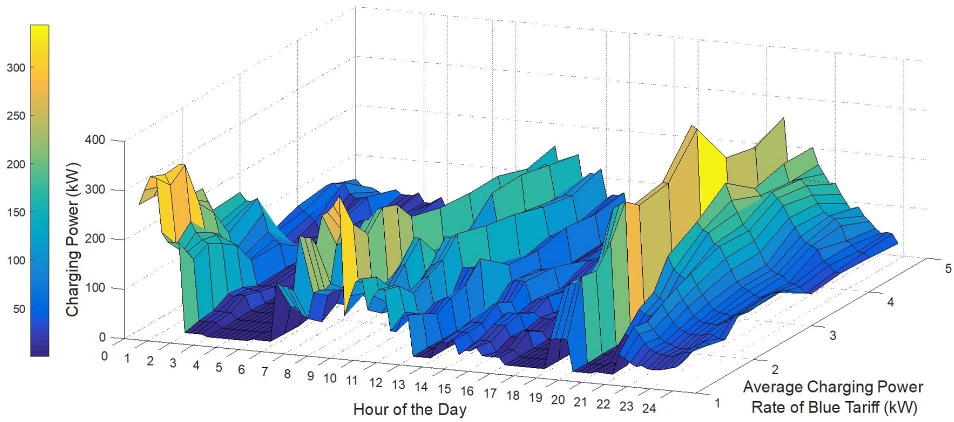


Figure 5.23: EV Load considering different Strategies for Variation of Average Charging Power Rate of Blue CCP.

Table 5.8: Summary of mean values corresponding to different Strategies for Variation of Average Charging Power Rate of Blue CCP.

$P^{B,av}(kW)$	C^{B} (\$)	C_{VAR} (\$)	$E^{B,tot}$ (kWh)	$E^{EV,tot}$ (kWh)	$C^{B,eq}$ (\$/MWh)	C^{eq} (\$/MWh)
1.25	105.2	393.8	1,552.6	5,275.2	67.76	74.66
1.5	107.3	394.0	1,549.3	5,249.8	69.24	75.05
1.75	109.4	394.5	1,552.9	5,233.9	70.44	75.37
2	110.4	393.8	1,542.4	5,201.6	71.56	75.71
2.25	111.9	393.8	1,543.0	5,186.6	72.50	75.93
2.5	113.8	395.7	1,551.5	5,192.6	73.34	76.21
3	115.3	395.9	1,546.1	5,175.3	74.59	76.49
3.5	116.8	396.2	1,545.3	5,164.2	75.56	76.73
4	117.8	396.9	1,541.6	5,155.6	76.41	76.98
4.5	119.1	397.6	1,548.3	5,158.9	76.90	77.08
5	119.3	397.3	1,542.5	5,146.7	77.37	77.20

\$/MWh ($P_{B,av}$=1.25 kW) to 77.37 \$/MWh ($P_{G,av}$=5.0 kW), which represents an increment of 14.18 %. The total EV aggregator cost per energy delivered increased from 74.66 \$/MWh ($P_{G,av}$=1.25 kW) to 77.20 \$/MWh ($P_{B,av}$=5.0 kW), which represents an increment of 3.40 %.

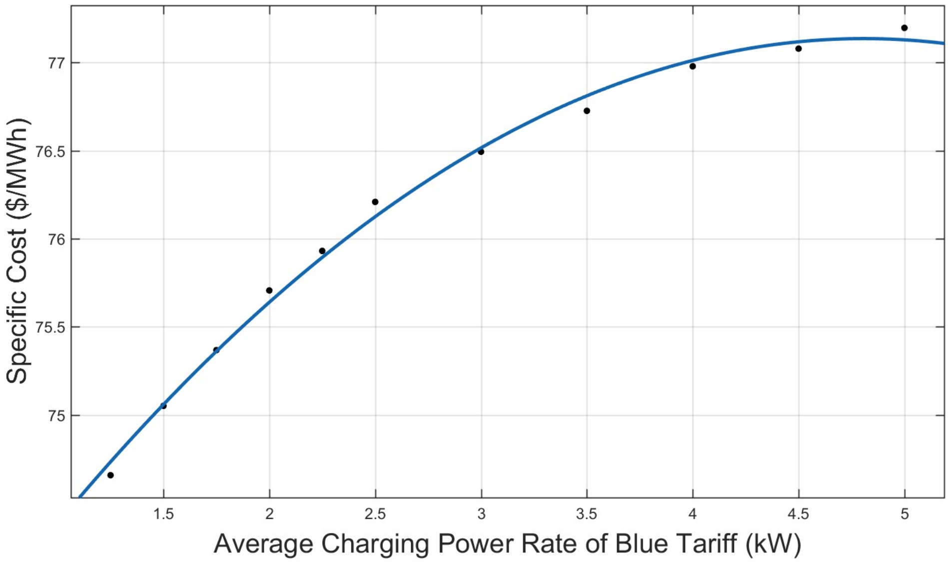


Figure 5.24: Regression Curve and mean points for Portion of Green CCP Users.

In Figure 5.24, it is represented the regression curve with the mean points of each scenario. The next regression function is obtained:

$$C_{eq}(P_{B,av}) = -0.19P_{B,av}^2 + 0.18P_{B,av} + 72.75 \tag{5.14}$$

The increase of average charging power for blue CCP leads to a increase of EV aggregator costs. Note that this variation is not so important.

5.5 Conclusion

This chapter studied the simulations of smart charging and two cases of uncoordinated charging performed under different EV penetration levels considering data analysis from a distribution feeder of the city of Quito, Ecuador. In the cases of uncoordinated charging, it was considered a constant charging power rate, which was fixed at 7.2 kW in the first one (maximum slow charging power) and at the average power of the proposed EV CCPs in the second one. Some assumptions were made according to some studies about work times and traffic conditions of Quito , and some information about the electric network from the studied area that was adapted from a previous work.

The results show that with the smart charging, aggregator can have benefits comparing to two cases of uncoordinated charging, while respecting technical conditions. The benefits are always significant, (surpassing at least 20 %). Savings become specially important (reaching a difference than more than 50 %) when penetration level increase because total EV uncoordinated charging overpass technical operator constraint, and then it is not feasible. .

Moreover, weekly studies were simulated, comparing the two cases of uncoordinated charging and smart charging. Simulations from green and blue CCP were separated. Results indicate that fixing the charging in a constant value, regardless the value of the charging power rate, is not efficient in the management of the grid, because costs are quite similar and do not respect conditions that can be fixed by DSO and TSO and managed by the aggregator. Also, an increase of the number of vehicles leads to an important increase of the benefits of the green smart charging, which demonstrates the benefit of the methodology when the proportion of vehicles is important compared to the capacity of the grid.

The methodology could be limited if the number of vehicles is too large and the duration of EVs plug correspond to the period when there is not enough energy available. In this case, minimum conditions of the grid capacity may exist.

A sensitivity analysis of crucial parameters was also performed. Regression analysis of the mean values of EV aggregator specific costs was also performed in order to represent the trends for each variation of the model considered. Some variations present a linear trend and others a quadratic trend. The different parameters leads on different variations of the EV aggregator expenses.

The variation of minimum required energy and average charging power rate of blue CCP has not presented important changes in EV aggregator expenses (2.03% and 3.40% respectively) which means that the EV aggregator has to establish this parameter according to EV user preferences. The variation of time delay of the starting charging time and share of green CCP users have more important expenses variations (5 % and 7.03% respectively). The most important expense variations has been observed in the variation of average charging power rate of green CCP (10.26%). Before implementing EV aggregator, this last parameter has to be studied depending on EV users behavior.

The main limitation of the sensitivity analysis lies on the computational time for each simulation because only 100 simulations of Monte Carlo were performed for each scenario of a parameter variation. Therefore, the accuracy of the results should be good enough.

Part of the content of this chapter has been presented in: (Clairand, Rodriguez Garcia, and Alvarez Bel 2017; Clairand, Rodríguez-García, and Álvarez-Bel 2017; Clairand, Rodríguez-García, and Álvarez-Bel 2018b):

Chapter 6

Smart Charging Application to provide Ancillary Services

6.1 Introduction

A methodology to supply energy to the EV in a Distribution system has been developed and justified in the previous chapters. Additionally to this, it is possible to take advantage of the EV flexibility in the charging process (or even to consider the possibility do discharge them) to provide ancillary services such as frequency control. EVs could participate in primary, secondary and tertiary response, but the purpose of this chapter is to study the participation of EVs in secondary, which will be explained in detail.

As mentioned in previous chapters, most of the works in the literature do not offer any advantage for EV users flexibility. Thus, the aim of this chapter is to complement the methodology presented in Chapter 4, considering the participation of the EV aggregator in ancillary services. The EV aggregator should also adjust slow charging power to fulfill technical constraints imposed by network operators while EVs are charged at the lowest cost, but also, it should provide regulation reserves to the power grid. The EV users should consider the same CCPs from Chapter 4, but the charging process will be different and is detailed in the methodology. The additional characteristics of the proposed method are highlighted as follows:

- The EV aggregator will be in charge of avoiding technical issues in the electricity network, while the charging costs and regulation services are optimized, both in the operational planning and in real-time.
- A charging and discharging management of the EV fleet is studied for determining if V2G is suitable or not for regulation services.
- The EV aggregator potential profitability from providing regulation services is studied.

This chapter starts with a background of ancillary services in section 6.2. After that, the methodology formulation, which complements previous chapters, is presented in section 6.3. Then, the different inputs of the case study are detailed in section 6.4. The results are discussed in section 6.5. Finally, section 6.6 is devoted to conclusions of the chapter.

6.2 Background: Ancillary Services

6.2.1 Control as Ancillary Services

With the liberalization of electricity markets, several services associated with the the generation, transmission, and distribution of electricity have been separated and offered by different agents. For instance, ancillary services are defined as the services needed to support the reliable transmission of the grid from suppliers to users, such as frequency and voltage regulation (US Federal Energy Regulatory Commission. 1996).

On the one hand, competitive markets for ancillary services are being designed, especially for frequency control, given the way that these services can be straightforwardly linked with active power and energy production, and henceforth can be promptly priced. On the other hand, markets for voltage control services are as of now immature in good part because these services are related to reactive power (MVar), which is more difficult to trade as the effect of reactive power in the voltage is more local (Andersson, Álvarez-Bel, and Cañizares 2009).

In spite of the fact that there is no unique market structure for the provision of frequency controls throughout most jurisdictions, frequency control markets, which are also alluded to as ancillary service markets, depend on bidding and contracting instruments intended for the purchase of spinning and non spinning reserves for frequency control, from both generators and loads (Bhattacharya, Bollen, and Daalder 2012).

6.2.2 Frequency Control

For satisfactory operation of a power grid, the frequency ought to remain nearly constant. Generally, close control of frequency guarantees steadiness of speed and induction and synchronous motors. The frequency of a system is subject to active power balance. A variation in active power demand at one point leads to a difference in frequency. Since there are several generators providing power into the system, a few capabilities must be given to allocating change in demand to the generators. The primary control function is given by a speed governor A speed governor on each generating unit gives the primary speed control function. In an interconnected system with at least two independently controlled areas, in addition to control or frequency, the generation within each area must be controlled in order to keep scheduled power exchange. The control of generation and frequency is commonly referred to as load-frequency control (LFC) (Kundur 1994).

Moreover, power system control is implemented for both frequency and voltage in three steps: primary, secondary, and tertiary. These steps have different objectives, time response, geographical conditions, but they are always in interaction between them. Firstly, the primary response is based on the local control performed by the generator, in order to stabilize the system frequency if a disturbance occurs. The response takes some seconds and it is not responsible for restoring the reference value of the system frequency. Then, the secondary control corresponds to the maintain of the power balance in a control area, as well as the maintain of the system frequency. The response takes several seconds to minutes. Finally, the tertiary control is responsible for modifying the active power set points in the generators in order to perform a global power system operating strategy. The response takes several minutes (Andersson, Álvarez-Bel, and Cañizares 2009). Hence, it is crucial to have generation reserves to account for abnormal conditions. Considering the time responses of the different reserves, the EV load can act especially as a resource for secondary reserves, such as presented in (Han, Han, and Sezaki 2011; Kempton and Tomić 2005).

6.2.3 Regulation services and EVs

Regulation must be under direct real-time control of the grid operator, with the generating unit capable of receiving signals from the grid operator's computer and responding within a minute or less by increasing or decreasing the output of the generator (Kempton and Tomić 2005). Regulation can be divided into two classes regulation up and regulation down. Regulation up is the ability to increase power generation from a prediction level and regulation down is to decrease power generation. For example, if load exceeds generation, the frequency will drop and an additional generation power is required, so in this case regulation up is required. In particular, the market can request both for regulation up and regulation down. The regulation calls for the generators are significant (more than 400 per day), so the energy offers are each day or even each hour and they are based on the purchase or sale of a quantity of electricity. Then the market matches offers and bids to determine the price and the amount of electricity that each one is awarded. Furthermore, the response of the power available from the EVs has to be quick for the participation in regulation services due to the possible significant calls. Hence, the authors of (Kempton and Tomić 2005) also demonstrated such feasibility.

A few works of EV participation in ancillary services exist in the literature compared to other fields of study. They were already described in 3.3.1. But, none of them offer to the EV customers the possibility to charge according to their preferences at the moment they need to charge. For this reason, the aim of this chapter is to give an approach based on the CCPs defined before. Moreover, in (*Grid for Vehicles*), it was demonstrated that the V2G mode offers small additional benefits more than the ones that can be achieved with modulating the charge (as proposed in this thesis), with significantly smaller cost (in control equipment and battery degradation). This chapter discusses the possible benefits with the inclusion of V2G mode in the green and blue CCP.

6.3 Methodology formulation

6.3.1 Optimization formulation

The previous chapters considered the minimization of the charging costs that is performed by the EV aggregator. Nevertheless, the benefits of the EV aggregator could be improved with the participation of it in te regulation services. Thus, in addition of taking advantages of time-varying electricity CCPs by charging the EVs, the EV aggregator should participate offering operational reserves during the operation horizon.

Based on the previous methodology of smart charging, a new methodology is developed, which maximizes the EV aggregator benefits considering ancillary services. It is based on an optimization formulation that is subject to different constraints. In addition, the methodology considers the study with and without the V2G mode. Depending on its experience, it could earn more benefits making higher regulation bids. The EV aggregators benefits are defined:

$$B = R - C \tag{6.1}$$

where the EV aggregator revenues are defined as follows:

$$R = E^D.\pi^{E,D} + E^U.\pi^{E,U} + \sum_{t=1}^{T} R_t^D.c_t^D + R_t^U.c_t^U \tag{6.2}$$

With:

$\pi^{E,D}$: Market selling price for regulation down (\$/kWh)

$\pi^{E,U}$: Market selling price for regulation up (\$/kWh)

R_t^U: Regulation capacity up available at time t (kW)

R_t^D: Regulation capacity down available at time t (kW)

c_t^D: Hourly regulation capacity price down (\$/kW-h)

c_t^D: Hourly regulation capacity price up (\$/kW-h)

E^D: Dispatched energy for regulation down (kWh)

E^U:Dispatched energy for regulation up (kWh)

The revenues include a first component for energy payment (\$/kWh), and the other component for availability (\$/kW-h), both of them for regulation up and down. The first term is considered the energy revenue and the second the capacity revenue. Note that the energy component corresponds to a revenue of the EV aggregator if it is matched by the regulation market, and the capacity payment is due for the power available.

The costs include a cost of energy, a penalty charge, an associated cost from battery degradation associated from discharging the EV battery (in case V2G is not used, this cost has not to be included), a cost for the bidirectionnal chargers, and a payment for the users; they are defined as follows:

$$C = C_E + C_P + C_B + C_H + C_U \tag{6.3}$$

where:

$$C_E = \sum_{t=1}^{T} P_t^{EV}.c_t^e.\Delta T \tag{6.4}$$

$$C_P = \alpha_P.E_P \tag{6.5}$$

$$C_B = \sum_{t=1}^{T} \alpha_{bd}.P_t^{EV,d}.\Delta T \tag{6.6}$$

$$C_H = \alpha_H.D.(N^G + N^B) \tag{6.7}$$

$$C_U = \alpha_U.R \tag{6.8}$$

In particular, equation (6.5) indicates that if the EV aggregator fails to comply with the given regulation bid in the real-time, a penalty will be imposed at the end of the current day. A penalty cost was assumed considering a penalty coefficient for the energy that was not consumed or delivered. Equation 6.6 indicates that the EV aggregator has to discount an amount for the battery degradation that is considered for the V2G mode when the EV supply energy to the grid. This penalty cost was not considered for the G2V mode since it is minimal compared to V2G. The parameter α_{bd} is a factor that defines the battery degradation per kWh absorbed from the EV battery. Equation 6.7 corresponds to the cost for the investment of bidirectional chargers, such as indicated in (Dallinger, Krampe, and Wietschel 2011). Since the cost was assumed in this work for 390 $ for the installation of a bidirectional charger, it is considered that the EV aggregator has to pay a cost per day and per EV charging, so the factor for the bidirectional charger was assumed to be α_B=0.2 $ per day and per charging station. Note that only green and blue CCP users are considered for this costs, because they are the only that they can use the bidirectional chargers. Equation 6.8 indicates that a part of the revenues from the EV aggregator has to be distributed to the EV users. In this way, EV users could be interested for participating in ancillary services. It is assumed $\alpha_U = 5\%$.

Observe that in this case, the revenues are not constant anymore and depends on the capacity of the EV aggregator for offering regulation services. This is because in this case the revenues depend on the regulation bids, which vary during the day, so the revenues can be maximized in the day horizon.

