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Coordinated Charging Strategy for a Network of Photovoltaic Charging Stations (PVCSs): a trade-off between Stations Operator and Electric Vehicles (EVs) users

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Abstract

Electric mobility has been positioned strongly in recent years as one of the transport trends. This technology has been consolidated as a promising alternative to address the environmental impact caused by the current transportation system. Therefore, a number of efforts have been made to encourage and promote the use of electric vehicles, resulting in a rapid growth of this market. Despite the advantages that electric mobility can provide, certain challenges are still associated with a massive implementation of this technology. These challenges include having an adequate charging infrastructure and energy supply to support the recharging of these vehicles. In order to incentivize the adoption of this technology, it is necessary to analyze charging alternatives and to manage them efficiently. For this purpose, coordinated charging schemes and strategies have been developed to control the operation of the charging points. Besides, the growth of the electric vehicle market leads to a higher energy demand on the distribution network. Therefore, the integration of alternative energy sources, such as photovoltaic energy, in the charging infrastructure has emerged as a solution to satisfy, in a clean and balanced way, the need for complementing the energy available for charging these vehicles. In order to support the growth and adoption of electric mobility, this research project presents a discrete-event simulation model that allows to evaluate and analyze the performance of a public charging infrastructure and the effects of a massive deployment of electric vehicles in a city. Additionally, the research proposes a coordinated charging strategy through a reservation mechanism, which is oriented to improve the quality of service provided by the operator of a network of charging stations. The coordinated charging strategy is implemented through an algorithm based on the GRASP heuristic. Both the simulation model and the coordinated charging strategy are evaluated through a particular case study of electric taxis and public charging infrastructure, where both coordinated and uncoordinated charging scenarios are compared.

Keywords: Electric Vehicle, Charging Infrastructure, Coordinated Charging, Electric Taxis, Electric Vehicle Scheduling, Charging Strategy, Photovoltaic Charging Station

Resumen

La movilidad eléctrica se ha posicionado con fuerza en los últimos años como una de las tendencias de transporte. Esta tecnología se ha consolidado como una alternativa prometedora para dar respuesta al impacto ambiental causado por el sistema de transporte actual. Por lo tanto, se han realizado esfuerzos para incentivar e impulsar el uso de vehículos eléctricos, dando como resultado un rápido crecimiento de este mercado. A pesar de las ventajas que puede brindar la movilidad eléctrica, aun se debe hacer frente a ciertos retos que trae una implementación masiva de esta tecnología. Entre estos retos se encuentran el tener una infraestructura de carga y un suministro energético adecuado para abastecer la recarga de los vehículos. Para incentivar la adopción de esta tecnología, es necesario analizar alternativas para la recarga y la gestión inteligente de estas, por lo cual, se han desarrollado esquemas y estrategias de carga coordinada que permiten controlar la operación de los puntos de carga. Además, el crecimiento del mercado de los vehículos eléctricos conlleva a una mayor demanda energética sobre la red de distribución, por lo cual, la integración de fuentes energéticas alternativas, como la energía fotovoltaica, en la infraestructura de carga ha surgido como solución para satisfacer, de manera limpia y equilibrada, la necesidad de complementar la energía disponible para la carga de estos vehículos. Con el fin de apoyar el crecimiento y la adopción de la movilidad eléctrica, este proyecto de investigación presenta un modelo de simulación de eventos discretos que permite evaluar y analizar el desempeño de una infraestructura de carga pública y los efectos que trae la implementación masiva de vehículos eléctricos en una ciudad. Adicionalmente, la investigación propone una estrategia de carga coordinada mediante un mecanismo de reservas, la cual está orientada a mejorar la calidad del servicio prestado por el operador de una red de estaciones de carga. Esta estrategia de carga coordinada se implementa mediante un algoritmo basado en el heurístico GRASP. Tanto el modelo de simulación y la estrategia de carga coordinada son evaluadas a través de un caso de estudio particular de taxis eléctricos e infraestructura de carga pública, donde a la vez se comparan los escenarios de carga coordinada y no coordinada.

Palabras Clave: Vehículo Eléctrico, Infraestructura de Carga, Carga Coordinada, Taxis Eléctricos, Programación de Vehículos Eléctricos, Estrategia de Carga, Estación de Carga Fotovoltaica

Personal publications

Several scientific articles were generated and published during the development process of this research project:

Conferences with book series chapter:

- Cárdenas-Gómez, I., Fernández-Montoya, M., and Mejía-Gutiérrez, R. (2018). **"Analysis of relevant variables to monitor a photovoltaic charging station through the Function to Data Matrix (FDM) method"** *MOVICI-MOYCOT 2018: Joint Conference for Urban Mobility in the Smart City.* ISBN 978-1-78561-963-2. DOI: 10.1049/ic.2018.0018
- Sánchez, S., Cárdenas-Gómez, I., Mejía-Gutiérrez, R., and Osorio-Gómez, G. (2019). **"A Remote Monitoring System for Charging Stations with Photovoltaic Generation"** In *Applied Computer Sciences in Engineering WEA 2019 (Communications in Computer and Information Science, Vol. 1052)*, Figueroa-García J., Duarte-González M., Jaramillo-Isaza S., Orjuela-Cañon A., Díaz-Gutierrez Y. (eds), Springer. pp 584-595. ISSN: 1865-0929. DOI: 10.1007/978-3-030-31019-6_49

Scientific indexed journals:

- Isabel Cárdenas-Gómez, Ricardo Mejía-Gutiérrez, Alejandro Montoya. **"Analysis of Charging Infrastructure Demand Based on Discrete Event Simulation: Case Study of Electric Taxis Fleet"** Submitted and under evaluation in the *Journal of Public Transportation.* ISSN: 1077-291X. Indexed in Clarivate (Q4) & Scopus (Q2).
- Isabel Cárdenas-Gómez, Ricardo Mejía-Gutiérrez, Alejandro Montoya. **"Analysis of Photovoltaic Charging Stations (PVCSs) with a Coordinated Charging Strategy: Case Study of Electric Taxis Fleet"** To be submitted to the *IEEE Transactions on Automation Science and Engineering.* ISSN: 1545-5955. Indexed in Clarivate (Q1) & Scopus (Q1).

Project context

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Chapter 3 - Simulation Model

$\overline{t_w}$	Average waiting time of charging events with waiting cases.
A	Origin-Destination Matrix.
B_l	Occupancy of charging station $l \in C$.
C	Set of charging stations.
c_i	Central point (centroid) of zone $i \in Z$.
o_l	Location of charging station $l \in C$.
p_{ij}	Probability of transition between zone $i \in Z$ and zone $j \in Z$.
Q_l	Maximum queue size of charging station $l \in C$.
R	Set of charging protocols.
S_f	Percentage of failed charging events due to the time limit.
S_u	Percentage of failed charging events due to lack of SoC to reach CS.
SoC_m	Minimum battery state of charge to go charging.
t_c	Energy consumption of a trip.
t_d	Travel distance of a trip.
t_t	Travel time of a trip.
t_w	Waiting time of charging events with waiting cases.
u_l	Charging power to charge a vehicle at charging station $l \in C$.
V	Set of electric taxis.
V_w	Number of taxis that must wait when arriving at a charging station.

y_l Maximum capacity of charging station $l \in C$.

Z Set of zones.

Chapter 4 - CCS model

α Minimum percentage of energy thet must be supplied by the PV source.

ϵ_{ijk} Charging finish time for the user $i \in V$ scheduled at charging point $k \in Y_j$ of station $j \in C$.

γ_{ijk} Share of energy that comes from the PV source for the user $i \in V$ scheduled at charging point $k \in Y_j$ of station $j \in C$.

κ_{ijk} Amount of energy (kWh) charged by the user $i \in V$ scheduled at charging point $k \in Y_j$ of station $j \in C$.

κ_{ijk} Total energy charged by the user $i \in V$ at the charging point $k \in Y_j$ of station $j \in C$.

ϕ_j PV energy available at charging station $j \in C$.

τ_{ijk} Charging start time for the user $i \in V$ scheduled at charging point $k \in Y_j$ of station $j \in C$.

θ_{ijk} Total charging duration of the user $i \in V$ at the charging point $k \in Y_j$ of station $j \in C$.

a_i Charging start limit time of user $i \in V$.

C Set of charging stations.

d_{jh} Distance from the charging station $j \in C$ to the center point of zone $h \in Z$.

f Size of PV array.

l_i Charging finish limit time of user $i \in V$.

SOC_i Initial SoC of user $i \in V$.

SOC_i Target SoC of user $i \in V$.

V Set of users requesting charging services.

v Maximum allowed travelled distance.

x_{ijk} Binary variable, is equal to 1 indicating that user $i \in V$ is scheduled at the charging point $k \in Y_j$ of station $j \in C$. Otherwise, it is zero 0.

Y_j Charging points of charging station $j \in C$.

Z Set of zones.

Chapter 1

Introduction

1.1 Background

The transportation sector is one of the main sources of air pollution, which is considered as one of the major environmental problems (Müller, 2018). By 2013 this sector generated almost 40% of primary $PM_{2.5}$ emissions in Europe (EEA, 2017) and by 2015, it caused 18% of all man-made CO_2 emissions (International Transport Forum, 2017). Hence, looking for alternatives that help to reduce this air pollution caused by transportation, technologies such as EV have emerged and become stronger in recent years (Habib et al., 2018; EPA, 2015).

EVs can be classified in four groups (Un-Noor et al., 2017):

1. Battery Electric Vehicle (BEV).

2. Hybrid Electric Vehicle (HEV).

3. Plug-in Hybrid Electric Vehicle (PHEV).

4. Full Cell Electric Vehicle (FCEV).

Vehicles that belong to the groups of BEV and PHEV can be plugged-in and charged from the electrical grid or any other external source of electrical power (Richardson, 2013). These two types of vehicles are the ones to be considered in this research and from here on referred to jointly as EVs.

The global market of EVs is expanding quickly, from 2015 to 2017 the growth rate of the global EVs' stock was around 60% per year, having by the end of 2017 a stock of 3.1 million cars (IEA, 2018). And by 2018 already more than 5 million of these light-duty vehicles were on the roads (IEA, 2019). Along with the growth of the EVs market, comes the necessity of a bigger charging infrastructure able to support the charging demand. This infrastructure can be deployed privately at places like home and work, or rather, as public service (Ahmad et al., 2017). Currently, the availability of public CSs is limited, which increases the chances that EV users do not find an available spot to charge when arriving at them (Un-Noor et al., 2017) and have to wait long times for a free charging plug. However, users' willingness to accept waiting for the service is low (Philipsen et al., 2016), and this congestion at stations is becoming an important issue in charging infrastructure (Moradipari and Alizadeh, 2018). Congestion problems are increasing, not only the charging delays but also the chances to not complete a charging service request. Thus, the Quality of Service (QoS) provided by stations' operator and perceived by customers can be negatively affected. Therefore, there is a necessity of building more public charging infrastructure, which development is already happening. One telling example is the case of China, the one with the largest stock of EVs, where the government plans to have 500.000 publicly accessible chargers by 2020 compared with the current 213.260 available points (IEA, 2018) (See Fig. 1.1).

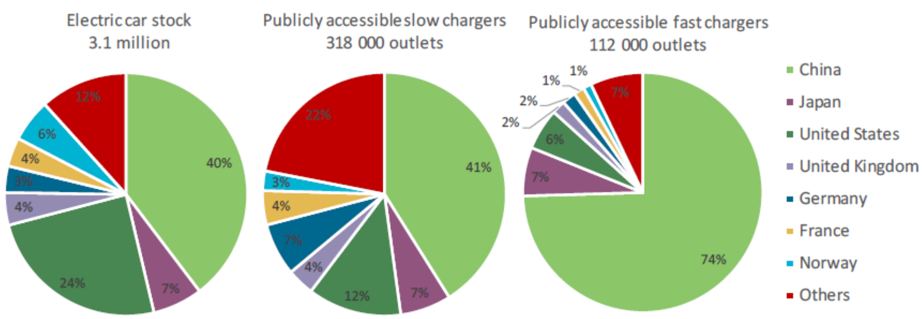


Figure 1.1: Electric car stock and publicly accessible chargers (IEA, 2018)

The increment in EV production represents not only a challenge for the charging infrastructure, but also the power grid. Higher penetration of EVs leads to higher energy demand. By 2017 the EV fleet represented an electricity demand nearly 54 terawatt-hours (TWh) and is expected to reach 404 TWh by 2030 (IEA, 2018). Then, despite the possible environmental benefits of electric transportation, there are some concerns about the impact on the electrical grid. Such as "increase in load profile during peak hours, overloading of power system components, transmission losses, voltage deviations, phase unbalance, harmonics and system stability issues that reduce the power quality and the reliability of the power system" (Habib et al., 2018).

To overcome the impacts of EVs over the grid and to improve the deployment and operation of public CSs, some alternatives have been proposed in literature such as:

1. Incorporating Renewable Energy Source (RES) in charging infrastructure.

2. Employing Energy Storage Systems (ESSs).

3. Developing strategies to coordinated the charging of EVs.

The first option of integrating RE not only allows to decrease the dependence level with the grid

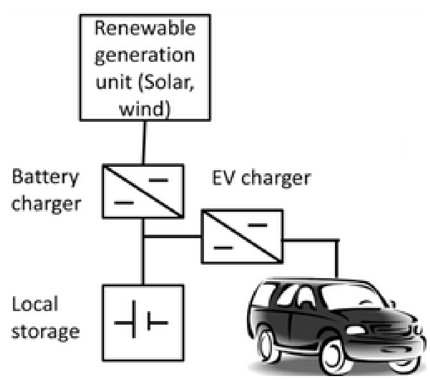
(Abdalrahman and Zhuang, 2017) but also helps to reduce the emissions caused by EVs since the charging process is made from green energy sources (Amjad et al., 2018). Among existing REs, the integration of wind and solar energies into the electric power grid has shown to be feasible and has increased recently (Mwasilu et al., 2014). However, facts associated with wind energy, like higher electricity transport losses, larger spatial and temporal variation, and farther installation from city areas, cause that integrating solar energy directly with charging infrastructure to be more suitable than using wind energy (Nunes et al., 2016),(Li et al., 2009).

There are two main CS's architectures when integrating PV energy:

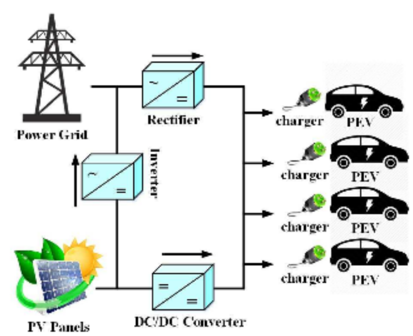
- If the station uses PV as the only power source, as shown in Fig. 1.2a, it is called off-grid solar charging system (Khan et al., 2018) or PV standalone system (Akmal et al., 2018).

- If the station uses PV as a second electric source in addition to the power grid (see Fig. 1.2b), it is called hybrid solar charging system (Khan et al., 2018), PV grid-connected system or commonly named in literature as PVCS.

The last configuration is more feasible to charge EVs due to its capacity to support energy requirements (Akmal et al., 2018). Due to the advantages of integrating REs in the charging infrastructure, PVCSs will become popular (Cheng and Liu, 2017).



(a) Off-grid solar CS (Chen et al., 2016)



(b) PVCS (Colmenar-Santos et al., 2014)

Figure 1.2: Charging stations with RE

In order to tackle this issue, by 2015, as a result of a research project, *Universidad EAFIT* developed a Charging Station, under a Solar Tree shape, to recharge electric bicycles. The prototype was called "Ceiba Solar"[1] and it was the first stand-alone PVCS in the campus, with a generation capacity of 1.5 kW and including a solar tracking system (see Fig. 1.3a). Even as it was built to recharge bicycles or low power devices, it is the basis to future research around Vehicle Recharging

[1] *Ceiba* is one of the most relevant Trees in Latin-America and Colombia. More info about this EAFIT's PVCS can be found at: `http://www.eafit.edu.co/innovacion/transferencia/Paginas/estacion-de-carga-solar.aspx` [Last accessed on 31/01/2019]

alternatives with renewable energies, as it is nowadays used in some places (e.g. See Fig. 1.3b).

(a) The PVCS at *Universidad EAFIT*

(b) PVCS example in California (USA)

Figure 1.3: Examples of charging stations with RE

The second alternative mentioned above, utilization of ESSs, alleviates the variation of RE generation and could help to reduce the charging time, the strain on the power grid, and the charging cost (Abdalrahman and Zhuang, 2017). These storage units can be used jointly with dynamic charging tariffs to decrease charging costs. Their use allows providing power during peak hours when the energy price is higher and at peak moments of EV demand (Chaudhari and Ukil, 2016).

By last, the third alternative, which is known as coordinated, controlled, or smart charging (Un-Noor et al., 2017), attempts to efficiently manage the charging process through the control of different parameters. These parameters will depend on the main purpose of the strategy. For example, the charging strategy can be designed to distribute the total charging load demand of a set of EVs among the available CSs (Ahmad et al., 2017), to define charging schedules for EVs at a station, to control the charging rate or the power allocation from the grid (Michailidis, 2013), among others.

In the charging system, three main actors can be identified: the grid, the aggregator [2] and the customer (Wang et al., 2016). Usually, most of these Coordinated Charging (CC) strategies are designed favouring only the interest of one of the three actors, while few others consider two of them at the same time (Mukherjee and Gupta, 2015). During the design and implementation of CC schemes, it is frequent to make use of mathematical modelling and optimization techniques that allow setting the main objectives and constraints of the system. Depending on the charging strategy's orientation, the optimization objectives and methods vary (Amjad et al., 2018). For example, if a strategy is oriented to the grid, the main goal can be to reduce power losses, to regulate frequency and/or voltage on the power grid, or to minimize irregularities & the peak load on the distribution network. But in a user-oriented strategy, the objective can be to minimize the total cost of charging for EV users.

[2] Who is the connection between the grid and the EV user (e.g. power networks substations, charging stations, parking lots, residential area, etc.)

In a strategy oriented to the station's operator, it can be to optimally employ RE for charging, to save aggregator's cost or to increase its profits while guaranteeing the satisfaction of customers (Wang et al., 2016). Thus, a wide variety can be found within the existing alternatives.

1.2 Research Problem Definition

The rapid growth of the EVs market brings on the challenge of providing a proper and efficient charging environment. To allow a higher penetration of EVs, not only the development and implementation of the charging infrastructure must be optimized (Ahmad et al., 2017), but also the operational issues of these recharging points should stay under control. It is necessary to find solutions for the management of the charging infrastructure (de Weerdt et al., 2013) through CC strategies, including efficient reservation (Conway, 2017) and admission mechanisms (Atallah et al., 2018). The operation of the CSs under a coordinated scheme strengthens the adoption of EVs, by contributing to the proper satisfaction of the charging demand (Tucker and Alizadeh, 2020), to the improvement of aspects such as congestion at stations (Zhang et al., 2018b), utility of the charging points (Conway, 2017), charging costs and times, to the reduction of the adverse effects on the power grid (Das et al., 2019), and to fulfill the interests of both EVs users and CSs operator (Wei et al., 2018).

Although there are already some CC strategies seeking to manage properly technical and operational aspects of EV charging, due to future increase of EVs, there is still a need for more research about it (Un-Noor et al., 2017). Moreover, most of the existing studies on CSs' management, concentrate on the operation of a single CS, rather than on a network of multiple CSs considering the interaction among them (Zheng et al., 2018). But the growing market of EVs and the projects to electrify public transportation, necessitates the development of CSs networks (Gabsalikhova et al., 2018; Faridimehr et al., 2019), which in a future are expected to become as widespread as gas stations networks (Moghaddam et al., 2019).

The performance of such CS networks under a CC scheme can be evaluated with different metrics according to the objective of the system. Within the metrics selected by various authors, can be found: the total energy cost for the customers, the net power balance (Yu et al., 2016), the stations' economic profit (Cheng and Liu, 2017), the system energy cost for the charging service (Zheng et al., 2018) and the customer satisfaction, that can be defined in terms of the average travel time of EVs (Hess et al., 2012), the percentage of energy demand fulfilled respect to the initial target of each user (Collado et al., 2017) or associated to the QoS offered by the station (Bayram et al., 2013b), among others.

Since EVs users and CS's operator can be considered as the main stakeholders in the problem of charge scheduling, a metric to evaluate the charging strategies designed for the operation of these stations should consider both actors (Chung et al., 2018), such as the QoS. Still, in most cases, the charging strategy focuses on the cost-benefit study of either the CS's operator or the customer (Islam et al., 2018). The QoS concept is directly related to the satisfaction level of users (Kong et al., 2016) and, at the same time, can be associated with the station's operator, who is particularly interested in providing a high QoS to customers while obtaining a considerable profit (Zenginis et al., 2018)

There has been a growing number of works that address charging infrastructure issues from different perspectives. Some studies propose scientific solutions related to the management of CS networks, considering issues from the planning steps until operation. A clear example can be the work presented by Bayram et al. (2015b), which introduces a planning framework for computing the minimum amount of grid resources to offer a service with a target level of QoS. In addition to an operational framework that uses a pricing-based method to incentivize customers to go to a certain CS and distribute the charging demand. In fact there are proposals and studies related to CC in networks of CSs. Nevertheless, despite the existing works, to the best of our awareness, there is no evidence of a study that develops a coordinated charging strategy for the operation of a PVCSs network, considering the existence of multiclass customers and the charging behavior of an EV's battery, and that is oriented to both stations operator's and customers' interests.

1.3 Research Question

The previous sections address the gaps and challenges found in coordinated charging strategies oriented to CSs operator and EVs users in a network of PVCSs. Therefore, the following research question has been set:

How to coordinate multiple charging necessities of EVs users in a Photovoltaic Charging Stations network to improve the so-called "Quality-of-Service"?

1.4 Objectives

1.4.1 General Objective

To develop a Coordinated Charging Strategy for a Photovoltaic Charging Stations (PVCS) network through optimization techniques to improve the so-called "Quality-of-Service".

1.4.2 Specific Objectives

- To analyze charging strategies developed in related works through a review of the state of the art, in order to identify the main variables involved in the system's operation, and the methods and techniques implemented with their benefits and gaps.

- To analyze a scenario (EVs and charging infrastructure) through the development of a simulation model to represent the integration of electric mobility in a given area.
- To develop a Coordinated Charging Strategy (CCS) based on optimization techniques through its implementation in a simulation model to validate the strategy's performance by comparing it with an non-coordinated charging scenario.

1.5 Research Justification

This research project contributes to the correct penetration of electric transportation alternatives by alleviating the coming issues associated to the rapid growth of this market, such as range anxiety experienced by EV users and congestion at CSs caused by the long waiting times. From the review of related works, there is still a gap in the charging coordination of EVs in a network of charging infrastructure, that may include PVCSs. The algorithm for a coordinated charging strategy represents the main theoretical contribution of this project, in addition to a simulation model to recreate an electric mobility environment. The case study and computational simulation implemented in this project illustrate the advantages of charging EVs under a coordinated scheme.

The project anticipates to the forthcoming deployment of CSs networks (ITV Channel TV, 2018; Lambert, 2018), contributing to improve aspects such as the energy management, economic profits and service quality. Besides, this project, considering the growing implementation of renewable energies, seeks to make the most of PV energy on the EV charging process.

1.6 Research Scope

This research project delivers an algorithm to coordinate the charging of EVs in a network of PVCS. The algorithm is based on optimization techniques and mathematical representation of such system. Due to the highly cost and time that represents the deployment of such system, and the lack of real operational data, the validation of the proposed algorithm can not be tested physically in a real operation. Then, it is evaluated through computational simulation.

The proposed charging strategy is limited to the charging of small EVs (in this document the term EV refers to PHEV and BEV) and does not consider a multimodal mobility system with other types of electric vehicles such as buses and bikes.