The EV aggregator has to set an hourly prediction load profile so it can provide the frequency regulation service by varying its charging loads above or below the prediction. Under this mechanism, the default status of all the EVs at any decision stage is "charge". (Ke, Wu, and Lu 2017). The prediction of the EV aggregator is defined:

$$P_t^{bas} = \sum_{i=1}^{N} P_{i,t} \tag{6.9}$$

The objective function can be written as follows:

$$maxB = maxR - C \tag{6.10}$$

Observe that the objective function is developed based on equations (6.2) and (6.3).

The methodology is subject to the different constraints:

$$\underline{P^{EV}} \leq P_{i,t} \leq \overline{P^{EV}_{max}} \tag{6.11}$$

$$\underline{SOC^{EV}} \leq SOC_{i,t} \leq \overline{SOC^{EV}} \tag{6.12}$$

$$R_t^{D,B} \leq R_t^D \tag{6.13}$$

$$R_t^{U,B} \leq R_t^U \tag{6.14}$$

With:

$R_t^{D,B}$: Offered regulation bid down for time t (%)

$R_t^{U,B}$: Offered regulation bid up for time t (%)

Equation (6.11) indicates the limits of the power supplied or demanded from an EV charger. Equation (6.12) defines the SOC limits for a better operation of the EV battery for mitigating the effects of degradation. Equations (6.13) and (6.14) ensure that the regulation bids for the day ahead are at their minimum available. In some works, the minimum reserve is assumed to be 0.1 MW for participating in regulation services, considering the values of PJM Market (Zhang et al. 2017; Lam, Leung, and Li 2016; Dallinger, Krampe, and Wietschel 2011). But, since the power levels of the Ecuadorean grid are smaller, a value of 50 kW is considered. In addition, the offered regulation bids are assumed to be 50 % of the EV availbale load. Depending on the performance of the EV aggregator, it can be increased for receiving higher benefits.

6.3.2 Aggregate Model

For the ancillary services participation, the EV aggregator needs to sum the energy and power boundaries of all the EVs, depending on the CCPs the owners request. In particular, EV users who select green or blue CCP are able to participate both in regulation down and up, but red CCP users are only able to participate in regulation down, because they do not allow flexibility for decreasing the charging power rate. Observe, that red CCP do not participate in V2G mode but also their users charge at maximum power.

The aggregate charging power of all the EVs can be calculated as follows:

$$P_t^{EV} = \sum_{i=1}^{N_{EV}} P_{i,t}^{EV} = \sum_{i=1}^{N_{G,EV}} P_{i,t}^{G} + \sum_{i=1}^{N_{B,EV}} P_{i,t}^{B} + \sum_{i=1}^{N_{R,EV}} P_{i,t}^{R} \tag{6.15}$$

The additional constraints for the CCPs are listed as follows:

$$R_t^{D,B} \leq \sum_{i=1}^{N_{G,EV}} P_{i,t}^{G} + \sum_{i=1}^{N_{B,EV}} P_{i,t}^{B} + \sum_{i=1}^{N_{R,EV}} P_{i,t}^{R} \tag{6.16}$$

$$R_t^{U,B} \leq \sum_{i=1}^{N_{G,EV}} P_{i,t}^G + \sum_{i=1}^{N_{B,EV}} P_{i,t}^B \tag{6.17}$$

Equations 6.16 and 6.17 indicate that all the power available for regulation has to be higher than the offered regulation bids. The constraint is performed based on the forecast of the day before. At the end of the day, the EV aggregator has to pay the penalty cost for the energy that fail to comply with the regulation bids.

6.3.3 Charging prices

When an EV i is plugged the EV aggregator calculates the corresponding price to pay that is defined:

$$p_i = \sum_{k=1}^{k=D} \pi_k . P_{k,i} + p^F - \frac{C_U}{N}, \forall k \in U_i \tag{6.18}$$

The EV user has to pay the variable electricity price and a constant value that corresponds to the benefits of the EV aggregator, which corresponds to its revenues for the service provided. The EV user has a discount corresponding to the participation in regulation services, which corresponds to the last term and comes from the cost of the EV aggregator from equation (6.8). Note that the price is calculated for each time horizon U_i, which is different for all users.

6.3.4 Forecast and Real-Time Implementation

The methodology is divided in two time parts:

- The first considers the day-ahead optimization considering the prices for the next day of the regulation up and down, and electricity prices, and considering the forecast of the EV users behavior, such as hour of arrival, energy required, and CCP selected.
- The second time considers the real-time optimization. The model is optimized in real time, considering the new arrivals and the updated prices of regulation up and down and electricity prices. For the real-time optimization, the different values are updated each 15 minutes.

The methodology should guarantee a high accuracy and the maximum exploit of the potential regulation services.

Furthermore, the EV users requirements from the previous chapters were also considered, as presented in 4.2.3.

The different steps are considered for this methodology:

- At the end of the previous day to the day in which the charging process is going to be scheduled, the EV aggregator receives from the electricity market the predictions for the next day of the electricity price and regulation services requirements. Furthermore, the EV aggregator has to build the EV load prediction curve, based of the forecast of the charge of the EVs that is obtained from the information of the arrivals and energy required from the EV users from the current and previous day. Then it performs the different regulation offers and send to the Operator.

- At the start of the new day, it has to be considered EV charging that was not completed the ending day. This is a result available from the optimization performed for this day.

- At the beginning of every 15 minutes step, the aggregator has to receive real time information of new cars plugged in. This will be done through smart meters installed in the customer facility, where the EV users will have the information of the costs from the different CCPs in real-time. If new cars are connected for loading, each smart meter has to send the associated information to the aggregator: State of Charge and CCP selected. The aggregator will combine this information with the information about the actual and short term EV status.

- An optimization process is performed to obtain a charging profile for each EV taking into account the calculated charging period U_i and the total power needed. As a result, it will also be known the moment when an EV will be totally charged. The optimization is performed for each EV connected in a specific moment and not for the sum all of them. The dispatch ratio is used to calculate the dispatched energy. The optimization process will determine the new charging according to both the network constraints and the committed charging in previous steps. The optimization process takes into account the possible energy calls. In a case that in real-time, there is not enough energy available, the EV aggregator will pay the penalty cost, instead of not satisfying the EV users requirements.

- This process will be repeated every 15 minutes until the end of the day ahead. The optimization will consider that the EV charging will continue in the next day if charging start late in the day ahead, but this charging pattern has to be considered as mentioned at the beginning of the new day.
- At the end of the day, the benefits of the EV aggregator are calculated.

The flowchart of the proposed methodology is shown in Figure 6.1.

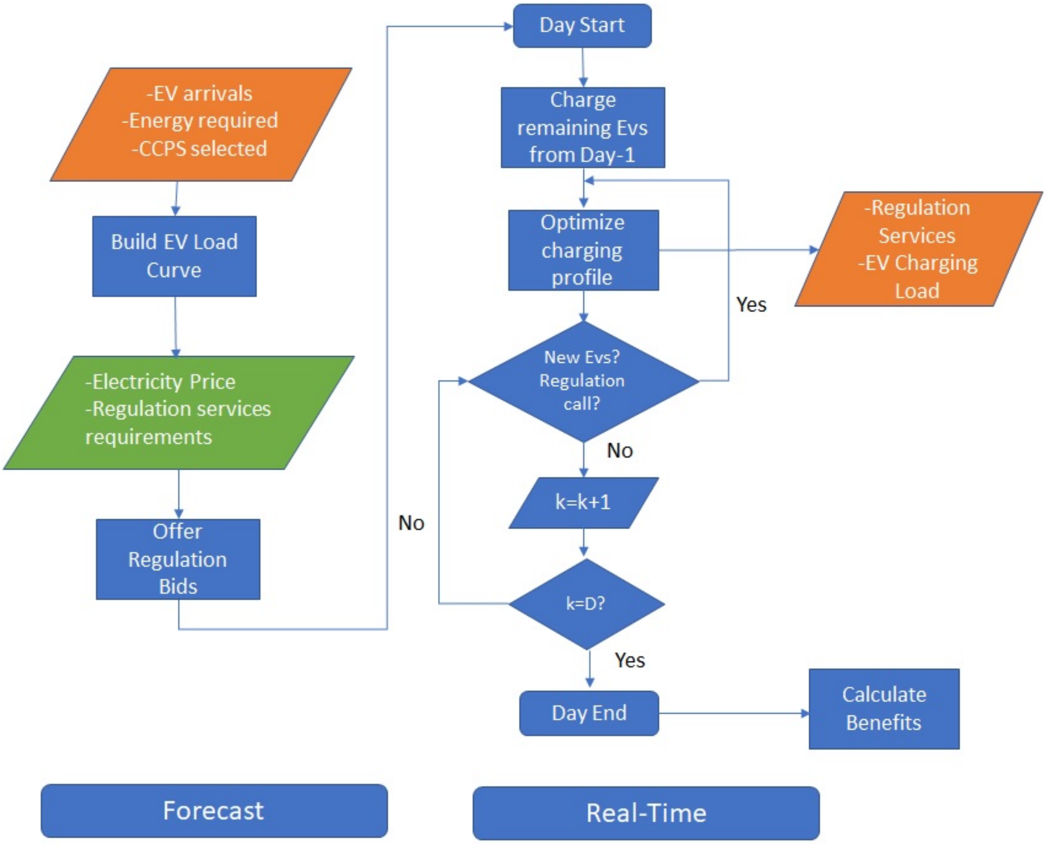


Figure 6.1: Flowchart of regulation participation

6.4 Case study

A case study is presented that demonstrates the effectiveness of the proposed methodology. The data from the traffic of Quito, Ecuador is considered again. In this way, the information used in the previous chapter is the same, such as the charging duration, the EV users requirements, number of EVs, starting charging time, daily energy needed and the same share of the three CCPs. The following information was presented in in 5.2.2 and 5.2.3.

Ecuador do not have an electricity ancillary services market, especially for regulation services. The national operator of electricity CENACE as to manage the frequency control. The secondary control is carried out through the generating units assigned by CENACE for this purpose, which are generally thermal and hydroelectric (CONELEC 2015).

For this reason the data from ESIOS of Red Eléctrica España is selected, for validation purposes (Esios 2018). Note that this information is added as an input, so as if the market existed in Ecuador, it could be considered for this methodology. A typical day of the week is selected for the study. Figure 6.2 represent the price profiles for regulation up and figure 6.3 the price profiles for regulation down. Note that the forecast and real-time prices are represented. The battery degradation cost α_{bd} was fixed at 0.004 \$/%-h according to (DeForest, MacDonald, and Black 2018) and the penalty factors α_p at 0.004 \$/kWh according to (Ke, Wu, and Lu 2017). Moreover, the energy revenue could be defined by dispatch ratios defined:

$$r^D = \frac{E^D}{P_t^{EV}.U_i} \tag{6.19}$$

$$r^U = \frac{E^U}{P_t^{EV}.U_i} \tag{6.20}$$

The energy dispatched for regulation services is some fraction of the total power available and contracted. For this reason, this ratio is used (Kempton and Tomić 2005). The values from (Luo et al. 2012) are considered: 0.033 and 0.062 for regulation up and down respectively.

6.5 Results

6.5.1 Daily Operation

In Figure 6.2, the hourly regulation up for both in the forecast and in real-time are illustrated. Note that the variations between the real-time and the forecast are not significant. The peaks correspond to periods when the electricity is relatively expensive and the regulation up prices are high.

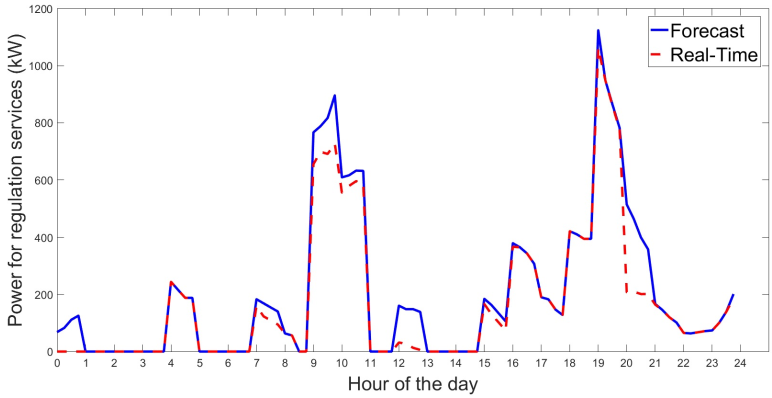


Figure 6.2: Up Regulation.

In Figure 6.3 the hourly regulation down for both in the forecast and in real-time are illustrated. It is observed different variations during the day, which correspond to the charging needs from the EV aggregator, which has to exploit at maximum the lower electricity prices and significant down regulation prices. Note that the EV aggregator can provide at the same time both regulation up and down. This is because the time arrival of the EVs are different, so the EV aggregator can increase the charging power rate of some of them and decrease others, depending on the problem conditions. Moreover, the points power of regulation that is below the curve of the forecasted correspond to the time periods that the EV aggregator cannot satisfy the regulation it offered the day before, so it has to pay the penalty cots corresponding to the energy difference.

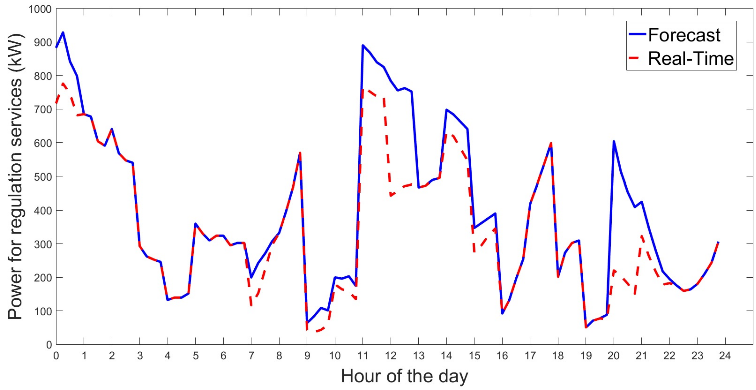


Figure 6.3: Down Regulation.

6.5.2 Daily Benefits

Results of the calculations of the daily benefits with V2G are shown in Table 6.1. Results of the calculations of the daily benefits without V2G are shown in Table 6.2. It is clear that regulation Down offers much more incomes to EV aggregator. In the case of the V2G mode, it is observed that the revenues are significant, but also the costs. In the case without the V2G mode, it is noted that the revenues for the regulation up are very small and for the regulation down they are not so significant. This can be explained due to the higher amount of power that the EV aggregator can manage with the V2G mode. Nevertheless, note that the indicated investments are indicative and can result more significant, and it is not sure that the EV users are willing to let their EV battery to discharge to the grid. Moreover, the regulation could be higher if EV users stay parked longer time than considered for the case study, but it is crucial to study the willingness of the EV users to remain parked a more extended period. Note that the number of EV users are 1000 because it corresponds just to a zone of Quito. The benefits for the regulation services may be much higher in a whole city, and the regulation services more significant. Finally, the total benefits are not significant between the forecast and the real-time application, and the difference is mostly because of the penalty charge from the deviations of the regulation that is not provided by the EV aggregator. Thus, the methodology works correctly.

Table 6.1: Economic factors for EV participation in Regulation Markets considering the use of V2G.

	Forecast ($)	Real-Time ($)
Reg. Down Capacity	485.3	501.0
Reg.Up Capacity	158.2	154.7
Reg. Down Energy	138.7	143.1
Reg.Up Energy	26.4	25.8
Total Revenues	808.6	801.6
Energy	333.7	335.2
Penalty Charge	0	7.2
Bat. Deg.	19.9	19.4
Bidirectional electronics	80	80
Payment to users	40.4	40.0
Total Costs	474.0	481.8
Total Benefits	334.6	319.8

6.6 Conclusion of the Chapter

This chapter presented the formulation and development of the proposed methodology for regulation services, with and without the consideration of the V2G mode. An evaluation of the revenues of the EV aggregator was analyzed.

Moreover, the regulation services were applied to the Ecuadorean grid, which does not have a regulation market. For this purpose, the information from Spanish market was used as an input for the model.

This study has shown, that the EV aggregator has a substantial potential for providing regulation services in electricity markets, especially considering the use of the V2G mode. But, the model does not present significant benefits for regulation up, with and without the V2G mode, mainly because of the considered flexibility of the EV users. It is crucial to mention also that the V2G could create uncertainty in the users about the real use of the EV battery from the EV aggregator and it requires significant technical requirements during the installation of V2G equipment. In the case study of Ecuador, it was demonstrated the effectiveness of the participation in regulation services for EV. First, the EV aggregator receive benefits for this participation. Then, the results prove that the Ecuadorean grid could avoid grid payments to foreign countries for regulation purposes.

Table 6.2: Economic factors for EV participation in Regulation Markets without V2G mode.

	Forecast ($)	Real-Time ($)
Reg. Down Capacity	306.5	308.0
Reg.Up Capacity	24.7	29.0
Reg. Down Energy	87.5	88.0
Reg.Up Energy	4.1	4.8
Total Revenues	422.8	429.8
Energy	329.7	333.2
Penalty Charge	0	7.4
Bat. Deg.	0	0
Payment to users	21.1	21.5
Total Costs	350.8	362.1
Total Benefits	72.2	67.7

In these chapters, the smart charging methodology was applied to a typical distribution grid. Thus, it could result crucial to develop a methodology in distribution grids with a high presence of high RES.

Chapter 7

New Methodology: EV Charging mechanisms for Distribution systems with high penetration of renewable generation

7.1 Introduction

In the previous chapters, two methodologies for the EV operation in distribution systems were studied. Nevertheless, these EV charging strategies dealt with typical distribution systems connected to transmission systems. It is crucial to study the operation of EVs in systems that are mostly composed by only a local distribution system and are generally connected to Distributed Energy resources, such as renewable generators. These distribution systems and their problems are presented next.

Climate change has become one of the major focus for energy policies. Electricity generation and transportation are the energy activities that emit the highest amounts of greenhouse gases as CO_2 (Labatt and White 2007).