For the scope of this project, the term QoS is evaluated, as detailed in Section 2.3, in terms of:

- service availability
- service execution duration
- service execution price

1.7 Research Approach

The methodology framework proposed to accomplish the general objective of this research project is based on the Research in Design Context methodology (Horváth et al., 2007). This approach is closely related to the steps of the fundamental scientific research method. For this project, the methodology phases are configured ad shown in Figure 1.4

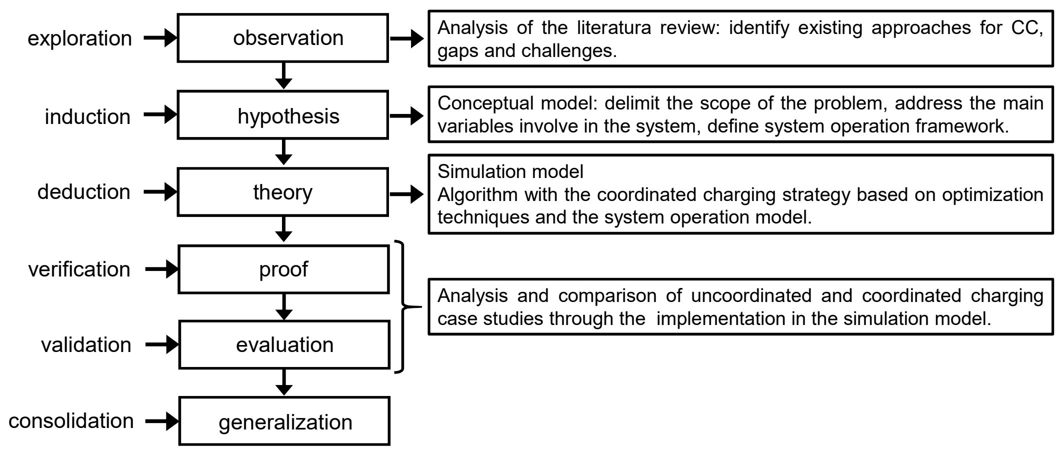


Figure 1.4: Research Methodology adapted from Research in Design Context (Horváth et al., 2007)

The exploration and induction phases concentrate on studying and analyzing the background of the research field, identifying the gaps, delimiting the problem and defining potential solution methods. The deduction phase leads towards a simulation model and an algorithm with the coordinated charging strategy. The third phase consists on the validation of the proposal through the evaluation and comparison of non-coordinated and coordinated case studies. Finally, there is the analysis of results and the generalization of the strategy to implement it in other electric mobility scenarios.

1.8 Thesis Organization

This research is structured in 5 chapters as follows. Chapter 1 presents the research problem, objectives and proposed methodology. Chapter 2 corresponds to the review and analysis of the state of art related to management of EVs and charging stations, modeling of such systems and use of photovoltaic in charging infrastructure. Chapter 3 presents the development of a simulation model and a case study that illustrates a non-coordinated charging scheme. This simulation provides inputs for the evaluation of the CC strategy, which design with the corresponding parameters and algorithm is detailed in Chapter 4. Finally, Chapter 5 presents the conclusions of the research and the future work.

Chapter 2

State of the Art

This chapter presents a review of other works related with the management of CS networks. There are many scheduling algorithms oriented to the same problem, but they differ on the parameters, constraints and methodologies implemented (Mukherjee and Gupta, 2015) which are analyzed below.

2.1 Coordinated Charging in CSs Networks

When having multiple CSs, it is necessary to implement an operational control or coordinated charging strategy in order to have a stable and balanced system through the regulation of some issues, such as the impact on the power grid and the QoS provided to customers (Bayram et al., 2013a). This section is interested in the examination of different CC strategies for CS networks that have been developed and their limitations when contextualized in the background of this project.

Table 2.1 presents a summary of reported studies addressing the main points related with this project. These are, works considering the management problem of CS networks.

According to the strategies developed in related works, these can be divided in three main categories: i). Works using price-based control, ii). Works using energy management strategies and iii). Works using admission and reservation mechanisms.

In the first category can be classified the works presented in Bayram et al. (2015a); Ban et al. (2012); Bayram et al. (2015b); Kong et al. (2018); Wong and Alizadeh (2017); Xu et al. (2018). Each of them proposes a strategy based on the assumption that EV users are sensitive to prices; thus, aspects such as arrival rate to stations can be controlled through dynamic charging tariffs. Accordingly, Bayram et al. (2015a) present a vehicle routing strategy with price variation according to stations' congestion level. The main goal of the strategy is to maximize operator's profit by serving as many customers as possible, so stations with available spots are given lower prices, trying to incentivize customers to go there. But users are the ones who decide at the end to which CS to go. Their decision is modeled with a cost function, which considers service and driving costs, and their objective is to minimize the overall cost. Similarly, in (Xu et al., 2018) prices vary depending on station's load demand, with the objective to minimize the overall waiting time for users in the system and keep grid's stability under control. Charging fees and other stations' information is communicated to interested users through a notification system. In this case, users' decision is based on a dissatisfaction function that includes the predicted waiting time of the station, travel distance to it and its service fee. On the other hand, Kong et al. (2018) and Wong and Alizadeh (2017), look for the optimal arrival rate that should have each station in order to maximize operator's profit, and to minimize the total latency experienced by users and the CS network's electricity costs respectively. To achieve these arrival rates, they modify stations' charging fees accordingly, expecting that users shift charging demand to non peak-off hours. In the event that arrival rates exceed the optimal value, Kong et al. (2018) also consider the possibility that the operator buys more energy to the power system to increase the station's capacity. Likewise, Ban et al. (2012) follows this kind of mechanism to minimize the waiting time and Bayram et al. (2015b) use it to maximize an aggregate utility that is defined in terms of the arrival rates and blocking probability. The latter work considers multiclass customers, which are differentiated by parameters such as battery size and available charger technology, and are high-relevant aspects to consider for the charging service. Assuming that stations have this price variation, Moghaddam et al. (2018) propose another vehicle routing scheme where users choose the station that minimizes their charging cost and travel time, which is the sum of travel time to station, waiting time, charging time and travel time from station to a destination. Most of these works, based on the stochastic nature of users' mobility, use queuing theory to predict parameters like arrival rate, waiting times, charging demand, among others. And propose non-cooperative games to model the price variation and routing decision between users and CSs network.

The second category is more related with the control of energy flow between subsystems and charging powers. Authors in (Cheng and Liu, 2017) consider a network of stations with PV generation. They take the amount of vehicles parked around them and their departure times; then, based on this information, they compute the total charging demand and set the charging rate for these vehicles with the objective to maximize station's profit, which comprises an economic profit and an environmental profit associated to the amount of charging energy that comes from the PV subsystem. To control this kind of profit, they also manage the purchase and sale of energy among PVCSs, power plants and grid. In (Zheng et al., 2018) the goal is to minimize the operational cost of a distribution system with renewable distributed generators by controlling the charging rate for each EV. Similarly, in Shi et al. (2018) the goal is to minimize the energy cost of the distribution system operator and the charging cost for EV users. So that, they propose an optimal power flow problem to decide the amount of power generated by distributed generators and the vehicles' charging rate. Another illustrative example of this energy management strategies, is presented in Li et al. (2018), they consider a real-time traffic flow and its interaction with the power system to schedule charging in a network of Fast Charging Stations (FCSs). By choosing the active power of each CS, taking into account the day-ahead scheduling of the power system, and by defining the charging status of EVs at the station, they seek to minimize the load variance in the network and the waiting time cost of users.

By last, the third category presents admission and reservation systems that attempt to set aside from working with the uncertainty of users' arrival rates and charging behaviors and offer a more deterministic control over station's operation and service's availability. In this way, (Liu et al., 2018) introduces a reservation and routes planning system for a single EV who needs charging. The reservation system, taking into account user's location and intended destination, offers him/her multiple route options to various stations with the corresponding charging times and fees. Then, the user, according to his/her preferences, selects the option that minimize charging expenses or minimize time consumption, and waits for reservation system's confirmation. Their work is based on the affirmation that the two factors that mainly affect user's decision are "energy cost and time consumption". Moradipari and Alizadeh (2019) propose an approach where users are not allowed to charge wherever they want; instead, they need to select the stations they are willing to visit, a priority level for charging and the amount of energy requested. With this information, the operator presents different service options and the user chooses one of these. However, the service options offered to the customers are designed using pricing policies to influence users' decision with the objective to either maximize a social-welfare, i.e optimally use capacity-limited CSs, or to maximize operator's profit. Furthermore, for a set of EV users requesting charging service, (Atallah et al., 2018) introduce a reservation system that operates over this set of requests and find an optimal schedule for each user so that the maximum waiting time experienced by a customer in the network is minimized. User are not able to charge at any stations without being previously scheduled. Due to traffic conditions, there exist the risk of not arriving on time for reservations, thus Cao et al. (2018) integrate a traffic model to frequently update EV traveling's status and allow modifications in the reservation system. Different from others, this reservation system, which uses waiting time estimations, only tells users the station to go in order to minimize users' trip duration, but they are not assigned charging times before arriving at stations; once there, users are scheduled based on the First Come First Serve (FCFS) scheme. The CC strategies implementing reservations mechanisms and scheduling in advance before users' arrivals, can decrease the congestion (Cao et al., 2018) and waiting times at stations, as well as the probability of denying charging service to customers (Atallah et al., 2018).

As can be seen, works differ not only on the type of strategy, but also on the main objective and the way the strategy is implemented. The third category is of special interest for this research. CC strategies implementing reservations mechanisms and scheduling in advance before users' arrivals, might decrease the congestion (Cao et al., 2018) and the waiting times at stations, as well as the probability of denying charging service to customers (Atallah et al., 2018). Consequently, an extended review of this kind of strategies is presented below.

Reference	Charging strategy	Main objective	Oriented to
(Moghaddam et al., 2018)	Vehicle routing scheme	Minimize total travel time and charging cost	User
(Bayram et al., 2015a)	Vehicle routing scheme with price variation	Operator: maximize profit User: minimize overall cost for users	Operator User in a second level
(Ban et al., 2012)	Pricing scheme	Minimize waiting time	User
(Bayram et al., 2015b)	Pricing scheme	Maximize aggregate utility, in terms of arrival rate and blocking probability	User
(Kong et al., 2018)	Pricing scheme and energy purchase mechanism	Maximize operator's profit	Operator
(Wong and Alizadeh, 2017)	Pricing scheme	Minimize total latency for users and stations' electricity cost	User Operator in a second level
(Xu et al., 2018)	Pricing scheme and notification system	Minimize overall waiting time	User Grid in a second level
(Cheng and Liu, 2017)	Charging load allocation	Maximize total profit of PVCS	Operator
(Zheng et al., 2018)	Charging power allocation	Minimize operational cost	Distribution system
(Shi et al., 2018)	Power flow	Minimize energy cost and charging cost	Distribution system User in a second level
(Li et al., 2018)	Real-time traffic flow and power system scheduling	Minimize load variance and users' waiting time cost	Power system User in a second level
(Atallah et al., 2018)	Reservation system	Minimize the maximum waiting time	User
(Cao et al., 2018)	Reservations with traffic conditions	Minimize drivers' trip duration	User
(Liu et al., 2018)	Reservation and routes planning system	Minimize charging expenses or time consumption	User
(Moradipari and Alizadeh, 2019)	Admission control using pricing policies	Maximize social-welfare or operator's profit	User or Operator

Table 2.1: Related works for management of CS networks

2.1.1 Admission and Reservation Mechanisms

There are many parameters and variables involved during the charging process of EVs. Considering all of them is a challenging and yet unsolved task. Hence, existing works can differ in the incorporation or not of some of them. Issues related to the battery charging behavior and the current variety of charging protocols in EVs are of main concerned in this research, besides the integration of PV energy.

CSs can offer multiple charging options according to their technology. As explained in (Shareef et al., 2016), there are three charging levels, (i.e., Level 1, Level 2 and Level 3), and different charging protocols, e.g., CHAdeMO and SAE J1772 Combo, which limit the charging power. The compatibility with the charging protocols is determined by the technology of each vehicle and each CS. The variety of charging modes is commonly found in real-life scenarios (Awasthi et al., 2017) and allows to improve QoS by satisfying charging requirements of multi-class customers (Zhang et al., 2018b).

Multiple energy storage technologies can be used in EVs, among them, the Li-ion battery has been widely adopted in the industry of electric mobility, in spite of its benefits in costs and energy characteristics (Saw et al., 2016). Research about topics related to the battery performance and life cycle has lead to the development of different recharging algorithms that differ not only in their implementation complexity, but also affect aspects such as charging times, charging efficiency and impact on life cycles (Weixiang Shen et al., 2012). Normally, in EVs applications, batteries are charged using the technique of Constant Current - Constant Voltage (CC-CV), where voltage and current vary during the charging process (Liu, 2013). In some works, this charging process is often assumed to be linear with a constant charging rate, but the real battery charging behavior directly affects the charging time and the utility of the station's operator (Wei et al., 2018). Thus, it is important to model it appropriately and not assume linearity in the whole charging process.

Table 2.2 presents the closest studies to our work, indicating if they take into account the aspects mentioned above. The table contains works for CS networks, as well as works with proposals for single CSs and related to admission and reservation mechanisms.

Reference	Charging infrastructure	RES	Charging protocols	Battery charging behavior
Atallah et al., 2018	CS network	-	-	-
Cao et al., 2018	CS network	-	-	-
Liu et al., 2018	CS network	-	-	•
Moradipari and Alizadeh, 2019	CS network	•	-	-
Wei et al., 2018	Single CS	-	-	•
Wang and Yang, 2018	Single CS	-	-	-
Tucker et al., 2019	Parking facilities	•	-	-

Table 2.2: Admission and reservation mechanisms and consideration of main aspects

Concerning the scenario of a single CS, authors in (Wei et al., 2018) introduce an admission control mechanism for a parking garage, which works as a CS to manage two main factors that affect its operation, these are profit and QoS. To schedule the charging tasks of vehicles, they consider, besides the effect of the electricity market prices regulated by TOU, a function to approximate the real battery's charging behavior. Wang and Yang (2018) present separately an admission and scheduling mechanisms, implemented by two different algorithms. They use an admission algorithm to accept or decline the requests according to whether these could be satisfied or not by the system. In this case, satisfaction is achieved if the user's initial energy demand is fulfilled by his/her deadline. Then, the scheduling algorithm determines the energy allocation for each accepted user in each time slot with the objective to maximize the revenue of the station. Differently from the previous work, the battery charging is associated with a linear behavior during the whole charging service. With respect to the coupling of RES and how to schedule vehicles according to the available energy of this type, the two last works omit this aspect, as well as the compatibility of existing charging protocols. On the other hand, authors in (Tucker et al., 2019) propose a reservation system for multiple parking facilities that include solar generation. The main goal is to maximize the user's utility; thus, a service request is accepted or rejected depending on the utility it could have. In the scheduling phase, the system determines the amount of energy received by each user at each time slot according to the energy price, that is affected by the solar generation and influences the user's utility. However, the energy allocated to each user is only limited by the energy capacity that can be drawn from the grid and the solar generation capacity, but the maximum charging rate accepted by vehicles due to their chargers technology and battery characteristics is neglected. Within the works considering networks of CSs and reviewed in the previous section, only Liu et al. (2018) includes a special model for the battery charging process with a piecewise linear profile. While other authors assume constant charging power, having thus the same linear behavior during the whole time. Regarding RES, its integration is only considered in (Moradipari and Alizadeh, 2019). None of these works deal with the diversity of charging protocols and the limitations of the charging power derived from the compatibility between these and the vehicles.

The present work differs from the others in that it develops an admission control mechanism, that jointly considers multiple CSs with their interaction, the non-linear battery charging behavior throughout the whole process, the existence of multiple charging modes and the integration of PV.

2.1.2 Optimization in Coordinated Charging

Optimization has been presented in the literature as a suitable approach in coordinated charging. The way on how the system is modeled, with its respective constraints, variables, and objective functions, determines the type of problem and affects the selection of the optimization method to solve it (Mukherjee and Gupta, 2015). The numerous approaches that have been implemented in this field to model the problems include the conventional such as Linear, Quadratic, Nonlinear and Mixed-Integer Nonlinear Programming, which allow finding the exact best solution for the problem (Tan et al., 2016) and can be handled with numerical solvers (Hoarau and Perez, 2018). However, these methods perform better in simple scenarios (i.e., problems with a small number of variables), because the complexity for finding the best solution is highly sensitive to the increment of the search space size (Islam et al., 2018), demanding large execution times. The coordination and scheduling of a large population of EVs can be considered as a hard problem (Hernández-Arauzo et al., 2015). The solution to this problem involves a great number of variables and computational requirements; thus, other optimization techniques, such as heuristics and metaheuristics algorithms, become a good alternative (Hu et al., 2016), (Zheng et al., 2019). These algorithms are known as approximate methods, contrary to the previous methods that provide the exact optimal solution, these do not guarantee to find the global optimum but can give a satisfactory solution within an acceptable execution time (Muthuraman and Venkatesan, 2017). This section reviews how researches have implemented different approximate algorithms to solve problems in the field of EVs and charging infrastructure.

As mentioned above, approximate algorithms comprise heuristics and metaheuristics. The second defined as “an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space, learning strategies are used to structure information in order to find efficiently near-optimal solutions” (Osman and Laporte, 1996). In turn, heuristics can be divided into constructive and local search or improvement methods. The first is used to build an initial solution, which is empty at the beginning, but iteratively the components are incorporated until getting an entire solution. The second, as its name suggests, takes that initial solution and seek to improve it in each iteration, either randomly or by using a specific method (Syam and Al-Harkan, 2012). Metaheuristics have been given different classifications, one of them is the division between single point (or trajectory) and population-based algorithms. It depends on whether the algorithm considers only a single solution at a time or it works on multiple solutions during the search process (Muthuraman and Venkatesan, 2017). The single-based methods comprise the Greedy Randomized Adaptive Search Procedures (GRASP), Simulated Annealing (SA), Tabu Search (TS), Variable Neighborhood Search (VNS), among others. The population-based group includes, but is not limited to: Ant Colony Optimization (ACO), Scatter Search (SS), Particle Swarm Optimization (PSO) and the well known Evolutionary Algorithms (EAs) (Gendreau and Potvin, 2005).

A wide diversity of applications with these heuristics and metaheuristics methods can be found in the literature. For example, García-Álvarez et al. (2018) develop a scheduling algorithm to minimize the total tardiness at a CS. They implement two different approaches. The first is a hybrid metaheuristic based on the GRASP method, which consists on a constructive phase using a Sequential Greedy Stochastic algorithm guided by a Due Date and Apparently Tardiness dispatching rules, (i.e., all vehicles are sorted according to their departure times to be scheduled), and a second phase concerning the improvement of the initial solution through a Local Search (LS). The second approach is a memetic algorithm inspired by a genetic algorithm previously implemented in other work. Similarly, a new approach for the same problem is proposed in (García Álvarez et al., 2018), but this time they work with an Artificial Bee Colony (ABC) algorithm enhanced by a LS. On the other hand, Arias et al. (2017) evaluate the performance of TS and GRASP methods to mitigate the operational costs of the electrical distribution system when coordinating the charging of EVs. Additionally, they propose a hybrid method using the construction phase of the GRASP and the short-term memory of TS for the LS phase. For the admission control mechanism proposed by Wei et al. (2018), where both profit and QoS are of main interest, authors present scheduling combining a greedy-based and a price-oriented algorithm. The first has excellent task admission performance and resource utilization ratio but is limited concerning price optimization. Whereas the second allows balancing this aspect. They compare the proposed scheduling with two widely used heuristic algorithms called FCFS and

Earliest Deadline First (EDF). Likewise, Wang and Yang (2018) examine in contrast their proposal with FCFS and Least Laxity First (LLF) algorithms. They employ a greedy algorithm to determine which charging requests are declined and a deadline-based algorithm to schedule the admitted services. Differently, Alonso et al. (2014) employ a Genetic Algorithm (GA) in their attempt to coordinate the charging considering the load profile caused on the transformer substation of the distribution network. And for the scheduling of electric buses, an Adaptive Large Neighborhood Search (ALNS) heuristic is presented in (Wen et al., 2016). All algorithms of previous works have demonstrated successful performance when compared either with other approximate methods or with non-coordinated charging schemes. Despite all the existing methods and their numerous implementations in the literature, none of them can be established as the best or predominant method to solve the EV scheduling problem (Yang et al., 2015) and the choice of the method is subjected to researcher's decision, which might not only depends on the problem's characteristics.

2.1.2.1 System Modeling

The modeling of an EV scheduling problem can incorporate a large number of parameters, depending on its dynamic and operational framework. The two main actors in a reservation system are the EV users and charging stations, which sometimes are considered to be under control of an operator. Table 2.3 indicates which information of these two actors is studied as input parameters in related works, either considering or not admission and reservation mechanism.

Reference	Charging infrastructure	Type of users	EVs parameters									CSs parameters			
			Origin	Destination	State of Charge	Battery Capacity	Energy demand	Arrival time	Departure time	Charging duration	Parking duration	Location	Capacity	Electricity price	Service price
Wei et al., 2018	Single CS	Parked	-	-	Initial Target	●	-	●	●	-	-	-	No. of EVs charging simultaneously	●	●
Kim et al., 2017	Single CS	Parked	-	-	-	-	●	-	-	●	-	-	No. of chargers	●	-
Tao et al., 2018	Single CS	Parked	-	-	Initial Target	●	-	●	●	-	-	-	-	●	-
Ki et al., 2018	Single CS	Parked	-	-	Initial Target (100%)	●	-	●	●	-	-	-	No. of chargers and max. charging power	●	-
Mathur et al., 2018	Single CS	Arriving	-	●	Initial	●	-	●	●	-	-	-	No. of chargers	●	-
Wang and Yang, 2018	Single CS	Arriving	-	-	-	-	●	●	●	-	-	-	Max. charging power at a time slot	●	●
Atallah et al. 2018	CS network	Traveling	●	●	Initial Required at destination	●	-	-	-	-		●	No. of chargers per CS	-	-
Cao et al., 2018	CS network	Traveling	●	●	Initial at origin Target (100%)	●	-	●	-	●	●	●	No. of chargers per CS	-	-
Liu et al., 2018	CS network	Traveling	●	●	Initial at origin Required at destination	●	-	-	-	-	-	●	No. of chargers per CS	●	●
Moradipari and Alizadeh, 2019	CS network	Traveling	●	-	-	-	●	-	-	-	-	●	Max. energy capacity	-	●

Table 2.3: Parameters for system modeling

Two ways of operating can be identified, one with users parked or arriving at a CS, and others with users traveling. The works that have strategies based on the first type of user also coincide with the type of charging infrastructure. Users' location information such as the origin and destination, is mainly neglected, except in (Mathur et al., 2018), where the distance needed to travel after charging is included. Differently, works concerning CSs networks and traveling users take into consideration their location, since the origin and destination can affect the system's decisions such as the assignment of a CS to an EV user if this depends on a traveled distance.

Concerning the users' energy demand, it is specified as an input parameter in (Kim et al., 2017), (Wang and Yang, 2018) and (Moradipari and Alizadeh, 2019). The rest of the works normally calculate it with other input data such as initial SoC, target SoC, and battery capacity. Ki et al. (2018) and Cao et al. (2018) assume all users will charge the vehicles to 100% of their capacity. Authors who consider SoC at origin or destination must also include the consumption rate of vehicles; so that, the SoC after traveling a certain distance can be estimated.

Parameters related to time are considered by most of the works because by computing the difference between arrival and departure times, the charging duration is delimited. This maximum duration is directly specified by the user in (Kim et al., 2017) and (Cao et al., 2018). On the other hand, Atallah et al. (2018), Liu et al. (2018) and Moradipari and Alizadeh (2019) omit any time input, as they do not include duration or time constraints in their problems.

With respect to CSs parameters, the location is essential for works dealing with traveling users and CSs networks. Generally, there is an input parameter that indicates the maximum service capacity of the station, such as the number of chargers, total charging power, total energy supplied, among others. Particularly, Tao et al. (2018) omit capacity constraints to schedule customers. By last, prices associated with electricity and service are included depending on the type of charging strategy.

As evidenced in the previous analysis, the system model varies depending on the context and scenario considered by researchers and the respective assumptions taken for the development. Despite there are parameters shared among some works, the information set as input is exposed to the subjectivity of the problem formulation in charge of a person.

2.2 Quality of Service (QoS)

QoS is a term widely used in communication networks. It refers to the set of techniques implemented to manage network resources and its parameters such as bandwidth, delay, delay variation, and packet loss (Cisco, 2016). However, this term has been adopted in other application fields, changing its meaning according to the context and the scientific scope (Marchese, 2007) of these fields. That is the case of EVs and CSs service.