In this way, Renewable Energy Sources (RES) appear as an alternative to address this problem. They are naturally restored sources that do not pollute locally and have a very low carbon footprint. These sources often produce energy, especially for electricity generation. However, some of the more critical problems of the use of RES in this area are the uncertainties of their generation availability and their integration to the grid(Geng et al. 2017; Verbruggen et al. 2010).

Different actions have been taken in several countries (Robalino-L??pez, Mena-Nieto, and Garc??a-Ramos 2014) to achieve the target of CO_2 reduction. One of these measures consists of taxing CO_2 emissions in order to increase renewable energy production. Some research works have focused on this carbon price. In (Kanamura 2016), the role of carbon swap trading and energy prices in volatilities and price correlations between the EU and Kyoto Protocol emissions trading schemes are examined. Authors of (Zhu et al. 2017) have proposed an empirical mode decomposition-based evolutionary least squares support vector regression in order to forecast carbon price. In (Gavard 2016), it was analyzed the impact of a carbon price in Denmark about the use of wind energy in comparison to fuel technologies.

Tariff mechanisms were proposed for involving customers to satisfy the energy requirements. A Brazilian Demand Response program called the Tariff Flag mechanism was qualitatively and quantitatively analyzed in (Lima, Perez, and Clemente 2017). The authors of (Khan, Ryan, and Abebe 2017) proposed an optimal scheduling for industrial HVAC energy cost through binary integer linear programming and based on based on Peak/Off-Peak Tariff. An optimal pricing scheme considering voltage security cost was proposed in (Tamimi and Vaez-Zadeh 2008). In particular, networks with high RES are in focus for tariff design methodologies, but some issues have to be addressed (Picciariello et al. 2015). Although some works exist about tariffs for EV charging, such as (O'Connell et al. 2012), the literature does not propose many tariff systems for charging EVs in DER networks.

Most of the works presented in Chapter 3 considered only one source of RES with EV loads, but only few works have considered the study with at least wind and solar.

In some places in the world, it is essential to change network conditions because of environmental situations and the introduction of green sources are compulsory. One of these places is the Galapagos Islands. They are an archipelago of volcanic islands in Ecuador, which are recognized by UNESCO as World Heritage site and as a biosphere reserve. For this reason, Galapagos is a protected area: Ecuadorean government has taken some politics to protect it, especially because of the growth of population and tourism. Moreover, electricity generation was very pollutant and also the transportation of fuels to the island create another concern due to the risk of possible spills. For that reason, the government of Ecuador decided to create the Program "Cero Combustibles Fósiles" which consists of reducing on a gradual reduction of fuel consumption in the islands (Vélez-Vega, Cedeño-Gómez, and Almeida-Chinga 2016). In that way, it implemented DER in the islands, such as solar and wind, as part of the policies for changing the matrix of electricity (Ponce-Jara et al. 2018). The government also has the initiative of introducing EVs for replacing internal combustion ones because of the environmental conditions mentioned before (*Plan Galapagos*). Thus, a methodology has to be implemented to avoid grid problems.

The aim of this chapter is to propose an EV charging scheme in isolated distribution systems, such as Off-grid Microgrids (Arriaga, Canizares, and Kazerani 2014) (localized group of electricity sources and loads that normally operates disconnected from a transmission grid) while using an optimized charging depending on grid conditions. Also, the methodology gives rise to increase the use of available DER generation and to result in a future increase of renewable energy production and reduction of CO_2 emissions. A case study of the Galápagos Islands is presented. The previous CCPs are not used in this chapter, because it is not the goal of this new methodology. Nevertheless, they can be easily adapted to the presented model in this chapter. Hence, the charging mechanism will not depend on customer choice, as in the previous methodologies, but in the EV type. The desired characteristics of the proposed method are highlighted as follows:

- A charging mechanism is proposed for EV charging in electricity networks with a high presence of renewable electricity generation. The case study considers wind and solar generation.
- The EV aggregator optimizes the EV charging profile, through charging power rate modulation, while respecting actual grid conditions and using renewable power excess that is not consumed by other loads.

- The methodology has to consider the participation of different kind of EVs such as electric cars, motorcycles, and buses. Thus, the different energy requirements will be taken into account

This chapter is structured as follows: in section 7.2, the methodology is described. The Case Study is presented in section 7.3. The results are discussed in section 7.4. Finally, section 7.5 is devoted to conclusions.

7.2 Methodology description

Several policies have been created for protected areas to reduce CO_2 emissions related to the growth of both RES and EV penetration. However, System Operator (SO) may have troubles if there are not both an adequate control system of RES and a smart charging program. EV users will have to install intelligent chargers and smart meters for participating in smart charging programs.

When they plug their EV into the grid, they will let the EV aggregator modulate the power demanded during EV charging. This agent will be in charge of all the EVs of the islands and it will interact with the SO in order to develop a smart charging respecting grid conditions and reducing user costs. The EV aggregator will be only responsible for managing the EV charging while the management of renewable electricity generation will be executed by SO. It is also possible to consider that the EV aggregator could be in interaction with residential customers aggregators that will manage energy hubs as buildings (Roldán-Blay et al. 2017). The EV aggregator will have to define a daily EV electricity cost curve, when a new day starts, based on the forecasts. Then, it will have to optimize the charging of the EV fleet, based on this electricity curve and considering the needs from the EV users. In order to control the different EVs and to receive information, such as the starting charging time, it is assumed that the EV users have to install smart meters in their homes or in the commercial stations. The operator will send the corresponding forecasts of the RES power to the EV aggregator to build the EV electricity cost curve. Several methodologies exist for the forecast of RES power, but it is outside the topic of this thesis, so these values are assumed to be accurate enough. Furthermore, it is also assumed that the operator can forecast the residential load in order to know the available power resulting from the excess of RES power.

The EV electricity cost, the problem formulation, and the EV charging methodology are detailed next.

7.2.1 EV electricity cost

EVs represent a new load, which has to be considered in the daily operation. Considering a high RES penetration, it could be advantageous to charge the EV when there is a high RES power available, which could result in an excess of generation if the demand is too low. Moreover, if there is not enough RES power available and the residential load is high it is crucial not to charge the EVs during this time. Some works have already considered to consume this excess of RES energy such as (Ekman 2011). For this purpose, it might be beneficial to encourage this load consumption through the charging of the EV batteries by the EV aggregator, based on electricity pricing mechanisms.

For these reasons, an electricity cost for EV charging is proposed. The formulation considers proposing lower costs when RES power is in excess for maximizing its utilization, and proposing higher costs when RES power is not available for minimizing electricity consumption from diesel. Note that this charging mechanism is only proposed for EV charging purposes. The residential load has to respect its respective tariff.

According to the characteristics of the pricing conditions of the case study, the daily specific electricity prices have to be between a minimum and maximum values and considering a mean value (ARCONEL 2016). For this purpose, a daily EV specific electricity cost for charging EVs is proposed to be between the minimum and maximum values, y_{min} and y_{max}, which have to be fixed by the EV aggregator. It is also assumed that the EV specific electricity cost has a daily mean y_m equal to the mean proposed by the Ecuadorean regulator for the residential load.

For the calculation of the EV electricity cost, the difference of the residential load and RES generation P_k^{dif} is considered:

$$P_k^{dif} = P_k^L - P_k^{PV} - P_k^W \; \forall k \in \tau \tag{7.1}$$

Note that this equation depends on parameters that are assumed to be known. For that purpose, it is assumed that the System Operator obtains an accurate forecast of this information.

In a day, the negative values of P_{dif} represent a RES power excess. If the value is 0, it means that RES power satisfies exactly the load. A positive value implies that there is not enough RES power to satisfy load demand and it is necessary to generate the missing power by fuel generation.

In this way, it is considered that the charging mechanism for EV is built considering the trend of P_{dif} during a day. As per (Picciariello et al. 2015), pricing approaches have to be considered for the consumers, so the lower costs will be when there is an RES power excess (negative values) and the most expensive ones when the electricity has to be generated by fuel (positive values). For the case study, electricity prices have to be positive. In order to consider the trend of P_{dif}, but with only positive values, a system of equations has to be solved.

Let's suppose $\mathbf{P}_k^C$, $\mathbf{P}^M$ and $\mathbf{P}^B$ the vector of decision variables for the charging power of cars, motorcycles and buses, they are defined based on the number of EV users they have.

$$\mathbf{P}_k^C = \begin{bmatrix} P_{k,1}^C \\ P_{k,2}^C \\ \dots \\ P_{k,N^C}^C \end{bmatrix}$$

$$\mathbf{P}_k^M = \begin{bmatrix} P_{k,1}^M \\ P_{k,2}^M \\ \dots \\ P_{k,N^M}^M \end{bmatrix}$$

$$\mathbf{P}_k^B = \begin{bmatrix} P_{k,1}^B \\ P_{k,2}^B \\ \dots \\ P_{k,N^B}^B \end{bmatrix}$$

EV Daily costs are defined as the sum of all the costs for all the time intervals k in a day:

$$C = \sum_{k=1}^{D} \pi_k.(\mathbf{P}_k^C + \mathbf{P}_k^M + \mathbf{P}_k^B) \tag{7.2}$$

The specific cost is obtained changing the scale of the curve of P_{dif} and adapting to a new interval, as represented in Figure 7.1.

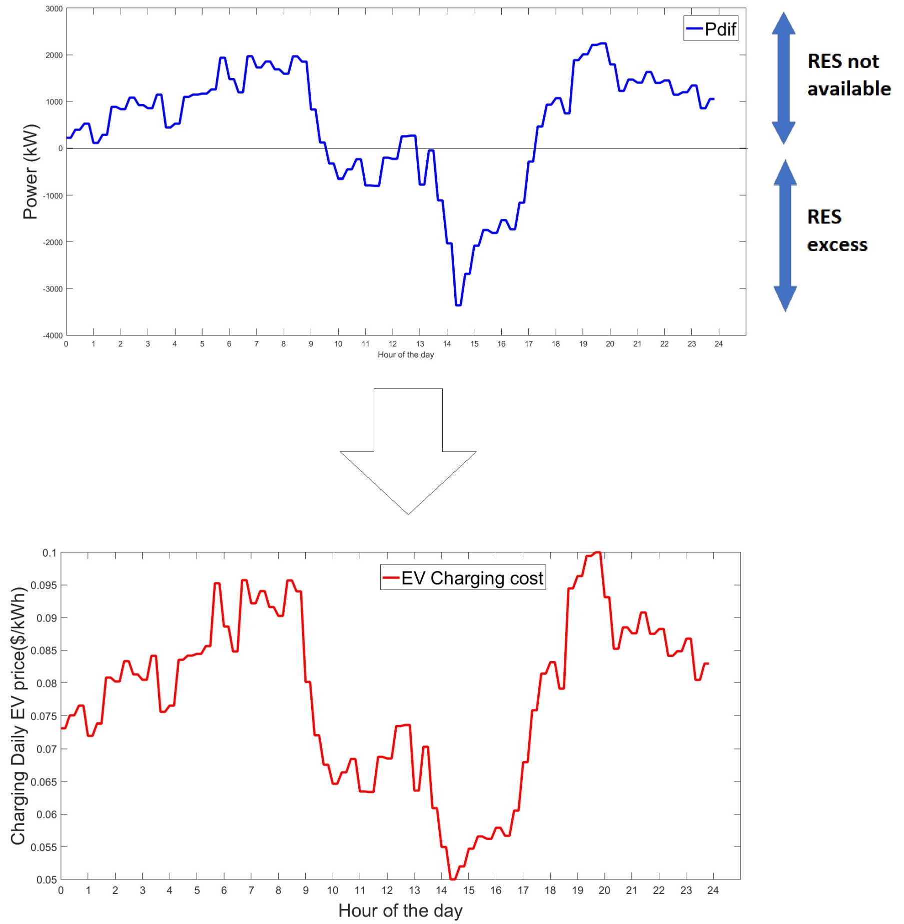


Figure 7.1: Difference of residential load and RES power, and EV charging specific cost.

7.2.2 Problem Formulation

The model maximizes the RES energy excess and minimize the electricity production from diesel, based on the charging of EVs:

$$min\ P^{dif} = min(\sum_{k=1}^{D} P_k^L - P_k^{PV} - P_k^W) \tag{7.3}$$

Moreover, the problem is equivalent of minimizing the daily cost of the EV charging:

$$min\ C = min(\sum_{k=1}^{D} \pi_k.(\mathbf{P}_k^C + \mathbf{P}_k^M + \mathbf{P}_k^B)) \tag{7.4}$$

The problem is subject to the following constraints:

- Supply-demand Balance in the grid

  Charging EV have to respect the maximum capacity of the grid. It means that the sum of all the EV charging power might be lower than the power balance of all the generation production minus the residential load (without EV), for each time interval time k. Expressed as:

$$P_k^{PV} + P_k^W + P_k^D \geq P_k^L + P_k^{EV} + P_k^{loss}\ \forall k \in T \tag{7.5}$$

- EV Charging Power Rate

  The EV aggregator will modulate EV charging power rate between zero and the upper bound, which corresponds to the maximum charging power that the charger from each kind of EV e allows.

$$0 < P_{k,i,e} < \overline{P_{i,e}^{EV}}\ \forall k \in \tau \tag{7.6}$$

- Daily EV user Energy required

  Each EV user i specifies at the beginning of the charging the energy that needs. The EV aggregator has to respect:

$$E_i^{req} = \sum_{k=1}^{k=D} P_{i,e,k}.\Delta T\ \forall k \in U_i \tag{7.7}$$

  Note that the time the EV user will need to wait will be:

$$T_{\tau,i} = \frac{E_i^{req}}{P_{k,i,e}}\ \forall k \in U_i \tag{7.8}$$

In this methodology, minimum and maximum power constraints of generators are not taken into account, because only a small part of this power is considered to be demanded by EV charging, so the other electric loads will demand the rest of power.

Transmission network constraints were not considered either because the grid is mainly composed of only a generation and distribution system.

The problem can be solved by a linear optimization for each EV.

7.2.3 EV Charging Methodology

- At the end of Day-1, the system operator process the information of RES Generation and Load Demand from all the day.
- After processing the information, the system operator has to build the specific electricity cost curve.
- At the beginning of a new day, it has to be considered EV charging that was not completed the day before.

  Every 20 minutes, real-time information on the new cars plugged are received. This new time between each step time was used considering the data available, which was different from the previous chapters. This information could be done through smart meters installed in the customer facility. If new cars are connected to the grid, the smart meter linked to them will have to send the information about the charging, such as the energy required by the EV user. The information will be sent in real time.

  After this, the cost optimization will be performed, which will be carried out through the charging power rate modulation between zero and the maximum EV Charging Power Rate $P_{EV,max}$. It will also be known the time at which the EV charging will be over. The optimization process will determine the new charging rate according to both the network constraints and the committed charging previously.
- EV aggregator will inform each step the EV load to the diesel generation in order to produce the necessary power required.

The flowchart of the methodology is illustrated in Figure 7.2.

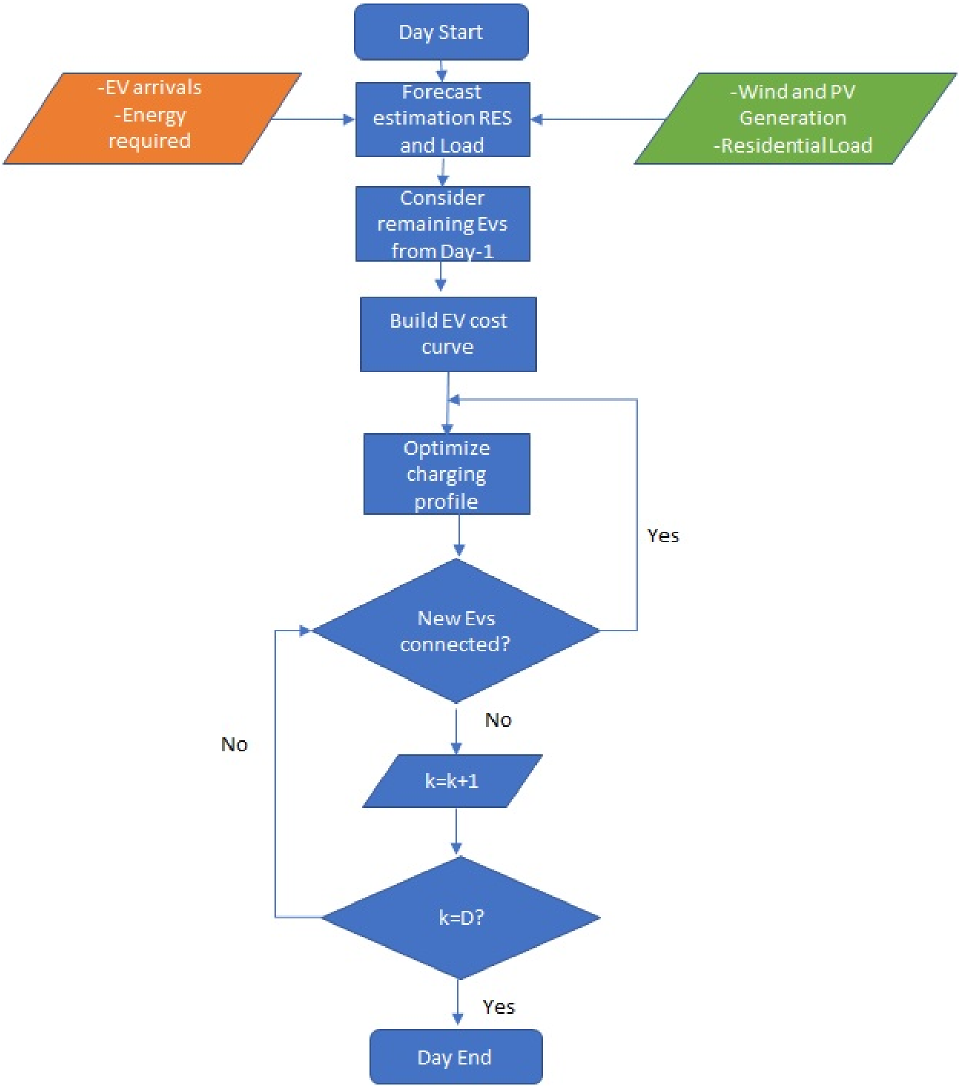


Figure 7.2: Methodology Flowchart.