Bayram et al. make use of QoS as a performance metric in some of their works related to charging strategies 2015a, 2015b, 2013b, 2011. The meaning given to this term in those works is "the user blocking probability" (i.e., probability that an EV driver arrives at a station and does not receive the charging service). The blocking probability in CS networks considering stochastic of users' behavior is normally calculated based on the multirate Erlang loss systems, as shown in (Bayram et al., 2015b)(Kong et al., 2017)(Vardakas, 2014). In these works the arrival rates of EVs are modeled with a Poisson distribution. Zhu et al. (2011) associate the probability that users cannot be charged to the grid resource limit capacity or to the shortage of energy. Meanwhile, Huang et al. (2012) explain QoS as the average number of EVs that are not fully charged to the target level within the departure time, and Ban et al. (2012) and Davidov and Pantoš (2017) relate this index with the available charging time specified by the user and the final expected time to charge. A definition including more aspects is presented in (Hess et al., 2012). This time QoS considers the energy price, the charging and discharging time of a battery, the charging delay, and the impact of the charging method on the battery performance. Similarly, authors in (Zhang et al., 2018a) interpret it as the charging rates, electricity price, and waiting time. The above references show the diversity meanings given to the metric of QoS in electric mobility applications.

The above interpretations of QoS coincides with some definitions given in the Web Service and Internet applications. Moorsel (2001) associates QoS in internet service to metrics such as availability, reliability, successful completion probability, waiting time, response time, among others. As explained by Zeng et al. (2003), new criteria can be added to the web service quality model. Thus, they specified five main criteria for this service quality concept: i). Execution price, ii). Execution duration, iii). Reliability, iv). Availability and v). Reputation. These five parameters are similar to some of the already mentioned meanings given to QoS in the electric mobility field. Therefore, an analogous relation is given below.

The execution price defined in Web Service as "amount of money that a service requester has to pay for executing the operation" (Zeng et al., 2003), could represent the charging cost for the EV user. The execution duration, which "measures the expected delay in seconds between the moment when a request is sent and the moment when the results are received" (Zeng et al., 2003) can be aligned with the time that takes for a customer to get the charging service completed, (i.e., driving time to station, waiting time and charging time). For the availability, explained as the "probability that the service is accessible" (Zeng et al., 2003), it can be related to the EV user blocking probability or declined service, which is already considered in some works. By last, the reliability and reputation are explained as "the probability that a request is correctly responded within the maximum expected time frame" and "measure of the trustworthiness of the service" respectively (Zeng et al., 2003). Since these two concepts dependent on historical data of services that have been successfully accomplished and on service evaluation from customers, they could be considered only in systems from which some data has been collected.

Subjected to the different interpretations given to QoS in the works reviewed, for the purpose of the present research, we adopt QoS in terms of availability, execution duration and execution price of the charging service.

2.3 Photovoltaic in Charging Stations

The integration of REs such as PV in EV charging infrastructure, has gained attention as an alternative energy source than using only the utility grid in the charging process. This has been prompted by looking for solutions to the strain on the grid caused by EVs Yang and Ribberink (2019), as well as by the purpose of making EVs a more sustainable technology by reducing their Greenhouse Gases (GHGs) emissions when being charged from clean energy sources Karmaker et al. (2018). However, the integration of PV causes some uncertainty on the station's performance. Its generation is inconsistent and is mainly affected by external factors such as weather conditions Habib et al. (2018). Thus, there are some developments regarding simulations tools and mathematical models that analyze the performance of PV systems. Since the scope of this project does not include the study and development of prediction models for PV generation, this section is limited to address how different computational tools have been used in literature.

Mathur et al. (2018) consider a CS with distributed generation of solar energy. To calculate the solar power generation of the system they use data from the National Renewable Energy Laboratory (NREL) website. Similarly, Bhatti and Salam (2018) implement the single diode model to compute the output power of a PV-grid charging system. As input parameters, they need the total irradiance on the PV module's surface and the operating module's temperature. Thus, the irradiance and temperature data for one year is also obtained from NREL. Authors in (Keskin and Soykan, 2017) are interested in evaluating the use of PV panels in a campus to reduce the peak energy consumption. They utilize two tools from NREL, PVWatts Calculator and JEDI PV Calculator, to assess the electricity generation and the financial feasibility of the system, respectively. Another tool from NREL, called HOMER is used by (Alghoul et al., 2013) to optimally design a station assisted with solar energy. Also, the authors use solar radiation data from the Surface Meteorology and Solar Energy (SSE) data-set sponsored by NASA. By last, with the purpose to evaluate the solar generation potential by determining suitable areas to install solar systems, Good et al. (2019) compute the energy produced by the PV system by jointly using the software PVsyst, meteorological data from the software Meteonorm and the horizon line from PVGIS, which consider shading objects. The previous works show a satisfactory application of different computational tools and encourage their adoption in the literature.

Chapter 3

Discrete-Event Simulation for Electric Vehicles and Charging Infrastructure

Despite the continuous growth of the electric mobility field, currently, the access to real data about EVs and charging infrastructure's operation is scarce. Thus, the evaluation of some studies in real-life scenarios is challenging. This chapter presents a simulation model that allows to represent and analyze the performance of the charging infrastructure of an urban area given the operation of multiple electric vehicles.

The potential of reducing Air Pollution, by implementing alternative mobility technologies in specific types of transportation means, is high. One particular group of vehicles, with high potential to operate with electric technology, are taxis because their majority of inner-city trips are of short length and, in total, they have high annual mileage. Additionally, researchers have found that taxi air pollution emissions are higher than a car, bus, and subway (An et al., 2011), being an exciting sector to implement cleaner technologies. Thus, if a significant share of taxis were electric, instead of conventional gasoline vehicles, they could highly contribute to reducing air pollution (Hagman and Langbroek, 2019). Despite the benefits of this kind of mobility technology, such as the environmental contribution, there are still some concerns regarding charging infrastructure and the charging process for a large scale deployment of Electric Taxis (ETs) in cities (Bischoff and Maciejewski, 2014). Due to conventional taxis' operation characteristics, such as their overall daily mileage or using one taxi for multiple shifts, there is a high probability that electric ones need to use public CSs during their working hours. However, if the charging infrastructure is not adequate to support the charging demand and in a moment runs out of charging spots, this could result in inefficient waiting times to charge and have repercussions in taxis' services (Hu et al., 2018).

The limited availability of CSs, that is related with the range anxiety experienced by EV users (Cen et al., 2018), is also leading to congestion problems caused by the long waiting times that users experience when arriving for a charging service. If an EV user arrives at CSs and finds that it is occupied, his/her willingness to accept waiting for the service is low (Philipsen et al., 2016). Hence, these congestion problems, which are becoming an essential issue in charging infrastructure (Moradipari and Alizadeh, 2018) are increasing, not only the charging delays but also the chances to not complete a charging service request.

Different governments have been promoting the deployment of ETs systems. Nevertheless, the massive implementation of ET fleet leads to some challenges for the currently installed charging infrastructure. The simulation model presented in this chapter allows evaluating the performance of this infrastructure, given the operation of an ET fleet. The simulation model is applied in a case study, based on the short-term scenario in the city of Medellín (Colombia), where the government set the goal of having 1500 ETs in three years, as part of the city's plan, on behalf of air pollution and sustainable mobility alternatives (Ángel Orrego Arenas, 2019b). For the initial phase of the project, it is expected that 200 taxis start operation by the end of 2019 (Ángel Orrego Arenas, 2019b). According to the current charging infrastructure in the city, the results of the case study provide insights about how would those taxis operate in the city with a non-coordinated charging scheme, and analyzing the infrastructure behaviour, trough variables such as waiting times and most congested CSs for different scenarios. Although the simulation is evaluated with the particular case of Medellín, the proposed model has been generalized, to be replicated to other cities.

3.1 Electric Taxis Background

The study of new transportation services and mobility solutions, oriented to sustainability, particularly to the reduction of CO_2 emissions, has been of an increasing interest in different transportation sectors. From the perspective of transit agencies, Mattson (2012) conducted a survey to evaluate motivations and obstacles for these companies for implementing hybrid buses and alternative fuels, distinguishing between the factors influencing small urban and rural transit agencies. Similarly, Galván et al. (2016) proposed an econometric model, which used surveys data and a discrete-choice approach, to determine the main reasons why Colombian transit agencies would choose or not to use alternative energy sources, different than diesel fuel and gasoline, in public buses to have cleaner powered vehicles. Another public transport sector that is promoting the discussion of using or integrating new technologies is taxi industry. Accordingly, there is a worldwide projection about implementing electric taxis (Hall et al., 2017). Thus, some governments have established projects and route maps to electrify public transport, such as the case of Costa Rica, where it is expected to have buses and taxis completely electric by 2050 (IEA, 2019). Most recent market research about electric taxis forecast a compound annual growth rate (CAGR) of 9.22% for the period 2019-2024 (ReportLinker, 2019). Given this forthcoming increment of electric taxis, different works have been developed to study issues such as technology adoption and to analyze the feasibility of technical and economic aspects.

Nowadays, ETs are not yet widely expanded but, for instance, stay as a future project in some cities. Consequently, one of the challenges studying ETs is the lack of information on real operation. Thus, several studies are based on simulations or use conventional taxis operation's data, and few works have been able to include real data of ETs' operation. Park et al. (2014) conducted a survey in South Korea and U.S to determine which factors could motivate conventional taxi-drivers to employ ETs. They collected a total of 951 samples, which allowed them to make a comparative study between the countries' results. Differently, Bischoff and Maciejewski (2014) and Gacias and Meunier (2015) made use of simulation tools, like MATSim and discrete-event simulation in C++, respectively. In Bischoff and Maciejewski (2014), authors wanted to include real traffic conditions to analyze the operation of an ET fleet. In Gacias and Meunier (2015) the purpose was to evaluate the most advantageous CSs' location for ETs and a proper dispatching rule for the taxi fleet considering charging events. The case study of the last work, considers 100 vehicles traveling in Paris and its surroundings. Each simulation consisted of 10 replicas, varying the number of charging terminals and the total number of taxis.

Another approach to evaluate the feasibility of replacing gasoline taxis with electric ones, is presented by Hu et al. (2018), who used data collected from conventional taxis. With these inputs, they analyzed travel patterns, such as trips' distances, number of daily shifts, daily traveled miles, among others, and they verified if ETs could operate under these travel conditions. Since they used data of conventional vehicles, it was necessary to make some assumptions for the charging patterns of the ETs; thus, they established the following conditions:

i. Taxi drivers go charging if the SoC is below 50%;

ii. The CSs available to charge are those within a travel radius of 0.5 miles; and

iii. Each taxi has a fixed consumption rate of 0.3kWh/mile.

The results demonstrated that, by that time, the charging infrastructure installed in New York, was not sufficient to support the deployment of a large ET fleet, even without considering congestion at CSs during the study. Similarly, for a case study in Nanjing (China), Yang et al. (2016) evaluated the feasibility of implementing electric 'BYD-e6' as taxis, through the analysis of GPS data recorded from 11914 conventional taxis, over two days of operation. Given the characteristics of the BYD (a travel range of 200km and a consumption rate of 0.2kWh/km), and the taxis trips' parameters (average daily traveled distance around 300km and average service trip length of 5.71km), they found that ETs would need to recharge during the day. Otherwise, they would not be able to cover all trips made by conventional taxis. They did not consider stations' capacity constraint, so that, like in previous work, they omitted any congestion at CSs, but highlighted its importance in future research.

In other study presented by Hagman and Langbroek (2019), it was possible to collect data from ETs. Their purpose was to conduct a financial analysis for the introduction of ETs. To do so, they combined data from electric and conventional taxis, operating during one year in Stockholm, together with interviews to taxi drivers. However, due to the lack of charging events' information, they could not include the fact that taxis might have to decline trips to go charging. Also the lost time while charging was omitted, which could have affected taxi's profitability. Likewise, Zou et al. (2016) show an analysis of drivers' behavior based on a dataset consisting of real operational data of ETs in Beijing. Some findings were that there are peak hours for arriving at and departing from CSs, that charging processes start when vehicles have a SoC between 30% and 50% and finish at a 90% or higher percentage of charge.

Consequently, with all these insights, a particular interest is set to the study of ETs operation in urban areas. The main goal of this chapter is to analyze and anticipate what may happen with the introduction of an ET fleet operating under a non-coordinated charging scheme, with a given charging infrastructure. To do so, a simulation approach is proposed, due to the lack of ETs operation, because during an initial phase of the implementation, it is difficult to have access to operational data. In comparison with the aforementioned works using simulation, the present study considers congestion issues, the nonlinear charging behavior of EV's battery and the compatibility between EV and CS's charging protocols.

3.2 Simulation Framework

The city of Medellín declared, as a goal, the entrance of 1500 ETs by 2020. Nowadays, the government is implementing some benefits for older taxis (more pollutant) to change to ETs. However, they have not started to operate (Ángel Orrego Arenas, 2019b), and the city authorities are expecting to have 200 by the end of the year 2019, as the legal process needs to be completed by the interested taxi operators. Consequently, as there are no ETs currently operating, there is no access to operational data of these vehicles. Due to this, a simulation is performed to analyze the currently installed public charging infrastructure with a simulated number of vehicles. The simulation method applied in this work is a discrete-event simulation. Within this approach, the system operation can be described as a sequence of events (e.g., the taxi drops off a passenger) and simulation time does not depend on clock-time but the occurrence moment of the events, which also determine the state's transition. This section explains the main steps and considerations in the simulation process.

Due to a lack of data, it is assumed that ETs' behavior follows the operational parameters of conventional taxis with the additional charging decisions related to EVs' autonomy. To emulate the operation, it is necessary to learn the travel patterns of conventional cabs. To do so, the city map was used to divide the metropolitan area in a set of zones Z according to areas of interest. A probability p_{ij}, with $i, j \in Z$, was set to define the transition of conventional taxis among zones, defining–origin-destination trips. Knowing this information, an origin–destination matrix A is created, including zone by zone and the probability p_{ij} of transition among them.

According to the activities performed by conventional taxis and the additional tasks required during the operation of an EV, the simulation considers five different states. The first state, `waiting_service`, corresponds to the moment when taxis are waiting for a new service request. Although gasoline taxis can be driving while awaiting for a service, it is assumed that ETs remain stopped until they receive a new service request, to avoid additional energy consumption. They are supposed to wait at the central point of the zone, corresponding to the last trip's drop–off location. This location will become the starting location of the next state. Thus, the service starts inside the same zone where the taxi is waiting. A second state, `travel_service`, is defined for the period during which the service is provided, making the trip from an origin to a destination.

Besides these two states, the following states illustrate the required actions when a charging event occurs. The state `travel_CS` indicates that the taxi travels from the center of the zone where it is located to a CS. It is assigned to the taxis when their battery is below a certain level of charge SoC_m. Once taxis arrive at CSs, there are two possibilities:

- If all charging plugs are occupied, the taxi must wait until one gets empty with the state value `waiting_CS`.
- If a taxi arrives and can connect immediately to a charging plug, the taxi's state becomes `charging`.

Just after the taxi finishes charging, it then starts waiting again for a new service request. The different states with their corresponding transition are illustrated in Figure 3.1.

The simulation considers a set V of ETs, where each vehicle is an independent object with its own state and attributes (e.g. home region, SoC, time, battery capacity, charging protocols available, etc.). The "time" will be the attribute used to synchronize states. This means, the time assigned to each taxi corresponds to the ending clock–time of its current state. This indicates the time of occurrence of the new event. Based on this value, the algorithm sets a 'processing list' to sort all vehicles according to its corresponding time value. This list enables to manage the whole set V, depending on the moment when events occur. The taxi with the lowest time value is placed at the top of the list. Figure 3.2 presents a general diagram, which details the simulation process with its corresponding steps.

To start the simulation, the following parameters are defined first:

1. Duration, that indicates the number of days during which simulation is run.

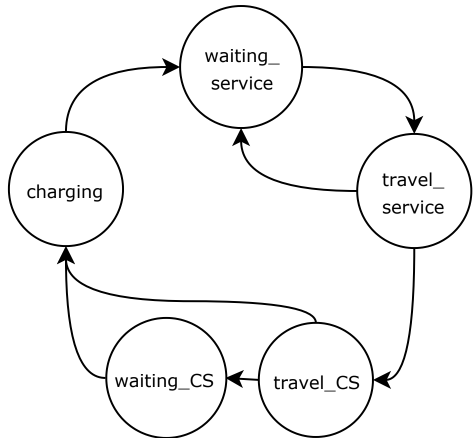


Figure 3.1: Simulation states and transitions

2. Vehicle type, which gives the characteristics of battery capacity, and compatible charger protocols and powers.
3. The number of taxis and taxi shift's starting and ending time.
4. CSs' parameters including location, number of charging spots, chargers' protocol and powers.
5. Travel area parameters, (i.e., number of zones and central point of each).

Once the settings are defined, the simulation may start. Each taxi is initialized with a fully charged battery, the state `waiting_service` and a random home region. This region is saved and it does not vary, so each taxi travels there after the shift ends and starts the next day's shift in the same region. The duration of the state `waiting_service` is random and, according to the order in the processing list, the first taxi at the top of the list is selected and it follows the described steps in the diagram (See Figure 3.2). The simulation keeps running while the list has taxis with a time value inside the shift hours, and the time does not exceed simulation duration set–up.

The simulation process requires two external modules, that are used to provide some information about the battery and the routes. They were built externally and are called by the simulation model to calculate specific values of battery and routes, needed in the simulation. These two modules are: i) The "Piecewise linear module" which allows to compute the charging time given the initial and requested SoC, the charging power and the battery capacity; and ii) The "Travel parameters module" that provides information about the routes assigned to each taxi service. These two modules are described below.

3.2.1 Piecewise Linear Module

To have a better estimation of battery charging process, an external model must be used to feed the simulation loops. Unlike other works that consider linearity during the whole battery charging

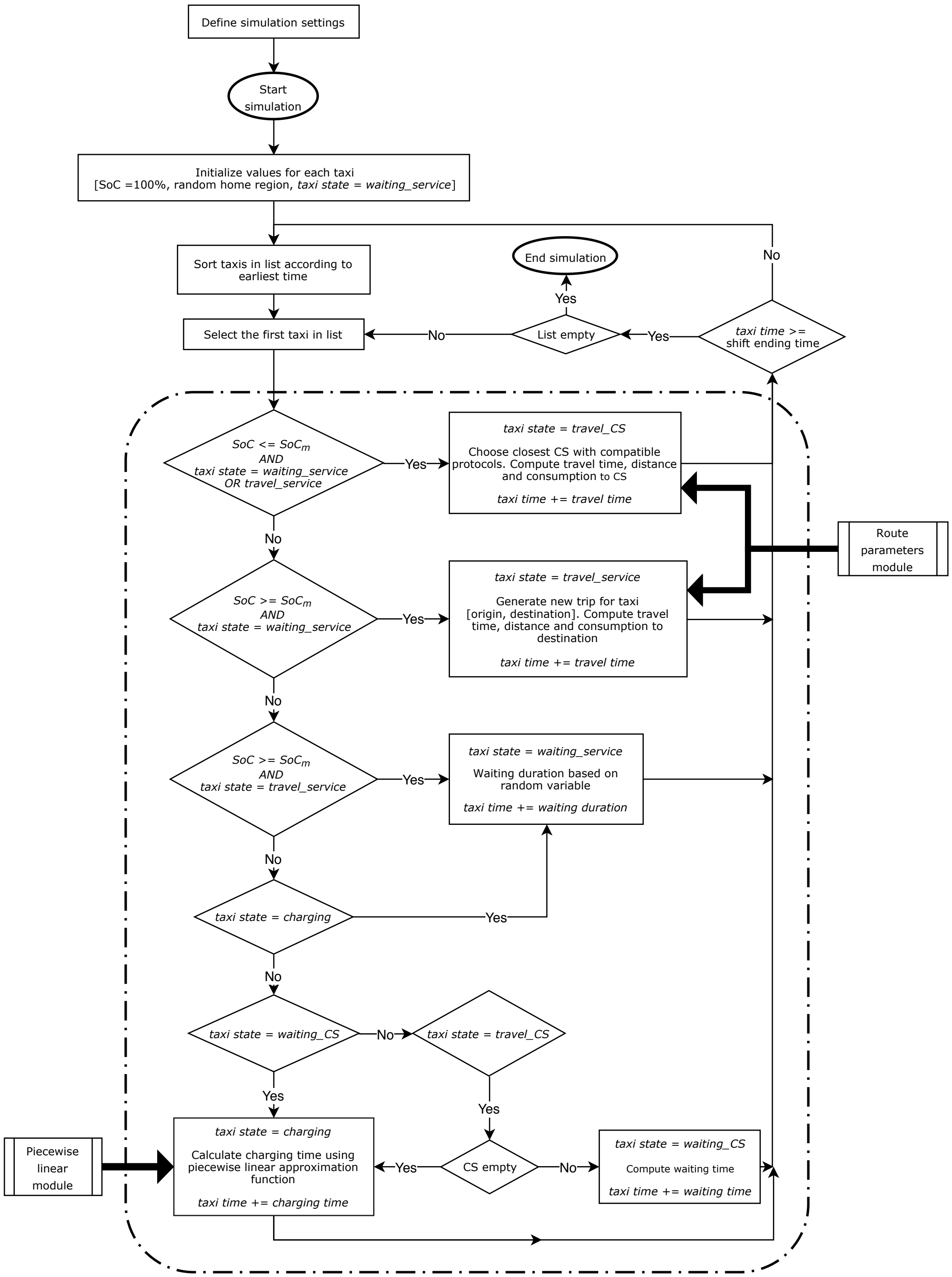
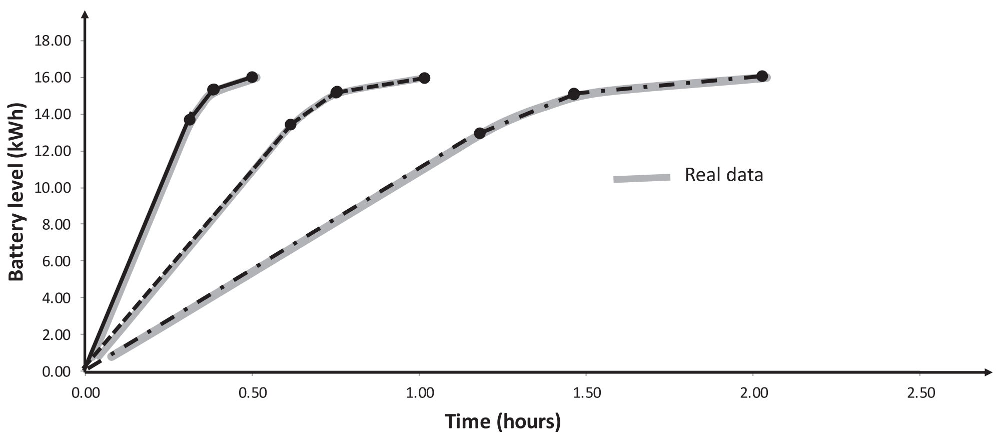


Figure 3.2: Simulation process

process, this simulation includes a non-linear charging behavior. Typically, EVs are charged using the technique of *Constant Current - Constant Voltage (CC-CV)*, where voltage and current vary during the charging. This means that, in a first phase of the process, the current is constant and in a second phase the voltage is constant. This creates a linear charging process (constant slope in the SoC) in the first phase and, in the second phase, as the current decreases exponentially, the SoC increases concavely entering a nonlinear region. Hence, the use of a piecewise linear approximation, as explained by Montoya et al. (2017), allows to have a better estimation of the time needed to charge an EV. Consequently, the piecewise linear approximation is associated with the vehicle's battery capacity and the charging power. The different linear segments of the function are established based on these values, and the function indicates the charging level for a given charging time. Figure 3.3 shows a piecewise linear approximation for a battery of 16kWh charging in a CS with three different modes: Slow at 11kW, Moderate at 22kW and Fast Charging at 44kW).