7.3 Case Study: Santa Cruz, the Galapagos Islands

The distribution system in Santa cruz is formed by wind turbines, PV installations and Fuel generators, that are described next.

To evaluate the proposed methodology, a case study was studied. The Galapagos Islands in Ecuador are an archipelago, whose islands are isolated from a main grid. Thus, the island of Santa Cruz was selected for this study.

In this section, it is described the distribution model that is going to be used in the methodology validation. For the first scenario, the actual conditions mentioned in (Elecgalapagos 2016a) are presented.

7.3.1 Generation Capacity

The Ecuadorean Government has identified the Galapagos Islands as a national priority for conservation and environmental management, developing the Galapagos Zero Fossil Fuels program, which consist of measures and actions to avoid habitat degradation and ecological impact (*Plan Galapagos*; Ponce-Jara et al. 2018). Thus, the Ecuadorean government invested and installed photovoltaic (PV) plants, wind turbines in Galapagos (*Proyectos*). The characteristics are detailed next.

Wind

There are three wind generators that are located in the Baltra Island, which are connected to the electric grid of Santa Cruz Island through a 34.5 kV power line of 50 km long. This wind farm has an installed power of 2.25 MW.

PV

The Photovoltaic plant is located near Puerto Ayora that is the main city in the Santa Cruz Island. It has a total amount of 6,006 PV panels that are connected to Puerto Ayora substation through a 13.8 kV power line. It has an installed power of 1,5 MWpeak (MWp).

Fuel

Seven Caterpillar diesel generators are installed with a total installed capacity of 5.26 MW (Paz and Anazco 2015). There are 4 Hyundai diesel generators that have been installed in recent years, and an installed capacity of 1.7 MW each (Paz and Anazco 2015). The total installed capacity is 12.06 MW.

7.3.2 Types of EVs

In the previous work presented in (Álvarez-Bel et al. 2016), some analyses of EV penetration were performed where some assumptions of future trends in EVs were done. In contrast, the particularity of this study consisted on that not only regular electric cars are considered, but also electric motorcycles and buses. In this study, the term electric car will refer to regular small size EV for differentiating to electric motorcycles and electric buses.

7.3.3 EV input variables

Values for the daily EV specific costs

The minimum and maximum values, y_{min} and y_{max}, are selected based on the values given by the Ecuadorean regulator Arconel, which are 0.05 \$/kWh and 0.1 \$/kWh respectively. It is also proposed to have a daily mean y_m equal to the mean proposed by Arconel that is 0.078 \$/kWh.

Number of vehicles from each type and model selected

In (*Plan Galapagos*), it is considered that there are 1,326 vehicles in Santa Cruz. Only the types of vehicles that could be replaced by the above-mentioned ones are considered in this study. The rest of types are smaller groups or more difficult to replace by a current equivalent electric model. The quantity and main features of each type are presented in Table 7.1.

The motorcycles in Galapagos require a speed up to 70 km/h to drive in the roads of the island safely. Thus, the model S-4100 is considered as the most suitable equivalent model in order to replace the existing ones. Its relevant features are presented in (Zelectricvehicle 2018). According to this, the maximum charging power rate is 1 kW. The charging time reaches up to 4 hours.

Regarding buses, the BYD K9 bus is the equivalent electric model that is considered in this study. This model has a maximum charging power rate of 60 kW (BYD 2018).

Considering that users of pickup trucks select these vehicle types due to the road conditions and their use like medium-sized taxis in Galapagos, the Kia Soul EV is found the electric model equivalent in this case. This model can replace the existing IC pick-ups and it has a maximum charging power rate of 6.6 kW (Kia 2018).

Start time of charging

In the Santa Cruz Island, Motorcycle users are usually people that work in government or tourism offices during traditional Ecuadorian work shift, which finishes between 4 PM and 8 PM. Considering the trip to their homes, it is estimated that motorcycle users will plug in their EVs between 4:30 PM and 8:30 PM.

According to the local bus timetable of routes in the island, bus drivers work only at the beginning and end of labor hours. For this reason, it is considered that half of the buses start their charging between 8:00 AM and 10:00 AM, and the other half between 4:00 PM and 8:00 PM (*Plan Galapagos*).

In the Santa Cruz Island, most of the car users are taxis drivers (*Plan Galapagos*). In this case, they usually work all day transporting workers and tourists. The start time of charging is considered later than the others because they have to supply the needs of people that won't take the buses. For this reason, electric cars are considered to start their charging between 10:00 PM and 02:00 AM. It is considered also a starting charging time between 05:00 AM and 12:00 PM because of transportation of tourists to the airport.

Energy Required

The distances that are covered by the different vehicles were considered in order to have an estimation of the energy required for each type of EV per day. Regarding the electric motorcycles, which are equipped with a battery of 2.86 kWh, and taking into account the existing road conditions it is assumed that they have an autonomy of 50 km. Furthermore, it is considered that motorcycle users drive 30 km per day; as a result the energy required per user is 1.7 kWh per day.

Table 7.1: EV characteristics.

EV type	Motorcycle	Bus	Car
N	611	46	467
$P_{EV,max}$	1 kW	60 kW	6.6 kW
E_V	4 kWh	324 kWh	27 kWh
E_{req}	1.7 kWh	280 kWh	24 kWh
st_i	16h30-20h30	12h00-22h00	05h00-12h00 & 22h00-02h00

In the case of electric buses, the battery capacity of BYD K9 bus is 324 kWh that corresponds with an autonomy of 250 km. The buses currently cover around 200 km per day and the value of their autonomy could be a bit lower because their routes usually go through the main roads on the island. Therefore the energy required of each electric bus is estimated at 280 kWh per day.

In the case of the electric cars, the Kia Soul EV has an autonomy of 180 km. The taxi drivers cover an average distance of 150 km per day and taking into account the road conditions, the energy required by each EV is around 24 kWh per day. This value is close to 27 kWh but, as mentioned above, it is considered that there are two periods of charging every day.

Plug Duration

In this study,it is assumed that the Plug Duration for each EV i is twice as long as the duration of charging at the maximum charging power rate what is expressed in the following equation. This assumption was done based on the behaviors of EV users (Schuller, Flath, and Gottwalt 2015; Sadeghian-pourhamami et al. 2018):

$$T_{\tau,i} = 2.T_{P,max,i} = 2.\frac{E_i^{req}}{P_{EV,max}} \tag{7.9}$$

7.3.4 Residential load

A daily load curve of a typical day for residential customers in the Santa Cruz island was selected from the data provided by Elecgalápagos (local distributor). The residential load is presented in Figure 7.3. The present RES generation of that day is also represented. In addition, it has been assumed 10% of electricity grid losses taking into account the information provided by Elecgalapagos.

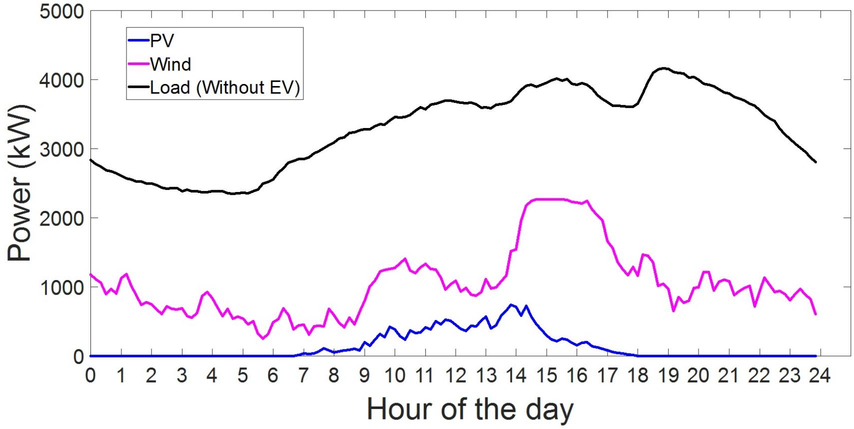


Figure 7.3: Present daily Santa Cruz load and daily Renewable generation.

7.3.5 Implementation

In a day, it is considered D=72 that is the number of time intervals per day, so the time intervals last 20 minutes.

$$\tau = \{1, 2, ..D\} \tag{7.10}$$

The plug duration γ_i is defined as the duration of the connection of the EV i to the charging station and the time of departure. In this case:

$$\gamma_i \subseteq \tau \tag{7.11}$$

The charging time δ_i is defined as the duration in which their EVs are plugged to perform the smart charging. If a user disconnects its EV before the charging time is finished, there will be no guarantee that at least some energy has been transferred to the batteries. If everything is fine, users will be able to unplug their EVs after the charging time when the interface shows the associated message. In this sense:

$$\delta_i \subseteq \gamma_i \tag{7.12}$$

Table 7.2: Energy and Costs comparison between each scenario.

Scenario	$IC^{PV}(MW)$	IC^{W} (MW)
1	5	5
2	5	7.5
3	5	10
4	7.5	5
5	7.5	7.5
6	7.5	10
7	10	5
8	10	7.5
9	10	10

7.4 Results and discussion

7.4.1 Scenarios Definition

To assess the influence of the methodology for different installed capacities of both wind and PV, nine scenarios are studied, which combine different installed capacities of PV (5, 7.5 and 10 MW) and Wind (5, 7.5 and 10 MW). All the scenarios are resumed in Table 7.2, depending on the assumed installed capacity of wind and solar.

Firstly, to evaluate the daily operation, the simulations of the smart charging methodology are compared to a case of uncoordinated charging, which consists that EV users start their charging at maximum charging power rate immediately they are plugged to the grid. For this evaluation, two scenarios are selected with very different installed capacity, which correspond to the first scenario (5 MW of PV and 5MW of Wind), and the ninth scenario (10 MW of PV and 10 MW of Wind). The analysis of daily operations are performed.

Then, all the costs of the nine scenarios are studied to show the importance of proper management of EV charging when there is a high presence of renewable electricity generation in the grid. These scenarios are studied in several months from the data available. It was not possible to do for an entire year because of missing information or because Wind or solar generators were turned off.

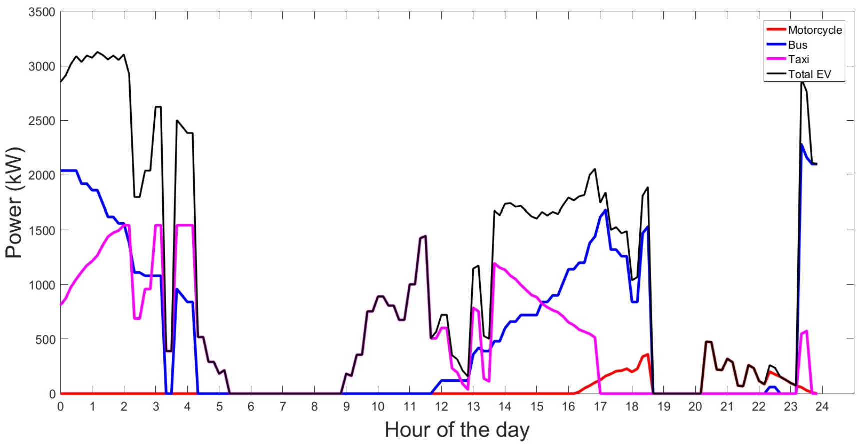


Figure 7.4: Charging pattern from each type of EV, with smart charging, for Scenario 1.

7.4.2 Daily Operation: Scenario 1

Scenario 1 corresponds to an installed capacity of 5 MW of Wind and 5 MW of PV. From the simulations of the proposed methodology, the charging patterns of the smart charging for all the EVS are represented in Figure 7.4, comparing the load patterns of the different types of EVs.

The energy required for charging electric motorcycles is very small compared with the energy for the other kind of EVs. Buses are the EVs that consume the most energy, especially during the night, when the RES power is not significantly available.

Figure 7.5 represents the different loads and the generation output. The EV Load is able to absorb a big part of the RES energy, particularly during the day. Moreover, from hours 10 to 16, diesel generation is very small.

In Figure 7.6, the patterns for both Smart and Uncoordinated Charging are shown. Significant peaks and valley periods occur in the Smart Charging pattern corresponding to the absence or surplus of energy from RES.

The excess power from RES is expressed:

$$P_k^{exc,tot} = \begin{cases} P_k^W + P_k^{PV} - P_k^D, & \text{if } P_k^W + P_k^{PV} > P_k^D \\ 0, & \text{otherwise} \end{cases} \tag{7.13}$$

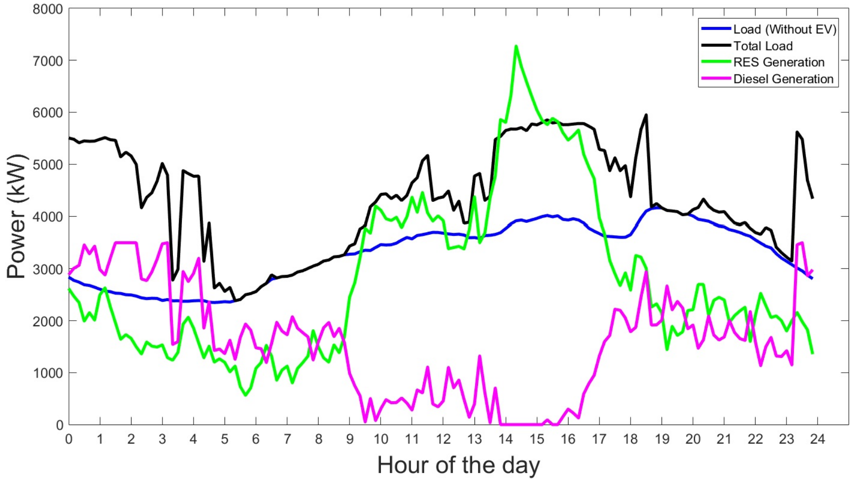


Figure 7.5: Loads and Generation Profiles, with smart charging, for Scenario 1.

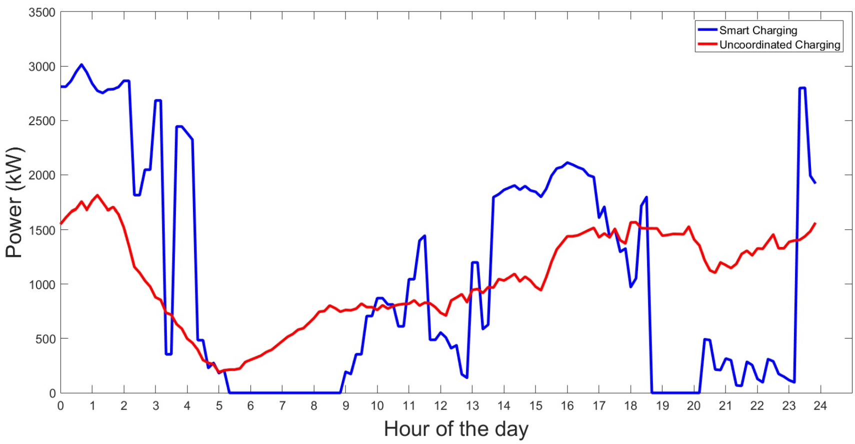


Figure 7.6: Smart Charging and Uncoordinated Charging Patterns, for Scenario 1.

The daily excess energy from RES is expressed:

$$E_k^{exc,RES} = \sum_{k=1}^{D} P_k^{exc,RES} . \Delta T \tag{7.14}$$

The excess power from RES consumed by EV is expressed:

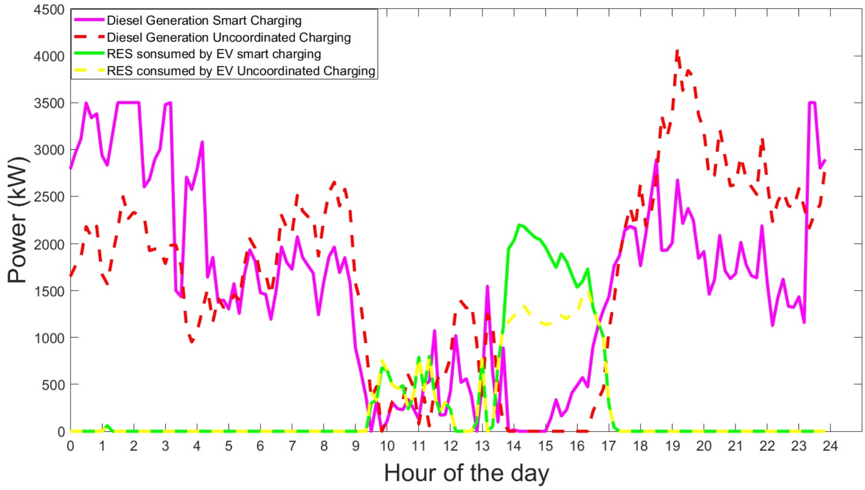


Figure 7.7: Diesel generation and RES power excess consumed by EVs for Scenario 1.

$$P_k^{exc,EV} = \begin{cases} P_k^{EV}, & \text{if } 0 < P_{EV} < P_k^{exc,tot} \\ P_k^{exc,RES}, & \text{if } 0 < P_k^{exc,RES} < P^{EV} \\ 0, & \text{otherwise} \end{cases} \tag{7.15}$$

The excess energy from RES consumed by EVs is expressed:

$$E_k^{exc,EV} = \sum_{k=1}^{D} P_k^{exc,EV}.\Delta T \tag{7.16}$$

Figure 7.7 present the electricity that has to be produced by Diesel generators and the RES energy excess consumed by EVs.