Type of CSs	Slow	Moderate	Fast
Charging power (kWh/h)	11	22	44
Piecewise linear approximation	— · —	------	———

Figure 3.3: Piecewise linear approximation for a 16kWh battery charging with 11, 22 and 44 kW (Montoya et al., 2017)

3.2.2 Travel Parameters Module

The purpose of this module is to compute values for a specific route, such as travel time, distance and energy consumption. Since there is not available data about real energy consumption of the ETs for the routes analyzed in this study, it is necessary to make a proper estimation. Instead of using an average consumption rate per drive distance, as assumed in other works (Yang et al., 2016; Hu et al., 2018), the proposed approach use the model developed by Yang et al. (2014). The required parameters to calculate consumption with this model include vehicle's characteristics[1], route's characteristics (i.e slope angle), and other aspects such as air mass density and gravity acceleration. The output of this module is the total travel distance, total travel time and total energy consumption during a trip from an origin to a destination point.

3.3 Case Study: Medellín, Colombia

The electric vehicle market in Colombia has been growing in the last years and its penetration in the public transportation sector has been of main interest. In 2013, the government of Bogotá, Colombia's capital city, launched a pilot project of ETs, planning to have 600 of these vehicles around the city three years after (Jairo Cárdenas, 2019). However, to date, only 43 are in operation. This difference with the initially expected number of vehicles is due to several factors, but the most relevant was the lack of charging infrastructure (Semana, 2019). Similarly, Medellín's government wants to make a massive implementation. With this project in mind and the continuous increase of EVs on streets, one of the challenges that shows up is related to the existing charging infrastructure and the charging process of these vehicles. The current public charging infrastructure of Medellín's and its surroundings, known as *Valle de Aburrá* (The *Aburrá* Valley), is limited to 22 CSs. Figure 3.4 illustrates the stations' location and the distribution over the *Aburrá* Valley area. The purpose of this study is to analyze this public charging infrastructure's operation for the forthcoming deployment of an ET fleet.

The travel pattern data, used in the case study, comes from the Origin-Destination (OD) survey of the *Aburrá* Valley of 2012 (Área Metropolitana del Valle de Aburrá, 2012), which is an important public effort from local authorities, in order to the policy making exercise. Since the target transportation group of this study are taxis, the dataset only includes travel patterns of this group. The data corresponding to other transportation means, such as private vehicles or buses is omitted, concentrating in the travel patterns of conventional taxis. This information, along with routes' characteristics, public CSs' information, EVs' energy consumption models and technical specifications of different EVs, lead to an approximate scenario if an ET fleet wants to be implemented in the city (with the current public charging infrastructure).

In the OD survey, the *Aburrá* Valley is divided into 476 zones, as shown in Figure 3.4. From the total amount of zones, only 360 are considered in this work, because these had complete information from taxi trips. Each zone is characterized by a central point c_i, $i \in Z$ (centroid) given by its latitude and longitude coordinates. The dataset contains the information of the probability p_{ij} of going by taxi from one zone to another in the Valley. This probability is used to simulate the taxi's operation by creating the Origin-Destination Matrix A and randomly generating the series of trips, given the

[1]Mass, rolling resistance, frontal area, aerodynamic drag coefficient, transmission efficiency, driving efficiency of the battery, vehicle's speed and acceleration.

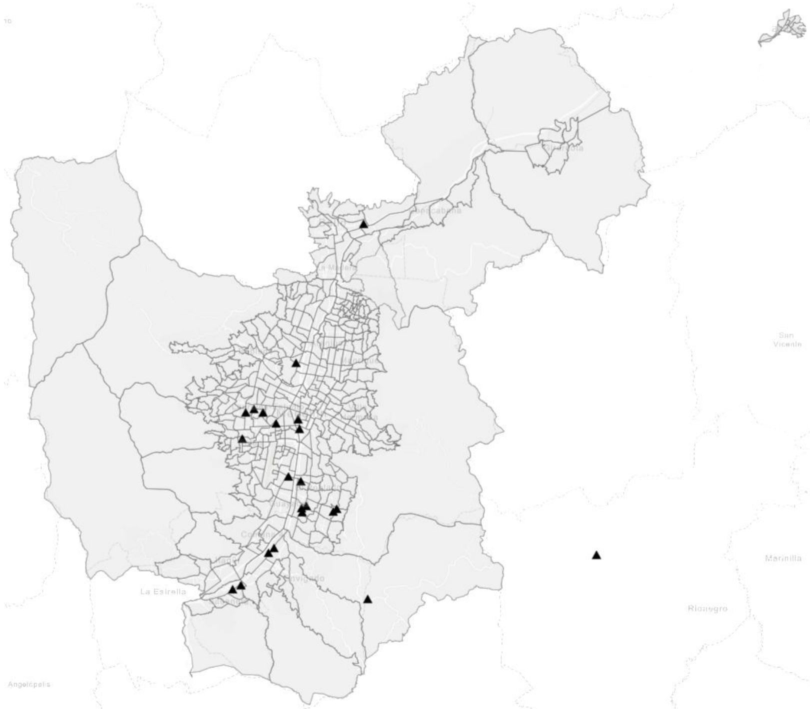


Figure 3.4: CSs of The *Aburrá* Valley

current location of a taxi. Once a trip is generated, the module described in section 3.2.2 is used to calculate travel time t_t, travel distance t_d and energy consumption t_c, from the central point of the origin (c_i) to the central point of the destination (c_j).

The data concerning charging infrastructure considers current installed CSs, represented by the set C. Each station $l \in C$ has a location o_l, maximum capacity y_l (number of charging plugs and charging spots available to park multiple vehicles at the same time), compatibility with the different charging protocols R and the power u_l used to charge the vehicles. These parameters associated with the 22 public CSs installed in the urban area are detailed in Table 3.1. As it can be seen, the technology varies among stations. Most of them are installed with fast AC chargers, while few others provide the rapid charging option.

The type of taxis to be used in Medellín is not yet defined, as it will be the Taxi owner decision. However, the type of taxi (brand and model) has a significant impact in the operation and charging tasks. That is why six different types of vehicles were considered in the simulation to evaluate the effects of having an electric taxi fleet of each model. Their characteristics and parameters, required to calculate the energy consumption using the model described in Yang et al. (2014), are listed in Table 3.2. Among the six models considered in the study, there are 5 brands where two models of one of them (BYD) were considered, given their high battery capacity. Those are considered great

Station	Latitude	Longitude	# of plugs	# of park. spots	Charging protocols and powers
CS1	6.1537	-75.5417	4	4	Type 1 - 7.4kW / Schuko - 2.3kW / Type 2 - 22kW
CS2	6.1766	-75.5911	4	4	Type 1 - 7.4kW / Schuko - 2.3kW / Type 2 - 22kW
CS3	6.1586	-75.6089	3	2	CCS - 50kw / CHAdeMO - 50kW / Type 2 - 43kW
CS4	6.3396	-75.5435	4	3	Type 1 - 7.4kW / Schuko - 2.3kW / Type 2 - 22kW
CS5	6.2426	-75.5761	4	3	Type 1 - 7.4kW / Schuko - 2.3kW / Type 2 - 22kW
CS6	6.2408	-75.5871	4	3	Type 1 - 7.4kW / Schuko - 2.3kW / Type 2 - 22kW
CS7	6.1788	-75.5883	3	2	CCS - 50kw / CHAdeMO - 50kW / Type 2 - 43kW
CS8	6.2462	-75.6022	4	4	Type 1 - 7.4kW / Schuko - 2.3kW / Type 2 - 22kW
CS9	6.1967	-75.5741	4	3	Type 1 - 7.4kW / Schuko - 2.3kW / Type 2 - 22kW
CS10	6.2460	-75.5936	4	2	Type 1 - 7.4kW / Schuko - 2.3kW / Type 2 - 22kW
CS11	6.2121	-75.5747	4	4	Type 1 - 7.4kW / Schuko - 2.3kW / Type 2 - 22kW
CS12	6.1969	-75.5587	4	4	Type 1 - 7.4kW / Schuko - 2.3kW / Type 2 - 22kW
CS13	6.2381	-75.5755	3	2	CCS - 50kw / CHAdeMO - 50kW / Type 2 - 43kW
CS14	6.2332	-75.6041	4	6	Type 1 - 7.4kW / Schuko - 2.3kW / Type 2 - 22kW
CS15	6.1755	-75.4276	3	1	CCS - 50kw / CHAdeMO - 50kW / Type 2 - 43kW
CS16	6.1998	-75.5722	4	4	Type 1 - 7.4kW / Schuko - 2.3kW / Type 2 - 22kW
CS17	6.1605	-75.6046	4	4	Type 1 - 7.4kW / Schuko - 2.3kW / Type 2 - 22kW
CS18	6.2709	-75.5773	4	3	Type 1 - 7.4kW / Schuko - 2.3kW / Type 2 - 22kW
CS19	6.2480	-75.5982	3	2	CCS - 50kw / CHAdeMO - 50kW / Type 2 - 43kW
CS20	6.1989	-75.5746	2	2	Type 1 - 7.2kW / Schuko - 3.6kW
CS21	6.2145	-75.5810	3	2	Type 1 - 7.2kW / Schuko - 3.6kW / Type 2 - 7.2kW
CS22	6.1985	-75.5568	3	1	Type 1 - 7.2kW / Schuko - 3.6kW / Type 2 - 7.2kW

Table 3.1: Medellín CSs characteristics

candidates for taxi fleets and available commercial offer in the city. Table 3.2 describes the vehicle's connectors, which determine charging compatibility with stations and limit the charging power.

Vehicle	Battery (kWh)	Weight (kg)	Frontal area (m^2)	Drag coefficient	Rolling resistance coefficient	Connector
BYD1	47.5	1900	2.997	0.30	0.015	Type 2
BYD2	61.4	2380	2.997	0.30	0.015	Type 2
Hyundai Ioniq	28.0	1420	2.220	0.24	0.015	Type 2, CCS
Kia Soul	27.0	1490	2.328	0.35	0.015	Type 1, CHAdeMO
Renault Zoe	22.0	1468	2.590	0.29	0.015	Type 2
Nissan Leaf	24.0	1475	2.276	0.32	0.015	Type 1, CHAdeMO

Table 3.2: Vehicles parameters

Therefore, the following assumptions are considered for the taxis' operation:

- The operational time is twelve hours (from 7:00AM to 7:00PM) as, in the local context, taxis work between 12 to 13 hours average, and travels around 200 and 250km per day (Ángel Orrego Arenas, 2019a).
- There is only one daily shift of 12 hours per taxi.
- Taxis can charge at public CSs and have access to domestic charge; thus, they start the shift with the battery charged.

- Each taxi drives to the closest CS when need charging.
- Different charging protocols might be available at a CS. If multiple chargers are available at a station when a taxi arrives, the fastest charger (i.e highest charging power) is chosen.
- The duration of the state `waiting_service` is generated using a random exponential distribution. Due to the lack of information about this parameter for the taxis' operation in Medellín, it is assumed that the service requests arrival rates follow a Poisson process.

In this study, one simulation was carried out for each type of vehicle of Table 3.2. Although the government has the final goal of 1500 taxis, the plan is to make a scaled implementation. For the initial phase of the project, it is expected to have 200 taxis to start operation by the end of 2019 (Ángel Orrego Arenas, 2019b). Thus, three different amount of taxis (100, 150, 200) were considered, having a total of eighteen scenarios to evaluate. The simulation time is set to 50 days, including 20 days as a warm-up period, and the number of replicates, for each scenario, is set to 114.

3.4 Preliminary Results and Discussion

The output variables to be analyzed for each scenario, in order to evaluate the scenarios' performance (with issues such as occupancy, waiting time, etc.) include:

1. How many taxis must wait when arriving at the station, V_w.
2. The waiting time t_w for those events. It is assumed that taxis only wait until one hour after the shift ends. Otherwise, if a taxi driver waits until this time at the station and the charging spots are still occupied, then the charging service is declared failed. Since the taxis have access to domestic charging, it is considered unfeasible that a taxi driver waits for a long period, even during night time, at public CSs.
3. Percentage of failed charging events. Two types of fails are considered: i)S_f, when waiting time t_w exceeds the time limit, ii)S_u, when taxis run out of battery traveling to the station (i.e., SoC is not enough to reach the closest CS).
4. Occupancy, i.e. Percentage of simulation time during which stations were occupied, described by $B_l, l \in C$.
5. The maximum queue size in each station, $Q_l, l \in C$.