It was observed that with the smart charging, the EVs consume more RES energy and less diesel energy. Note also that the RES energy excess is not very significant.

Table 7.3 summarizes the energy consumed, total costs and specific costs both for uncoordinated and smart charging for each type of EV. Smart Charging results in lower costs than Uncoordinated Charging for all types of EVs. The most important difference is for electric cars for which the Specific Cost has a

Table 7.3: Energy and Costs for each type of EV for Scenario 1.

EV Type	Motorcycle	Bus	Car	Total
$E^{EV,tot}$ (kWh)	1,039	12,880	11,208	25,127
C^{unc} (\$)	91	983	862	1,936
C^{coo} (\$)	87	918	777	1,782
C^{unc}_{eq} (\$/MWh)	87.6	76.3	76.9	77
C^{coo}_{eq} (\$/MWh)	83.7	71.3	69.3	70.9

Table 7.4: Diesel Generation and RES power excess used for charging EV for Scenario 1.

Type of Charging	Uncoordinated	Smart
Diesel Energy (kWh)	39505	37766
Excess RES Used (kWh)	5532	7271
Ratio excess RES (%)	22	29

difference of 9.9 % between uncoordinated and smart charging. The difference for all the EV charging between uncoordinated and smart is 7.9 %.

The ratio of RES energy excess consumed y EV $\eta_{exc,EV}$ is expressed as:

$$\eta^{exc,EV} = \frac{E^{exc,EV}}{E^{EV,tot}} \tag{7.17}$$

This relation demonstrates the RES excess energy that is consumed by EVs over all the total energy that was supplied for EV charging.

Table 7.4 shows the total amount of Electricity generated by Diesel and the RES energy excess that is consumed in charging EVs.

As can be seen, the Smart Charging of EVs involves 4.6 % less electricity produced by Diesel and 23.9% more consumption of RES energy excess compared to uncoordinated charging. Furthermore, the ratio of RES energy excess used for charging EV is 31.8 % more important for Smart Charging than for Uncoordinated Charging. Note that the values of the ratios for the two kinds of charging are relatively significant.

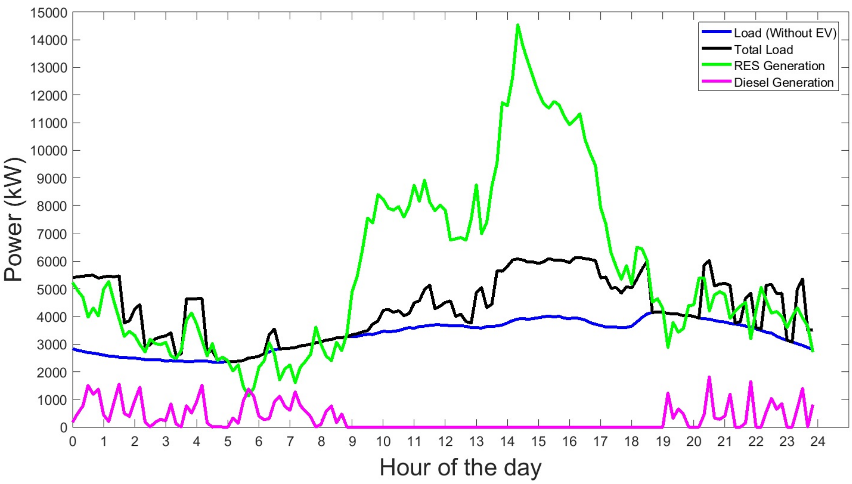


Figure 7.8: Loads and Generation Profiles for Scenario 9, with smart charging.

7.4.3 Scenario 9: Daily Operation

This scenario increased the PV and Wind Generation the same proportions, with an installed power capacity of 10 MW capacity for both PV and Wind. The different patterns from generation and loads are represented in Figure 7.8. The EV charging load is quite similar to that of Scenario 1, but as the RES capacity is higher, RES energy excess that was not seen in reference scenario is available at certain periods of the night. It can be seen that RES power peaks are absorbed by EV charging. But, since the RES installed capacity is very high, there is a significant amount of RES energy that cannot be consumed.

In Figure 7.9, the Diesel generation and RES energy excess consumed by EVs are represented both for smart and uncoordinated charging. As the RES power capacity increases, so do total Diesel generation and RES energy excess consumed by EV.

Table 7.4 shows the total amount of Electricity generated by Diesel and the RES energy excess consumed for charging EVs in Scenario 2. As in scenario 1, the costs and specific costs are lower with smart charging than with uncoordinated charging, but the total difference drops (7 % for the specific cost) and the total costs and specific costs are greater for smart charging between the reference scenario and scenario 2. This finding is due because the cheaper periods of electricity cannot be used for charging EVs because there is no significant demand for charging at these periods.

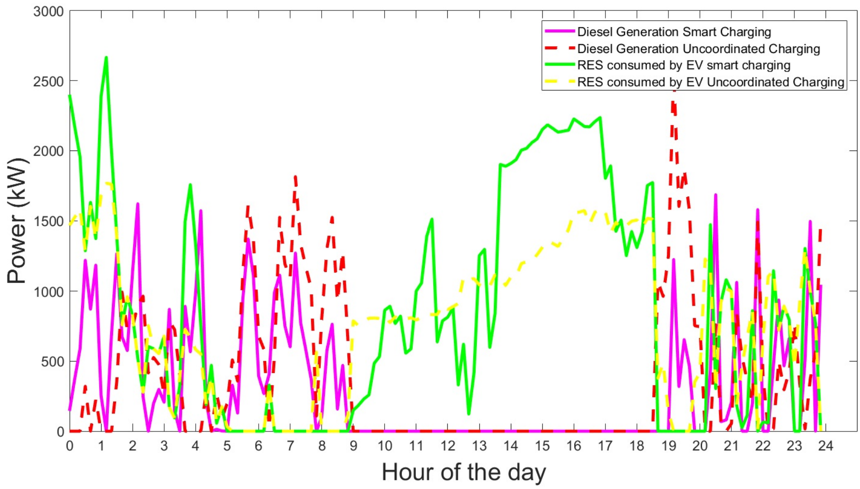


Figure 7.9: Diesel generation and RES power excess consumed by EVs for Scenario 9.

Table 7.5: Energy and Costs for each type of EV for Scenario 9.

EV Type	Motorcycle	Bus	Car	Total
$E^{EV,tot}$ (kWh)	1,039	12,880	11,208	25,127
C^{unc}(kWh)	86	937	888	1,911
C^{coo} ($)	83	909	797	1790
C^{unc}_{eq} ($/MWh)	90.2	72.7	79.2	76.1
C^{coo}_{eq} ($/MWh)	79.9	70.6	71.1	71.2

Table 7.4 shows the total amount of Electricity generated by Diesel and the RES excess energy that is consumed for charging EVs. The Smart Charging of EVs has 23.3 % less electricity produced by Diesel and 8.6% more consumption of the RES energy excess compared to uncoordinated charging.

7.4.4 Medium Term Operation

The different scenarios are evaluated from the data available from July to November 2015.

The results of the different parameters studied are represented in Table. 7.7. It is noted that the costs C are very similar in all cases and EV is able to store more the generation from Wind than Solar.

Table 7.6: Number of vehicles from each charging mechanism depending on penetration level.

Type of Charging	Uncoordinated	Smart
Diesel Energy (kWh)	9,019	7,317
Excess RES Used (kWh)	18,679	20,382
Ratio excess RES (%)	74	81

Table 7.7: Energy and Costs comparison between each scenario.

Scen.	$IC^{PV}(MW)$	IC^{W} (MW)	$E^{exc,EV}$ (MWh)	E^{D} (MWh)	C (k$)
1	5	5	292	9700	281
2	5	7.5	662	7680	280
3	5	10	1260	5980	278
4	7.5	5	616	8850	284
5	7.5	7.5	945	7050	282
6	7.5	10	1460	5520	281
7	10	5	867	8310	285
8	10	7.5	1130	6680	284
9	10	10	1570	5270	283

7.5 Conclusion

A charging mechanism for EV charging was proposed in this work, in order to encourage RES integration in isolated distribution systems, such as Off-grid Microgrids. Smart charging for EV was also proposed that considers RES power availability, through cost optimization. The smart charging was based on charging power rate modulation. This charging mechanism was simulated in Galápagos that is a protected island and work in off-grid mode. It was also proposed different kinds of EVs charging that will be introduced in the Galápagos Islands.

The methodology was compared to a case of Uncoordinated Charging. It was observed that the EV aggregator can reduce costs: 7.9 % for a case of 5 MW installed capacity (wind and PV each), 7% for a case of 10 MW installed (wind and PV each). In addition, it is observed an increase in the use of RES excess energy by EV load a decrease of the Diesel generation, while respecting grid conditions. Moreover, this will lead to an important decrease of CO_2 emissions and avoid contamination in the islands.

Nine scenarios from different installed capacities of wind and PV were studied, where two scenarios were illustrated for a daily charging. The costs of the nine scenarios were evaluated in a medium term, considering the data available. The increase in the RES installed capacity holds the EV aggregator specific costs almost equal but leads to a decrease of the Diesel use and in an increase of the RES excess energy consumed by EV.

The main limitation of this work lies in the important amount of RES excess energy that cannot be absorbed by EV in high RES capacity installation. In fact, EVs have a key role in the new power systems, but they are not the only ones. For a better RES integration, it is necessary to complement with residential load management strategies such as demand response, and integration of energy storage.

This chapter presented new strategies in the short-term operation of power systems. Nevertheless, for a better integration of EVs in such distribution systems, it is also crucial to study the impacts in the long-term and to find the optimal strategies. Hence, a long-term power generation planning considering the massive introduction of EVs is also needed, and is studied in the next chapter.

Part of the content of this chapter has been presented in: (Clairand et al. 2017; Clairand, Rodríguez-García, and Álvarez-Bel 2018a):

Chapter 8

Energy Planning in isolated environments considering integration of EVs: Application to Santa Cruz, Galapagos islands

8.1 Introduction

This thesis has mostly presented strategies for the operation of smart power systems, considering the massive penetration of EVs. However, long-term studies, such as energy planning are also crucial for the grid decision makers to upgrade system elements to adequately satisfy the new EV load in a foreseen future (Seifi and Sepasian 2011). Furthermore, the energy planning considering the EV integration in distribution systems, such as the one of Quito presented in Chapters 4-6 had widely been studied, but not in the case of microgrids.

Isolated microgrids, such as those in islands and remote communities, regularly face a variety of issues due to their geographical isolation. Some of these issues include limited installed capacity, aging generators, energy supply limitations, high fuel costs, high greenhouse gas emissions, and fuel logistics (Arriaga, Canizares, and Kazerani 2014). Over the past decades, Renewable Energy Sources (RESs) have been used to address some of these problems. Thus, in recent years, some researchers have studied the optimal control and operation of microgrids with RES. For example, in (Kanchev et al. 2011), the energy management and operation of a microgrid is analyzed from the perspective of integrating PV generators and distributed energy resources. The authors in (Yang et al. 2017) study the operation of microgrids with EVs for balancing wind power and load fluctuations. In (Che et al. 2017), an optimal interconnection operation of microgrids is presented, considering economics, reliability, and generation issues.

Some other works have examined investments in the context of microgrid planning. Thus, for example the authors of (Montuori et al. 2014) perform an economic evaluation of the integration of a biomass gasification plant in a microgrid, coordinated with demand response resources. In (Arriaga, Cañizares, and Kazerani 2012), the integration of RES planning in northern remote communities in Canada is discussed. This work is complemented in (Arriaga, Cañizares, and Kazerani 2016) by presenting a framework and models for long-term planning of RES integration in remote microgrids. Just a few works have investigated the addition of new loads in the planning problem, such as electric vehicles (EVs) in microgrids. For example, in (Hafez and Bhattacharya 2017), the planning problem includes the design of an EV charging station in a case of isolated microgrid based on some assumed data. To the knowledge of the author, the integration of EVs in the long-term power generation planning of real microgrids has not yet been studied; this is the main purpose of this chapter.

Galapagos is a protected volcanic archipelago of Ecuador where humans living or visiting the islands are negatively impacting its pristine environment, because of the limited resources and the fragility of the eco-system. Population and tourism considerable growth has significant increased the demand for services. In particular, the energy demand in different sectors such as the heavily subsidized transportation, electricity, and propane cooking has increased, raising the pollution in the islands. Furthermore, fuel transportation from the continent to the island presents a risk because of possible spills, which have already happened. For these reasons, as mentioned in the chapter before, the Galapagos Zero Fossil Fuels program was developed in order to take actions to avoid habitat degradation and ecological impact, investing in photovoltaic (PV) plants, wind turbines, and a battery storage systems in Galapagos. Nevertheless, these changes in generation mix are still not enough to fully address the existing environmental problems.

The Ecuadorean government is considering reducing subsidies for gasoline, diesel and propane (Ponce-Jara et al. 2018), which distort energy prices (ARCONEL and MEER 2013), thus creating uncertainties in generation planning.

In this context, the government is proposing additional solutions such as the change from Internal Combustion Vehicles (ICVs) to Electric Vehicles (EVs) (Elecgalapagos 2016b). All these changes require studies of the optimal generation planning for Galapagos microgrid, considering the introduction of EVs, which is the focus of this chapter. Thus, the desired characteristics of the proposed method are highlighted as follows:

- A proper energy planning model for renewable integration in a real islanded microgrid is developed based on actual data.
- The integration and impact of EVs on microgrid energy planning are studied, through adequate modeling of their load patterns.
- The optimal investments in RES are determined considering environmental impact and fuel cost uncertainties for a variety of realistic scenarios.
- The impact of the CCP from the previous chapter are studied in the optimal investments in RES.

The rest of the chapter is organized as follows: Section 8.2 presents a brief overview of microgrid energy planning. Section 8.3 discusses the HOMER model of the case study, particularly EVs. Section 8.4 presents the simulation results and analysis of different cases and scenarios. Finally, Section 8.6 highlights the main conclusions and contributions of the chapter.

8.2 Background

A microgrid energy planning process follows specific goals and constraints and has to take into considerations some uncertainties (Gamarra and Guerrero 2015). The planning goals typically include minimizing costs and minimizing emissions, considering power quality and reliability. The problem constraints depend on investments and operational considerations. For islanded microgrids, planning is similar to other microgrids, except that a connection to a main grid is not available. The three main problems that need to be considered in planning are (Gamarra and Guerrero 2015): power generation mix selection and sizing, equipment siting, and generation scheduling.

Different tools exist for planning a microgrid. In this chapter, the power generation mix selection and sizing planning is performed by using HOMER Energy Pro 3.11 (HOMER Energy 2018). The objective used in this software is, for each case or scenario, to minimize the Net Present Cost defined as follows:

$$NPC = \frac{CT}{CRF} \tag{8.1}$$

where the capital recovery factor (CRF) is the ratio of an annuity and is defined as follows:

$$CRF = \frac{r(1+r)^D}{(1+r)^D - 1} \tag{8.2}$$

where the total annualized cost CT includes the sum of total discounted costs, such as new equipment purchase, operation and maintenance, and fuel consumption for year y. The rest of the variables in these or another equations can be found in the Nomenclature section.

The levelized cost of energy is also used here for cost/benefit analyses, and is defined as follows:

$$COE = \frac{CT}{ET} \tag{8.3}$$

with ET, the Total electrical energy served [kWh/yr], and where the total costs for the planning horizon D does not consider previous investments, which are treated here as sunk costs. CO_2 emissions are also used here for evaluation purposes and are calculated based on the diesel generator characteristics, as per the following equation:

$$CO_2 = \sum_{g=1}^{N_G} \alpha_g ET_g \tag{8.4}$$

HOMER allows determining the technical feasibility and life-cycle costs of a microgrid for each hour of the year for the energy ressources of a microgrid (HOMER Energy 2018). It includes its own proprietary robust optimization algorithm for identifying least-cost options, simulating different cases for an entire year, and determining different outputs, such as NPC, COE, and CO_2 emissions, among others. For this purpose, the user has to specify the required equipment models and associated input data, such as microgrid location, demand (such as the EV load), generation search space, equipment costs, and operation, and maintenance costs. The considered microgrids include equipment such as solar PV, wind turbines, diesel generators, and others. It is also possible to make sensitivity analyses of variables, which allows to determine their impact on planning outputs. The HOMER model constraints include supply-demand balance and generation adequacy limits; generation limits; new generation capacity; useful-life of generation sources and batteries; operation and maintenance schedules; battery State Of Charge (SOC) and charging/discharging limits; and others.

8.3 Case Study: Santa Cruz, the Galapagos Islands

In this section, the microgrid model for studying the power generation planning problem of the interconnected islands of Santa Cruz and Baltra is presented. The main objective is to minimize the NPC, using the COE and CO_2 emissions reduction for cost benefit analysis. The schematic of the proposed configuration of the scheduled microgrid is represented in Figure 8.1. Several sets of input data are required for HOMER modeling, which are detailed next.

8.3.1 Electricity Costs

The electricity is distributed by the local distribution company Empresa Eléctrica Provincial Galapagos (Elecgalapagos). In Ecuador, the electricity sector is vertically integrated, and thus there is no electricity wholesale market. There is a tariff for each type of customer, which is not linked to the real costs of electricity generation, distribution, and transmission in real time. The electricity cost for all customers in Galapagos has been fixed at 9.1 c$/kWh (ARCONEL 2016).

8.3.2 Residential Load

As part of the supply-demand balance constraint, HOMER allows to define primary and secondary loads. The primary load selected here corresponds to the existing loads, and the secondary load is composed of the new EV loads.

In Figure 8.2, the residential load in Santa Cruz is depicted based on (Clairand et al. 2017). Note that the load is at its lowest in September and October, and at its highest in March and April, corresponding to months with low and high presence of tourists, respectively.

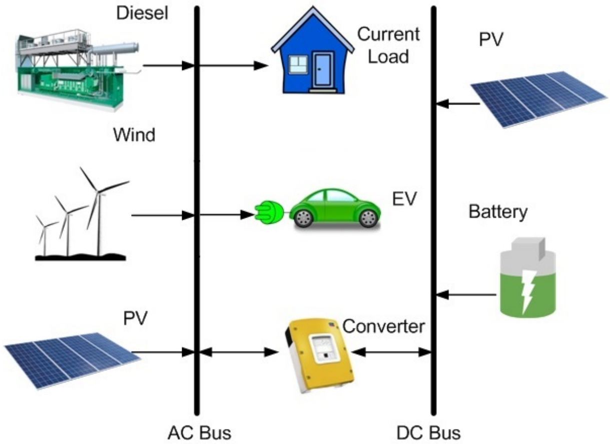


Figure 8.1: Configuration of the microgrid.

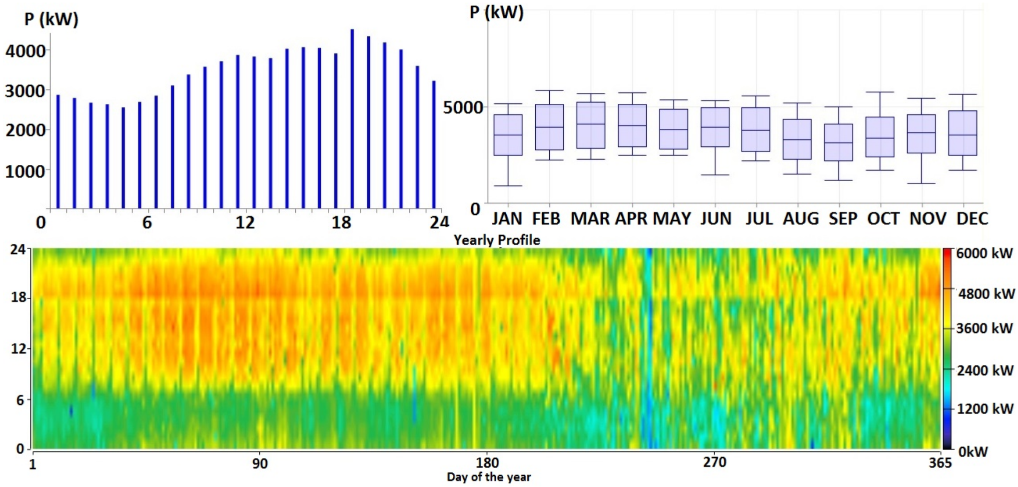


Figure 8.2: Existing Load in Santa Cruz: Box and Whisker plot of monthly profiles;annual load intensity plot; example of a daily profile.

8.3.3 Diesel Generation

The generator model in HOMER requires the following information: capacity, fuel resource, fuel curve, costs, emissions, lifetime, and maintenance schedules. Thus, seven Caterpillar diesel generators are installed with a maximum energy efficiency of 13.77 kWh/gallon, and a total installed capacity of 5.26 MW (Paz and Anazco 2015). There are 4 Hyundai diesel generators that have been installed in recent years, with a total cost of $1,500,000 each including building installation, and an installed capacity of 1.7 MW each, with a maximum efficiency of 15.5 kWh/gallon (Paz and Anazco 2015). Since Hyundai generators are not available in the HOMER library, the corresponding models were built for HOMER based on available manufacturer data sheets. All diesel generators are assumed to have a minimum load ratio of 25% (Vintimilla 2013).

Due to reliability issues, at least one generator is always running. The lifetime of diesel generators is commonly 90,000 h, and considering that 2 Hyundai generators were installed in 2015 and 2 others in 2016, it was assumed a remaining life of 75,000 and 80,000 h, respectively, for these generators. The remaining life of the Caterpillar generators was assumed to be 40,000 h due to lack of information, i.e. half life, given their age; however, their influence on the model is very small because of their low efficiency. Valve set and inspection maintenance takes place every 2,500 h, with 24 h of down time, and major maintenance overhaul takes place every 20,000 h, with 72 h of down time (Elecgalapagos 2015). The total operation and maintenance costs for all the diesel generators in 2015 were $195,000 for a total power of 7.41 MW (Elecgalapagos 2015); from these values, the operation and maintenance cost can be estimated to be 26,316 $/MW per year.

In the continent, operating reserves have a minimum value of 5% (CONELEC (Consejo Nacional de Eléctricidad) 2013). Considering that the islanded system is off-grid, these values were assumed here to be 10% of the load for diesel generation, 25% of the solar output, and 50% of the wind output wind based on (Das and Canizares 2016).

In Ecuador, the end-user pays only 23% of the overall cost of diesel (Sierra 2016). Hence, diesel end-user price is 0.27 $/l (GlobalPetrolPrices 2018); however, the real price of diesel in continental Ecuador is 1.17 $/l. Additionally, the fuel transportation cost to the island can be estimated at 0.50 $/l (Publicas 2013). Therefore, the total real diesel price used here is 1.67 $/l.

8.3.4 PV and Battery

The HOMER PV model requires the following information: capacity, solar profile, costs, lifetime, and ac or dc connection. To obtain the required supply profile for the solar PV array in Galapagos, the solar profile of the islands was used.

The PV plant is located near Puerto Ayora, which is the main city in Santa Cruz island. It has 6,006 PV panels of 250 W each, and is connected in ac to Puerto Ayora substation through a 13.8 kV feeder. It has an installed power of 1,500 kWp and it is directly connected to the ac bus. The total installation cost was $10,600,000, which results in 7,067 $/kW. The total operation and maintenance costs including converter is 58,032 $/yr (*Proyectos*); therefore, the individual operation and maintenance cost of each PV panel used here is 9.66 $/yr.

There is another PV plant in Baltra Island with dc connection and a converter system of 91 inverters of 17 kW each, with a power capacity of 200 kWp and an energy storage system of 4,300 kWh, with a total cost of $9,390,000 (*Proyectos*); its operation started in February 28^{th} 2016. Considering the 7,067 $/kW for the Santa Cruz PV plant, this yields a PV plant cost of $1,420,000 and a battery system cost of $7,970,000. For replacement, it is considered here that only 80% of the installation costs are required, since studies and some construction costs are not needed; hence, the PV replacement costs can be estimated to be 5,653 $/kW (Secretaria de Planificacion 2016).

Two hourly solar generation profiles were compared to obtain the most accurate. The first profile was generated through HOMER's solar database, which is linked to NASA's Surface Meteorology and Solar Energy Database, considering the latitude and longitude of Santa Cruz island (00°38'S and 90°21'W); for the PV plant located in Baltra Island, similar profiles were defined. The second profile was obtained based on (Clairand et al. 2017), resulting in very similar input. Hence, the first profile was used here for the model, because there was some missing information in the second one. Figure 8.3 illustrates the annual average daily radiation and clearness index used here; note that the solar radiation is high in March and October, while is low in June and July.

The HOMER battery model required the following information: battery quantities, costs, and lifetime. Hence, the existing battery system consists of 4,000 kWh Lead-Acid and 300 kWh Li-ion batteries; however, HOMER only allows to define one battery system, thus a 4,300 kWh Lead Acid system was used here, with a string size of 39 modules of 12 V adding up to 468V, which cor-

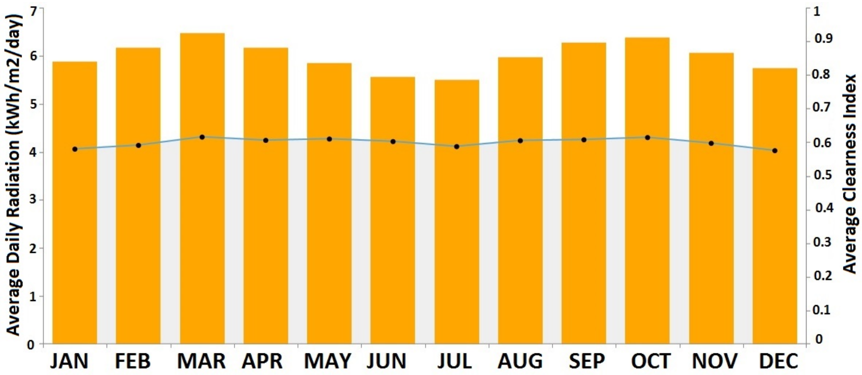


Figure 8.3: Annual average daily radiation and clearness index.

responds to the grid voltage. Therefore, based on the estimated cost of the battery system, the battery replacement was estimated to be 1,481 $/kWh, with a life of 10 years or 1,100 cycles, as per (*Plan Galapagos*) and (Secretaria de Planificacion 2016).

8.3.5 Wind

The HOMER wind model requires the following information: capacity, wind profile, costs, lifetime, and power curves, so that from the wind profile, the generation curve can be obtained. There are 3 U57 wind generators with a hub height of 68m located in Baltra island, which are connected to the electric grid of Santa Cruz island through a 34.5 kV line. Each wind turbine has an installed capacity of 750 kW, for a total wind capacity of 2.25 MW. The wind turbine power curve was modeled based on the information in (*U57*), due to the absence of this wind turbine model in the HOMER library.

The total deployment cost of the three turbines and its equipment was 27,655,606 $/yr, as per (Vélez-Vega, Cedeño-Gómez, and Almeida-Chinga 2016), where 80% of this value was used as replacement cost in HOMER, as in the case of PV. The total operation and maintenance costs are 183,968$/yr (Elecgalapagos 2015); therefore, an individual turbine was estimated to have a maintenance cost of $61,323.

Three hourly wind generation profiles were compared to obtain the most accurate. The first profile was generated through HOMER's database, which is based on NASA's Surface Meteorology and Solar Energy Database, the second was obtained based on (Clairand et al. 2017), and the third was obtained

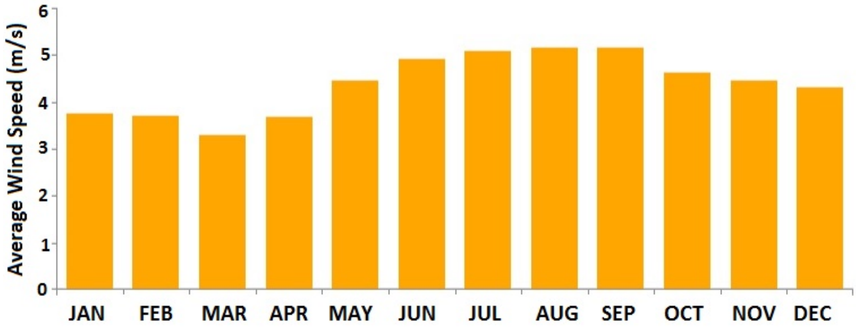


Figure 8.4: Annual average wind speed.

from a simulation with VAISALA Energy (*Supporting the Energy Revolution*), which allows simulating the wind profiles in the islands. The second profile was not reliable because of significant variations on the obtained wind profiles, with the third being finally selected, since the simulation can be considered more accurate than the first one, as it is based on real measurements as opposed to satellite data. Figure 8.4 illustrates the average wind profile, whose range is 3.3 m/s to 5.16 m/s, which is relatively low; note that the average maximum wind speeds appear from July to September, and the lowests can be observed in March.

8.3.6 Electric Vehicle Demand

The vehicle fleet in Santa Cruz is composed by 1,326 vehicles (Consejo de Gobierno del Regimen Especial de Galapagos 2013). The most important type in the vehicle fleet is motorcycles, because of their cost and their easier transportation to the islands. The government has tried to limit the number of motorcycles, but limited controls in shipments has not allowed to enforce this. Santa Cruz is the island with the largest vehicle fleet in Galapagos with 53% of all vehicles (*Plan Galapagos*).

The present cost of the EVs is much higher than ICVs. However, the Ecuadorean government is taking actions to preserve the eco-system of Galapagos, including incentives to change from ICVs to EVs, to address greenhouse gas and fuel transportation issues (*Plan Galapagos*; Elecgalapagos 2016b).

Several works on modeling EV demand profiles have shown that these depend on local conditions. Hence, the EV demand model developed here was based on traffic data information for the Galapagos Islands (Álvarez-Bel et al. 2016).

Table 8.1: EV characteristics

EV type	Motorcycle	Bus	Cars
$\overline{P_e^{EV}}[kW]$	1	60	7,2
BC_e [kWh]	4	324	28
$ER_e[kWh]$	3	280	24
N_e^{EV}	611	46	467
$\delta_e[h]$	16-20	12-22	05-12 & 22-02

Three different types of vehicles were considered: motorcycles, buses, and cars; other types were not included because they are not numerous and hence present low demand. Based on (Álvarez-Bel et al. 2016), distances and schedules were analyzed in order to obtain the EV characteristics shown in Table 8.1. The charging starting time for each EV $st_{e,i}$ was defined as a random number generated within the given time horizon δ_e in Table 8.1. The time horizon for the charging of each EV was then defined as: $\tau_{e,i}=\left[st_{e,i},st_{e,i}+\frac{ER_e}{\overline{P_e^{EV}}}\right]$, assuming that all EVs charge at its maximum power $\overline{P_e^{EV}}$, defined in Table 8.1, until its maximum SOC is reached. Therefore, the demand of each EV can be defined as follows:

$$P_{e,j,t} = \begin{cases} \overline{P_e^{EV}} & \text{if } t \in \tau_{e,i} \\ 0 & \text{otherwise} \end{cases} \tag{8.5}$$

Hence:

$$P_t^{EV} = \sum_{e=1}^{3} \sum_{j=1}^{N_e^{EV}} P_{e,i,t} \;\forall t \tag{8.6}$$

In Figure 8.5, the total EV demand for 100% penetration is illustrated for a day. This demand was modeled in HOMER as a secondary load depending on different penetration levels for various scenarios. Note that this EV load is uncoordinated, and a comparison with the smart charging is performed in next section.

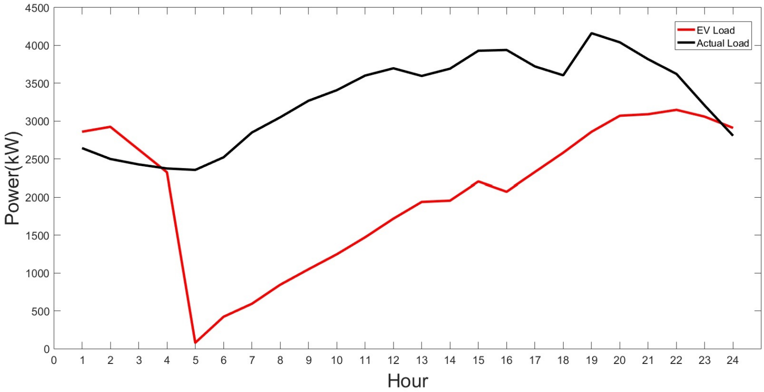


Figure 8.5: EV and other loads for a day.

8.3.7 Additional Inputs

A discount rate r of 12% was used as proposed in (ARCONEL and MEER 2013; CONELEC (Consejo Nacional de Eléctricidad) 2013), together with an inflation rate of 2%. The assumed planing horizon was 20 years.

8.4 Results and Discussion

Five different scenarios were studied with different penetration levels of EVs (0, 25, 50, 75, and 100%). These different scenarios were considered based on the interest of the Ecuadorean government on introducing EVs, and to reflect the fact that the exact penetration of these new loads would be uncertain. These scenarios considered the EV load described before. A sixth scenario was also studied, considering an EV smart charging load from Chapter 7, to assess its influence on the energy planning.

For all the scenarios, two cases were simulated. The first case considers the existing generation configuration without new investments, and the second considers investment in both more generation capacity and battery storage, including renewables. For the latter, a search space was defined for all the scenarios in order to find the optimal generation configuration. In addition, several simulations were performed considering different types of wind turbines to determine which model is the most suitable for the wind profile; the U58 wind turbine was found to be the best.

Table 8.2: System Costs and Emissions at 1.67 $/l diesel

Scenario	EV Pen. [%]	COE [$/kWh] New Invest. No	COE [$/kWh] New Invest. Yes	NPC [M$] New Invest. No	NPC [M$] New Invest. Yes	CO_2 [kTon/yr] New Invest. No	CO_2 [kTon/yr] New Invest. Yes
1	0	0.383	0.381	106.97	106.17	18.43	15.92
2	25	0.390	0.386	123.69	122.61	21.44	18.55
3	50	0.395	0.391	140.43	139.03	24.45	20.84
4	75	0.398	0.394	157.05	155.45	27.43	23.30
5	100	0.402	0.398	173.93	172.09	30.47	25.88

Table 8.3: New PV and Capital at 1.67 $/l diesel

Scenario	EV Pen. [%]	New PV [MW] New Invest. No	New PV [MW] New Invest. Yes	New Capital [M$] New Invest. No	New Capital [M$] New Invest. Yes
1	0	0	2.28	0	12.9
2	25	0	2.60	0	14.7
3	50	0	3.24	0	18.3
4	50	0	3.72	0	21.0
5	100	0	4.12	0	23.2

Considering that the diesel price in the 20-year planning horizon is uncertain, a sensitivity analysis for the diesel price was carried out, based on an average increase of diesel price of either 50% or 100% for the considered planning horizon, as per (EIA 2017). This results in diesel prices of 2.26 $/l and 2.84 $/l, respectively, assuming the same transportation cost of 0.50 $/l.

8.4.1 Costs and Emissions Comparisons

In Tables 8.2, 8.3, the results for costs and emissions for all the scenarios for the current diesel price of 1.67 $/l are shown. Observe that the COE, NPC, and CO_2 emissions are lower for all scenarios considering new investments. The optimal results were obtained for new PV capacity only, since new wind turbines, diesel generators, and battery storage resulted in higher NPCs. It should be noted that replacing 100% of ICVs would reduce emission by at least 30 kTon/yr.

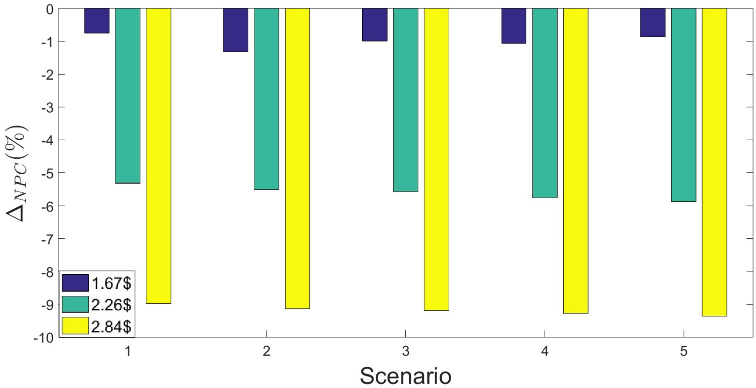


Figure 8.6: NPC differences with and without PV investments for different scenarios and diesel prices.

To compare the cases with and without new generation investments, the percentage changes in NPC, COE, and CO_2 were calculated, as in (Stevanoni et al. 2018):

$$\Delta_{NPC} = \frac{NPC_{inv} - NPC_0}{NPC_{inv}} \tag{8.7}$$

$$\Delta_{COE} = \frac{COE_{inv} - COE_0}{COE_{inv}} \tag{8.8}$$

$$\Delta_{CO_2} = \frac{CO2_{inv} - CO2_0}{CO2_{inv}} \tag{8.9}$$

Thus, Figs. 8.6, 8.7, and 8.8 depict respectively the NPC, COE, and CO_2 differences for all scenarios and various diesel prices. Note that all the changes are negative, which shows that with PV investments, all NPC, COE and CO_2 emissions decrease. For the highest average value of 2.84 $/l for diesel, the NPC and COE differences are significant, with reductions of more than 9% for NPC in Scenario 5, and more than 9% of COE for most scenarios. Note that the CO_2 reductions are significant for all scenarios and diesel prices, which would be desirable for the environment of the islands.

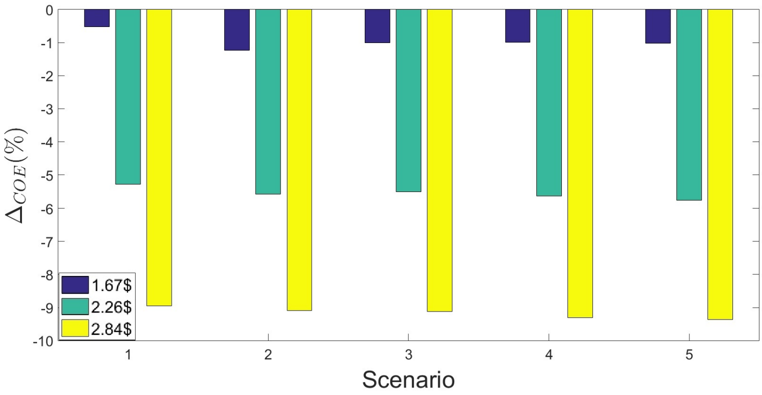


Figure 8.7: COE differences with and without PV investments for different scenarios and diesel prices.

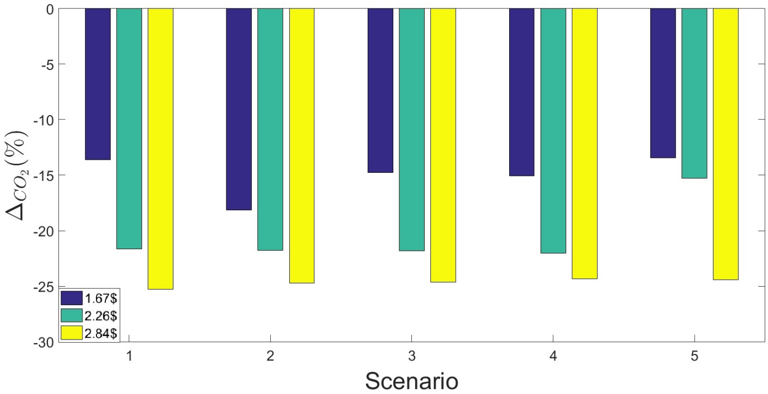


Figure 8.8: CO_2 differences with and without PV investments for different scenarios and diesel prices.

8.4.2 Cost Summary and Cash Flow

To compare the different cost between the cases with and without investments, the cost components for the planning horizon are compared. Figure 8.9 shows the cost components with no investments for Scenario 5 at 1.67$/l. This scenario was selected because it simulated the most important EV demand. In Figure 8.10, the cost components with investments for Scenario 5 at 1.67$/l are represented. It is noted that with no investments the Resource is mainly the only cost component, coming from the diesel generators. In contrast, with

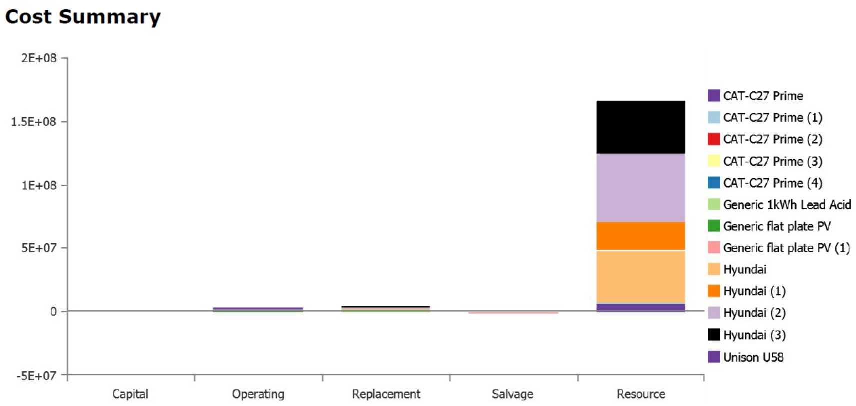


Figure 8.9: Cost components with no investments for Scenario 5 at 1.67$/l.

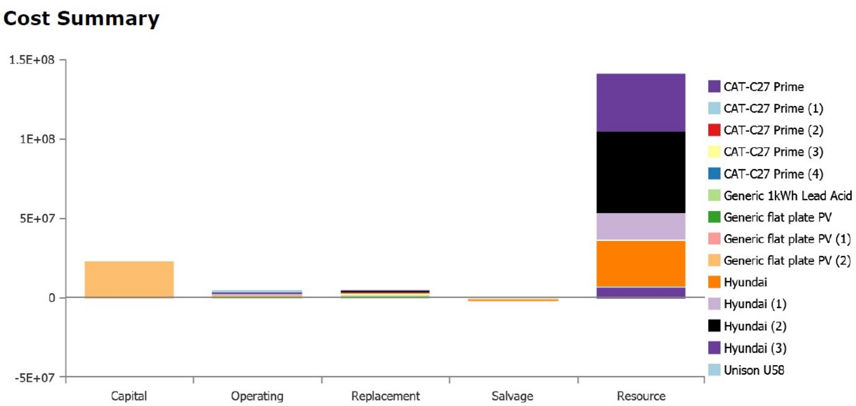


Figure 8.10: Cost Components with investments for Scenario 5 at 1.67$/l.

investments, the capital grows considerably due to the PV investments. Moreover, with investments, the resource decreases.

In Figures 8.11, 8.12, the Cash Flow without and with investments, respectively, are represented for Scenario 5 at 1.67$/l. In both cases, it is observed an significant replacement cost at year 10, which corresponds to the high battery replacement cost. Furthermore, note that the Salvage in the last year is more important in the case with investments than without. Finally, in the case with investments, the capital is observed in the first year, which corresponds to the additional PV investment.

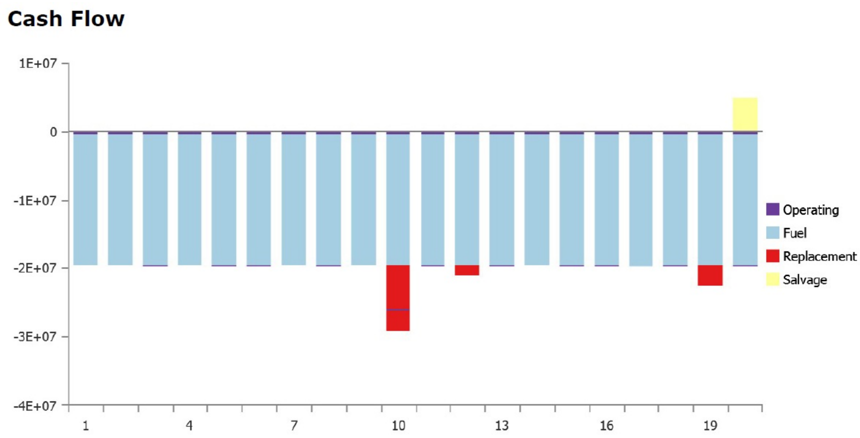


Figure 8.11: Cash Flow with no investments for Scenario 5 at 1.67$/l.

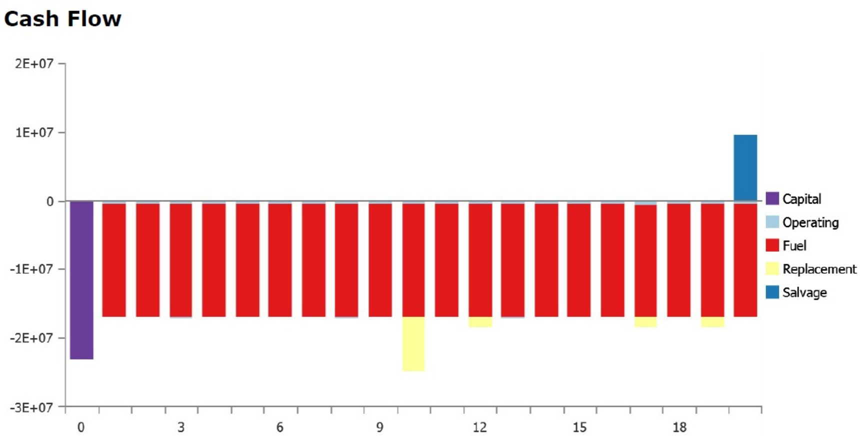


Figure 8.12: Cash Flow with investments for Scenario 5 at 1.67$/l.

8.4.3 Energy Supplied

In Figure 8.13, the amount of energy supplied for all the scenarios without investments at 1.67$/l is illustrated. Note that without PV investments, the RES energy supplied does not change between each scenario, with only diesel energy increasing. Figure 8.14 depicts the amount of energy supplied for all the scenarios with investments at 1.67$/l. It is noted that the RES energy supplied increases, but not enough compared to the Diesel increase.

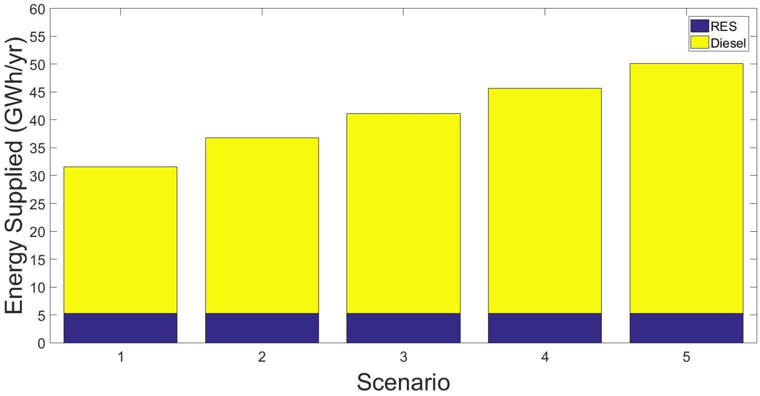


Figure 8.13: Energy supplied by source without investments and 1.67 $/l diesel

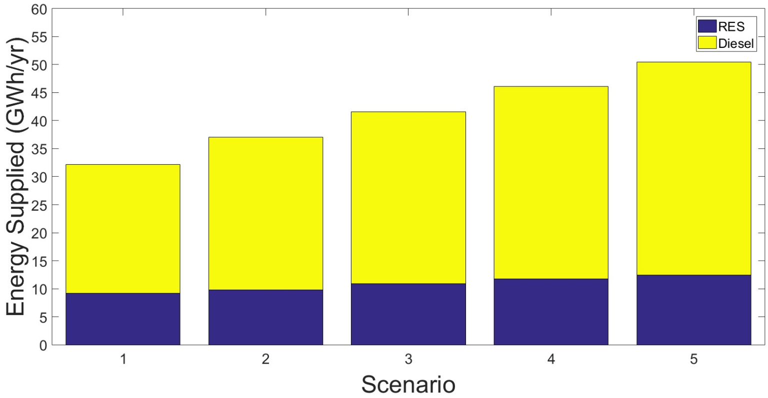


Figure 8.14: Energy supplied by source with investments and $1.67 $/l diesel

8.4.4 Daily Operation

Figure 8.15 depicts the daily profiles of the load, the diesel generation, and RES for Scenario 1, with and without PV investments, for a typical week. Observe a significant increase in RES power and a decrease in diesel around noon each day in the case of new investments.

In Figure 8.16, the daily profiles of the load, diesel generation, and RES for Scenario 5, with and without PV investments, for a typical week are illustrated. Note that in this case, which presents the highest EV loads, the RES peak is considerably higher with new PV investments compared to Scenario 1, which

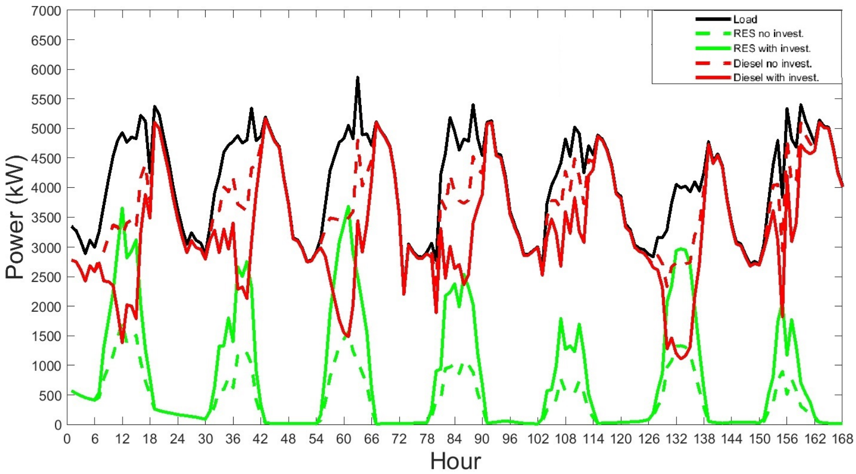


Figure 8.15: Scenario 1 load and generation profiles for a typical week.

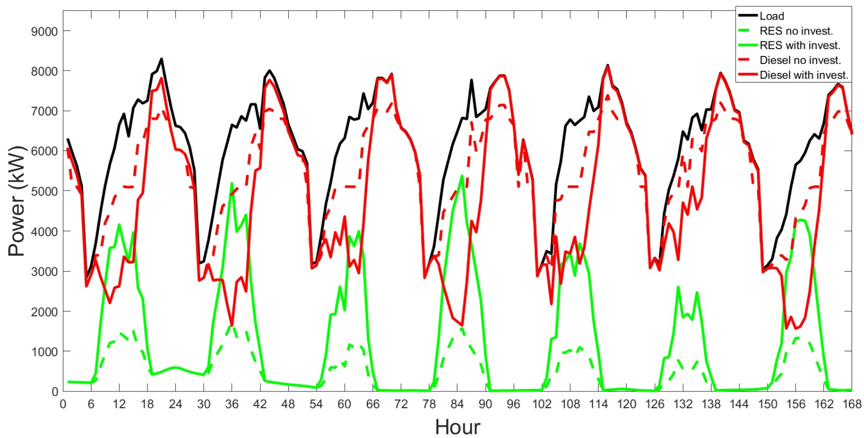


Figure 8.16: Scenario 5 load and generation profiles for a typical week.

has no EV loads. It should be highlighted that, due to high replacement costs, batteries are seldom dispatched.

8.5 Impact of the CCP System in the Energy Planning

Although the main purpose of this chapter is to study the power generation planning of this microgrid, it is also significant to evaluate the impact of the EV charging mechanism proposed in the chapter before in the energy planning. For that purpose, a sixth scenario is studied, considering 100 % of EV penetration, but assuming the smart charging technique of the previous chapter is applied during a year horizon. Only this additional scenario was taken into account because the simulation from the methodology of the previous chapter for an entire year and the HOMER simulation take very long time.

8.5.1 Electric Vehicle Demand

As part of the supply-demand balance constraint, HOMER allows to define primary and secondary loads. The new secondary load here corresponds to the simulation of the 100 % of EV penetration. Only this additional scenario was simulated, because the main purpose of this chapter was to study the EV load impact in the microgrid energy planning. Considering the results of Scenario 5, which gave an optimal investment of 4.12 MW of PV and considering the 1.7 MW already installed, the simulations of the smart charging were done with 5.82 MW of PV and 2.25 MW of Wind, which is the existent capacity. These two scenarios were compared because they have the same installed capacity of RES. In Figure 8.17, the calculated EV load in Santa Cruz is depicted. Note that the load presents significant variations, which correspond to the variations of wind and sun during the year.

8.5.2 Costs and Emissions Comparisons

To compare the different cost between the cases with smart charging and without, the cost components for the planning horizon are compared. In Tables 8.4, 8.5, the results for costs and emissions for scenarios 5 and 6 for the current diesel price of 1.67 $/l are shown. The factor Δ_{5-6} (%) express the variation between scenarios 5 and 6.

As observe with the previous scenarios, the COE, NPC, and CO_2 emissions are lower considering new investments. Furthermore, between scenario 5 and 6, there is a decrease of COE and NPC and CO_2. But, the variations of Δ_{5-6} show that this decrease is small, reaching up to 4.85 % for the CO_2 emissions. It can be explained by two reasons: first, the energy planning problem considers the total load for the analyses, but the EV load represents

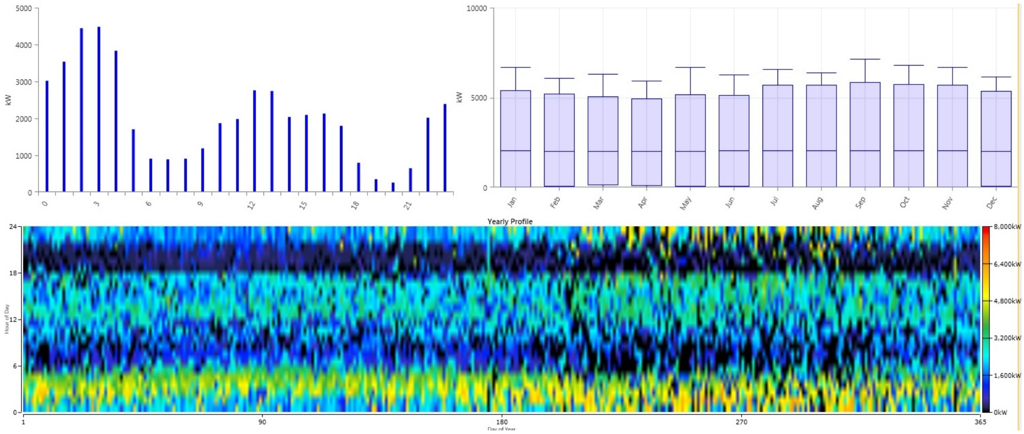


Figure 8.17: EV Load considering smart charging from Chapter 8: Existing Load in Santa Cruz: Box and Whisker plot of monthly profiles;annual load intensity plot; example of a daily profile.

Table 8.4: System Costs and Emissions at 1.67 $/l diesel

Scenario	Smart Charg. [%]	COE [\$/kWh]		NPC [M\$]		CO_2 [kTon/yr]	
		New Invest.		New Invest.		New Invest.	
		No	Yes	No	Yes	No	Yes
5	No	0.402	0.398	173.93	172.09	30.47	25.88
6	Yes	0.401	0.397	171.10	169.58	29.06	24.67
Δ_{5-6} (%)		0.25	0.25	1.65	1.46	4.85	4.67

only a little more than 50 % of the residential load. In that case, if only EV load was considered, the results could be much higher. Then, for the energy planning simulations, a step of one hour was used, so the smart charging methodology do not have advantage of managing in smaller time horizons. In any case, the smart charging methodology presents benefits for the energy planning.

Table 8.5: New PV and Capital at 1.67 $/l diesel

Scenario	Smart Ch.	New PV [MW]		New Capital [M$]	
		New Invest.		New Invest.	
		No	Yes	No	Yes
5	No	0	4.12	0	23.2
6	Yes	0	4.46	0	25.2

8.6 Conclusions

In this chapter, an optimal energy planning study has been presented for the microgrid of Santa Cruz and Baltra in the Galapagos Islands, to assess the impact of new EV loads. This planning model was built in HOMER Energy, where six scenarios were simulated to determine the impact of different penetration levels of EVs, with and without new generation and energy storage investments. To consider diesel price uncertain, a sensitivity analysis based on three different projected diesel prices was performed. The sixth scenario considered the smart charging methodology from the previous chapter in a year horizon.

The obtained results demonstrate that investing in new PV generation would improve system costs, especially if diesel prices are high. Moreover, it is shown that investing in PV would reduce considerably diesel consumption, thus CO_2 emissions, which would be environmentally beneficial for the protected islands. Note that the change to EVs would require significant commitment from the Ecuadorean government and users to adopt them, but it would mitigate transportation and cooking economic and environmental issues.

Part of the content of this chapter has been submitted for publication (Clairand et al. 2018):

Chapter 9

Thesis Conclusions

This chapter highlights the main conclusions of the dissertation, the future work that can be developed with this study, and the publications from the author during the Ph.D. thesis.

9.1 Conclusions of the Dissertation

This thesis dissertation presented new strategies for the operation and planning of Smart Power Systems considering the massive introduction of electric vehicles. The new strategies were evaluated and validated on different case studies in Ecuador.

In Chapters 2 and 3, a brief overview of EVs and different components of the Smart Grid was presented. Furthermore, the most significant present experiences of EV integration in power systems were highlighted. The principal strategies of EV charging were also explained, considering centralized and decentralized architectures, and detailing the inclusion of the EV aggregator. The limitations of the methodologies were finally discussed in order to propose new solutions.

Then, a novel methodology that optimizes EV charging process through charging power rate modulation in slow charging is presented in Chapter 4. The novelty lies in consideration of three different customer choice products (CCPs) that will be available depending on EV user preferences. Each CCP is characterized by a price, an average charging power rate, and so a duration. A relevant partner is necessary to implement these CCPs: the EV aggregator, which will also consider technical specifications as a maximum charging pattern given by the DSO and TSO.

To assess the impact of variations of different parameters of the methodology, a sensitivity analysis was also performed. The parameters under study were the minimum required energy, the time delay of the starting charging time, the portion of green CCP users, and the average charging power rate for green and blue CCP. The sensitivity analysis studied the effect of these parameters on the daily EV Load and on the charging costs, which is relevant for the EV aggregator when the prices of the different CCPs need to be fixed. The proposed methodology has been applied to a real distribution network, located in Quito, Ecuador, and its effectiveness was demonstrated, in Chapter 5. Moreover, the methodology can be implemented to any electricity network, independently of the country in which it may be located, and even if the demand conditions, electricity prices and users behavior is different from the case study.

Furthermore, the proposed CCPs have been applied to a power system application, the ancillary services, evaluating the impact with and without V2G mode, in Chapter 6. Since the Ecuadorian real case study does not have a regulation market, some data from the Spanish market was considered as input for evaluation purposes. The methodology does not present significant benefits for regulation up, with and without the V2G mode, mainly because of the considered flexibility of the EV users. It is crucial to mention also that the V2G could create uncertainty in the users about the real use of the EV battery from the EV aggregator and it requires significant technical requirements during the installation of V2G equipment. It has been proved that provision of ancillary services is also possible regarding the flexibility of EV users.

Concerning distribution systems which have high introduction of RES and are isolated from main grid, commonly named as off-grid microgrids, an operation and planning models were also developed, and described in Chapter 7. So, an EV charging mechanism was proposed to encourage the use of RES. This EV charging mechanism is also based on smart charging for EV, which considers RES power availability, through cost optimization. This model was simulated in the Santa Cruz and Baltra Islands, Galapagos, which are protected area. Different types of EVs that will be introduced in the Galapagos Islands were also considered. The methodology was compared to a case of Uncoordinated Charging and it was observed that the EV aggregator could reduce costs, increase the use of RES energy in periods with the load without EV is lower that RES production, decrease the Diesel generation, all of this respecting grid conditions. Moreover, this will lead to an essential decrease of CO_2 emissions and avoid contamination in the islands. Several scenarios were considered, with different RES power capacity. It was noted that this method allows optimizing the use of RES generation and costs, but it is necessary to establish strategies for users to plug their EVs in low-cost periods. This methodology can also be implemented to any electricity network with similar RES conditions, independently of the country in which it may be located, and even if the demand conditions and users behavior is different from the case study.

Finally, an energy planning for these islands was studied considering the integration of EVs, in Chapter 8. This energy planning model was built in HOMER Energy, where six scenarios were simulated to determine the impact of different penetration levels of EVs, with and without new generation and energy storage investments. To consider diesel price uncertain, a sensitivity analysis based on three different projected diesel prices was performed. The results indicate that investing in new renewable sources generation would improve system costs, especially in PV. The other generation sources were not found optimal to invest them, such as wind (especially for the low-speed wind). Moreover, it is shown that investing in PV would reduce diesel consumption considerably, thus CO_2 emissions, which would be environmentally beneficial for the protected islands. Furthermore, the smart charging methodology from chapter 7 was used in a year horizon to evaluate its impact on the energy planning in scenario 6. It was compared to the scenario 5, a scenario characterized by the uncoordinated charging and the same installed RES capacity. It was observed a small cost and emissions decrease, which demonstrated the benefits of the smart charging.

Considering the case studies, and based on all these conclusions, it is crucial to note that the change to EVs would require significant commitment from the Ecuadorean government and users to adopt them. The Ecuadorean government has to promote purchase of EVs based on fuel subsidies and public policies and to consider the inclusion of an EV aggregator in the electricity sector, such as proposed in (Vera, Clairand, and Álvarez-Bel 2017). The EV users would need to change their driving behavior, as specified in (Clairand and Vera 2014), and to participate in smart charging programs. These steps are significant challenges, but they would mitigate transportation economic and environmental issues.

9.2 Main Contributions

- A Smart Charging Methodology that takes into account EV user's flexibility considering charging costs reduction
- The provision of Ancillary Services based on EV charging considering EV user's flexibility
- A Smart Charging Methodology for isolated systems with high RES penetration to reduce RES power excess
- A long-term energy planning for isolated systems considering the massive introduction of EVs

9.3 Future developments

This thesis dissertation opens the gate to some future research developments that are suggested:

- A joint application of these new operational strategies with residential demand response. The benefits for the grid of these new operational strategies of managing EVs have been demonstrated, but they can be improved with residential strategies, especially when residential loads can consume an excess RES energy.
- A reinforcement grid planning considering the massive introductions of EVs. This thesis highlighted the benefits of new investments for the power generation planning of the microgrid, but further research in the reinforcement grid planning is needed to demonstrate the benefits of a change from ICVs to EVs.
- Planning of the massive introduction of Induction Stoves. The purpose of this thesis was to analyze the impact introduction of EVs, studying the cases of the Ecuadorean grid because it is one of the primary goals of the government. The change fro propane cooking to induction stoves is another significant purpose that can be studied in the long-term planning.

9.4 Publications

During the development of this thesis, some of the results have been published or submitted in the following journals, conferences, and book:

- Jean-Michel Clairand, Javier Rodríguez-García, and Carlos Álvarez-Bel. "Electric Vehicle Charging Strategy for Isolated Systems with High Penetration of Renewable Generation". In: *IEEE Access (submitted on July 13th, 2018)*, (2018), pp.1-12.
- Jean-Michel Clairand, Javier Rodríguez-García, and Carlos Álvarez-Bel. "Smart Charging for Electric Vehicle Aggregators considering Users' Preferences". In: *IEEE Access (submitted on June 29th, 2018)*, (2018), pp.1-12.
- Jean-Michel Clairand, Mariano Arriaga, Claudio A. Cañizares, Carlos Álvarez-Bel. "Power Generation Planning of Galapagos ' Microgrid Considering Electric Vehicles and Induction Stoves". In: *IEEE Transactions on Sustainable Energy* (submitted on March 19, 2018; revised on July 16th, 2018) (2018), pp. 1–11
- Jean-Michel Clairand, Javier Rodríguez-García, Patricio Pesantez-Sarmiento, and Carlos Álvarez-Bel. "A tariff system for electric vehicle smart charging to increase renewable energy sources use". In: *2017 IEEE PES Innovative Smart Grid Technologies Conference - Latin America*, ISGT Latin America 2017.
- Juan Fernando Vera, Jean-Michel Clairand, and Carlos Álvarez-Bel. "Public policies proposals for the deployment of electric vehicles in Ecuador". In: *2017 IEEE PES Innovative Smart Grid Technologies Conference - Latin America*, ISGT Latin America 2017.
- Jean-Michel Clairand, Javier Rodríguez-García, and Carlos Álvarez-Bel. "Evaluation of strategies for electric vehicle management of an Aggregator based on modulation of charging power rate". In: *2017 IEEE Transportation and Electrification Conference and Expo*, ITEC 2017. IEEE, 2017, pp. 57–62.
- Jean-Michel Clairand, Javier Rodríguez-García, and Carlos Álvarez-Bel. "Smart Charging for an Electric Vehicle Aggregator Considering User Tariff Preference". In: *2017 IEEE PES Innovative Smart Grid Technologies, ISGT 2017 (2017)*, p. 5

- Carlos Álvarez-Bel, Patricio Pesantez-Sarmiento, Javier Rodriguez-García, Manuel Alcázar-Ortega, José Carbonell-Carretero, Patricio Erazo-Almeida, Diego-Xavier Morales-Jadan, Guillermo Escrivá-Escrivá, Andrea Carrillo-Díaz, Mary Ann Piette, Ramón Llopis-Goig, Elisa Peñalvo-López, Víctor Martínez-Guardiola, María-Isabel Trenzano-García, Vicente Pastor, Verónica Orbea-Andrade, Jean-Michel Clairand. *Análisis para la implementación de redes inteligentes en Ecuador - Metodología de Previsión de la demanda basada en redes inteligentes.* Ed. by Carlos Alvarez-bel. Editorial Institucional UPV, 2016, p. 287. isbn: 978-84-608-5432-6

Appendix

Mathematical tools

Mathematical tools are used to solved different objectives in the integration of EVs in a Smart Grid. In the literature, authors propose different decision makings. They are categorized in optimization problems in which the aim is to find the optimum one subjected to different constraints.

An optimization problem is composed of (Castillo et al. 2002):

- Decision Variables: they are independant variables which the decision maker has to determine their optimal values
- Dependent Variables: they are the other variables which are fixed and which depend the decision variables
- An Objective Function: it is the function in which an optimal solution has to be found
- Constraints: there are limitations of the problem that restrict the are of research of the optimal values. They are presented as equality or inequality functions.

Different optimization techniques are explained below:

Linear Programming (LP)

It refers to the optimization of a linear objective function subject to linear equality or/and inequality constraints.

Linear optimization with integer variables

It is called mixed-integer linear programming (MILP) when some (but not necessary all) of the variables are restricted to take integer variables. When all the decision variables are restricted to take integer values, it is named Pure-Integer Linear Problem. In the case the decision variables can take only the values of 0 or 1, such problems are considered mixed-binary or pure-binary optimization problems.

Non-Linear Programming (NLP)

If the objective function or one of the constraints are non linear it is considered a Non-Linear Problem.

Dynamic Programming (DP)

Dynamic Programming Optimization is used to solve problems by decomposing into a sequence of stages. The optimal solution is found for each stage.

Objective function example

An example of a linear objective function is presented. Other problems are not detailed because they differ just from the conditions mentioned before. Let suppose the next objective function f: $\mathbb{R} \to \mathbb{R}^n$:

$$f = \sum_{i=1}^{n} c_i x_i \quad \forall x, c \in \mathbb{R}^n, \quad n \in \mathbb{N} \tag{9.1}$$

The decision variables are x and the dependant variables c, n is the dimension of the variables.

Let suppose f is subject to the different equality constraints:

$$a_{1,1}.x_1 + a_{1,2}.x_2 + ... + a_{1,2}.x_n = b_1$$

$$a_{2,1}.x_1 + a_{2,2}.x_2 + ... + a_{2,2}.x_n = b_2$$
$$\vdots$$
$$a_{m,1}.x_1 + a_{m,2}.x_2 + ... + a_{m,2}.x_n = b_m \quad m \in \mathbb{N}$$

And let suppose that f is subject to the different inequality constraints:

$$a'_{1,1}.x_1 + a'_{1,2}.x_2 + ... + a'_{1,2}.x_n < b'_1$$
$$a'_{2,1}.x_1 + a'_{2,2}.x_2 + ... + a'_{2,2}.x_n < b'_2$$
$$\vdots$$
$$a'_{p,1}.x_1 + a'_{p,2}.x_2 + ... + a'_{p,2}.x_n < b'_p \quad p \in \mathbb{N}$$

A finally consider the lower and upper bounds of x:

$$l_1 < x_1 < u_1$$
$$l_2 < x_2 < u_2$$
$$\vdots$$
$$l_n < x_n < u_n$$

In the constraints, m is the number of equality constraints and p the number of inequality constraints.

The objective function and the constraints can be stated in matricial form:

$$f = c^T.x$$

With c and x two vectors:

$$c = \begin{pmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{pmatrix}$$

$$x = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}$$

$$A.x = b$$

With A a matrix and b a vector:

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} \cdots & a_{1,n} \\ a_{2,1} & \cdots & a_{2,n} \\ \vdots & \ddots & \vdots \\ a_{m,1} & \cdots & a_{m,n} \end{bmatrix}$$

$$b = \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{pmatrix}$$

$$A'.x < b'$$

With A' a matrix and b' a vector:

$$A' = \begin{bmatrix} a'_{1,1} & a'_{1,2} \cdots & a'_{1,n} \\ a'_{2,1} & \cdots & a'_{2,n} \\ \vdots & \ddots & \vdots \\ a'_{p,1} & \cdots & a'_{p,n} \end{bmatrix}$$

$$b' = \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_p \end{pmatrix}$$

$$l < x < u$$

With l and u two vectors:

$$l = \begin{pmatrix} l_1 \\ l_2 \\ \vdots \\ l_n \end{pmatrix}$$

$$u = \begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{pmatrix}$$

The objective problem can be stated as finding the minimum of the objecive function resumed as:

$$\min_x f(x)$$

$$\text{subject to} \begin{cases} A.x = b \\ A'.x < b' \\ l < x < u \end{cases}$$

Computational Solvers

Depending on the complexity of the problem, the software has to be selected. It is possible to solve optimization problems in MATLAB from Mathworks and GAMS. The last one is better suit when the complexity is considerable.

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