Considering the six types of vehicles (as described in Table 3.2), each has shown different behaviour during the simulation. Figure 3.5 presents the boxplots, by vehicle type, of the average waiting time $\overline{t_w}$ (in hours) of charging events for the scenarios with 100, 150 and 200 taxis. Figure 3.6 displays the boxplots of the percentage of failed events S_f due to waiting time limit. And Figure 3.7 indicates the percentage of charging events that required some waiting time S_w ($t_w > 0$). The mean of each scenario is marked by the squared points.

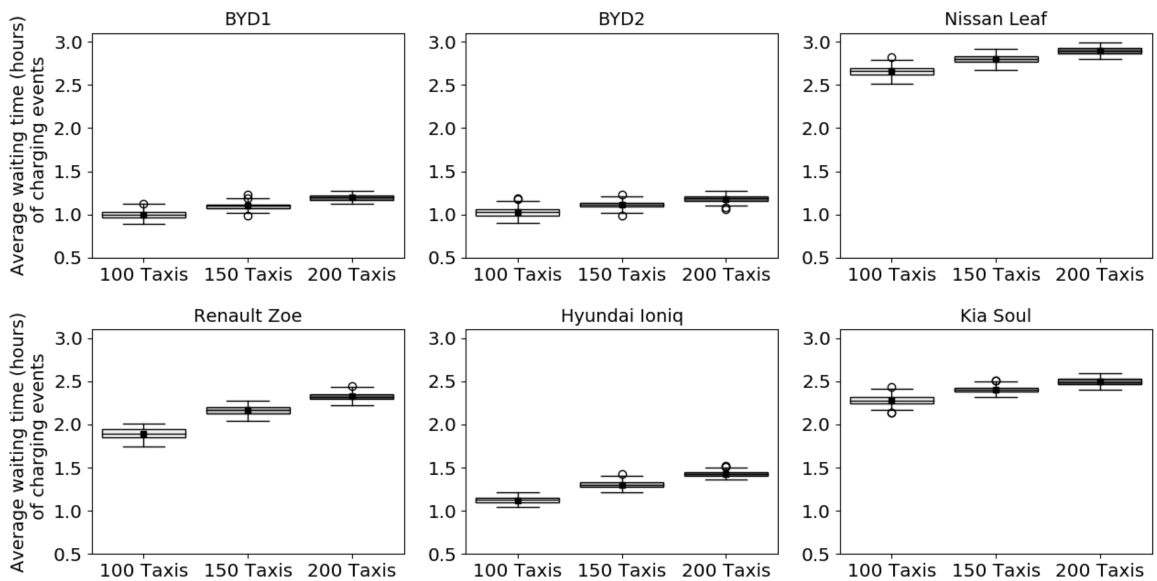


Figure 3.5: Average waiting time

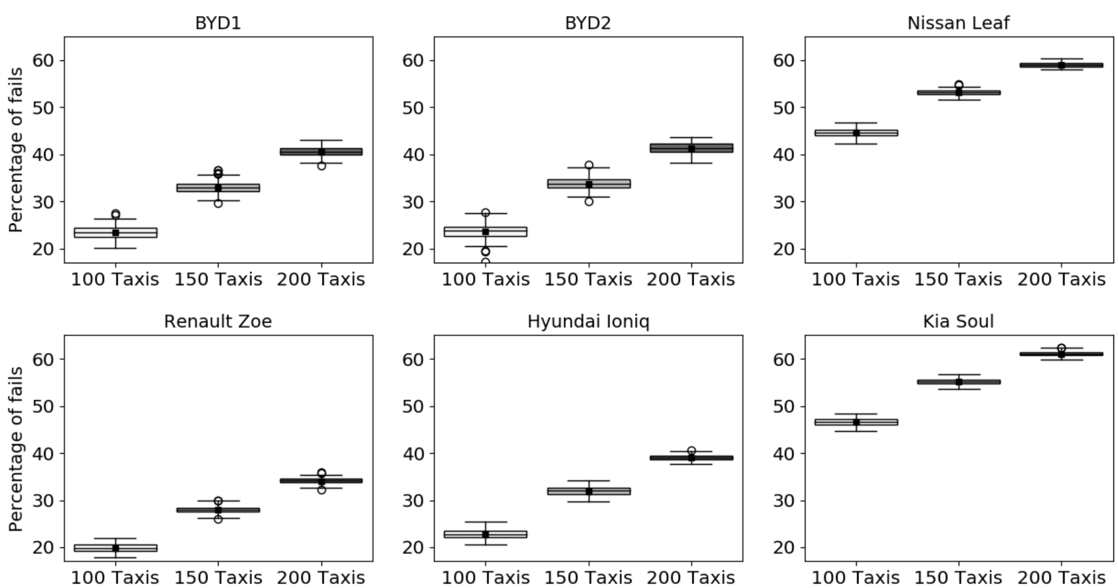


Figure 3.6: Percentage of failed events due to waiting time limit

As expected, in all cases, as the number of taxis increased, the value of the indicators also increased. In general, the Nissan Leaf (NL) and the Kia Soul (KS) had, both, the highest values for the three indicators ($\overline{t_w}$, S_f, S_w). Even though these two vehicles have a battery capacity similar to the Hyundai Ioniq (HI) (28kWh), their results show higher values compared to those from the HI. A reason for this,

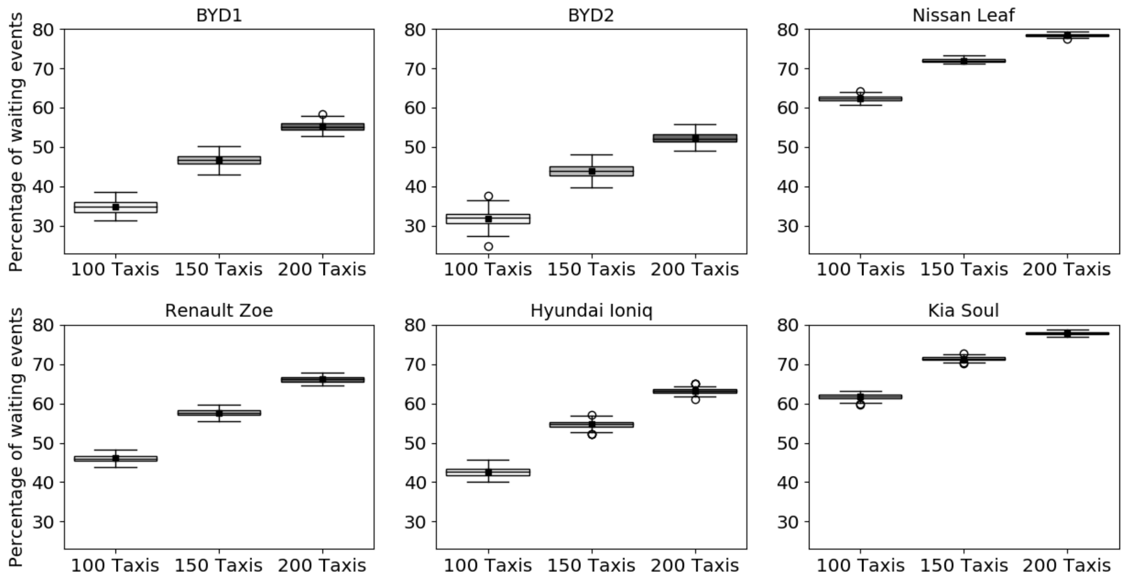


Figure 3.7: Percentage of waiting events

may be that the Type 1 connector, which is installed in NL and KS, supports a smaller charging power than the Type 2 connector of HI. This Type 1 connector, could cause longer charging times and longer time occupancy of station plugs. Although these vehicles are also equipped with a CHAdeMO protocol, few CSs provide this kind of charge and the majority are limited to offering AC level 2 charge. Furthermore, the percentage of wait events S_w for the smallest fleet scenario (100 Taxis) of NL and KS is higher than the values reached in the biggest fleet scenario (200 taxis) of BYDs and close to the Renault Zoe (RZ) and HI. These results shown that the NL and KS are the least favorable option, under uncertain charging patterns of a taxi fleet for the current infrastructure. From the above analysis, one key observation is that taxis with similar battery capacity can behave differently, according to charging connectors installed either on the vehicles or the stations.

When analysing the average waiting time $\overline{t_w}$ and percentage of fails S_f, it can be observed that the two BYDs and HI have similar behavior. However, the HI has a probability of waiting time around 10% more (as seen in Figure 3.7). Since charging a HI takes less time than the charging of BYDs (i.e. charging with the same power), this increment in the probability of waiting time, can be associated with higher congestion at some stations, caused by a greater charging demand. Due to a smaller autonomy of this vehicle, compared with the BYDs, it is more likely to have more taxis requesting a charge.

If the average waiting time is analyzed alone, values do not seem high, compared with the time that takes charging these vehicles. However, the high percentage of fails shows low availability at public CSs. Taking into account that the daily working hours of taxis are around 12 hours, if 30% or more of the charging events require waiting (as seen in Figure 3.7), with a mean waiting time between

1-3 hours, the taxi's availability and profitability could be negative affected.

Regarding the percentage of fails due to SoC, S_u, Figure 3.8 displays the results only for vehicles with $S_u > 0\%$. As expected, the vehicle with the smallest battery, (i.e. RZ), reached the highest percentage of fails due to SoC. This issue is associated with the vehicle's autonomy. Since taxis go charging when SoC is below 30%, 6.6kWh can be insufficient to reach a CS in the city, depending on the location of the taxi. As it can be seen, this indicator does not change significantly as the number of taxis increased, but it remains quite stable.

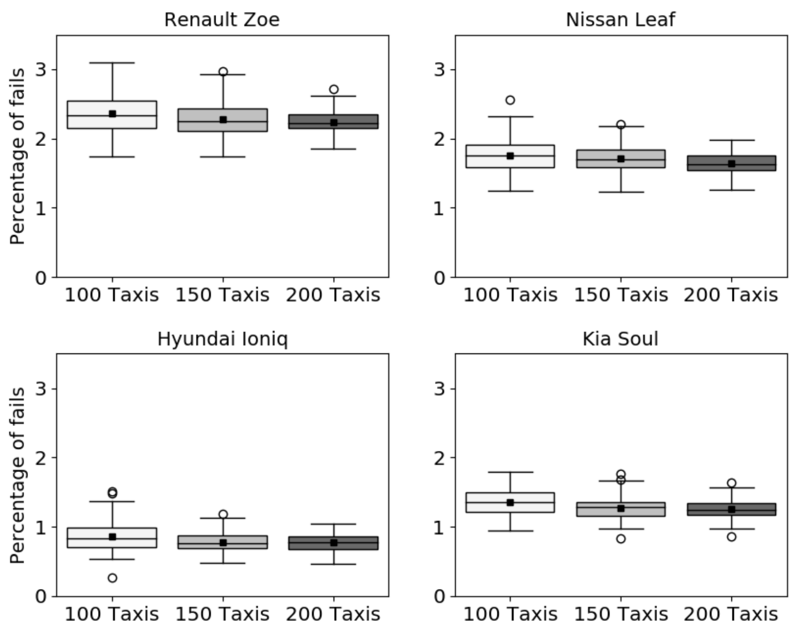


Figure 3.8: Percentage of failed events due to insufficient SoC

At the same time, occupancy of CSs is displayed in Figure 3.9. Each subfigure depicts vehicles that share similar characteristics of battery capacity and connector type. Each bar indicates the maximum queue size experienced at each of the 22 public stations, for the three scenarios (100, 150 and 200 taxis). Additionally, the average occupancy (i.e. the percentage of simulation time that each station was occupied, with at least one taxi) is indicated above each bar. As it can be seen, there is a similar behavior between charts of Figure **??**; Figures **??** and Figures **??**.

The two vehicles with the biggest charging capacity (BYDs), which also results in higher charging times, display smaller queues. Thus, a higher maximum queue can be associated with the incremental charging demand from vehicles with smaller battery, rather than charging times.

Moreover, looking closer to the size of the maximum queues, where you find queues of up to 50 taxis, it is important to analyze if it is physically possible to have that amount of taxis parked at stations while waiting during peak arrival times. This issue could bring other problems at stations and their surroundings. Since taxi drivers have access to domestic charge, they start the shift with

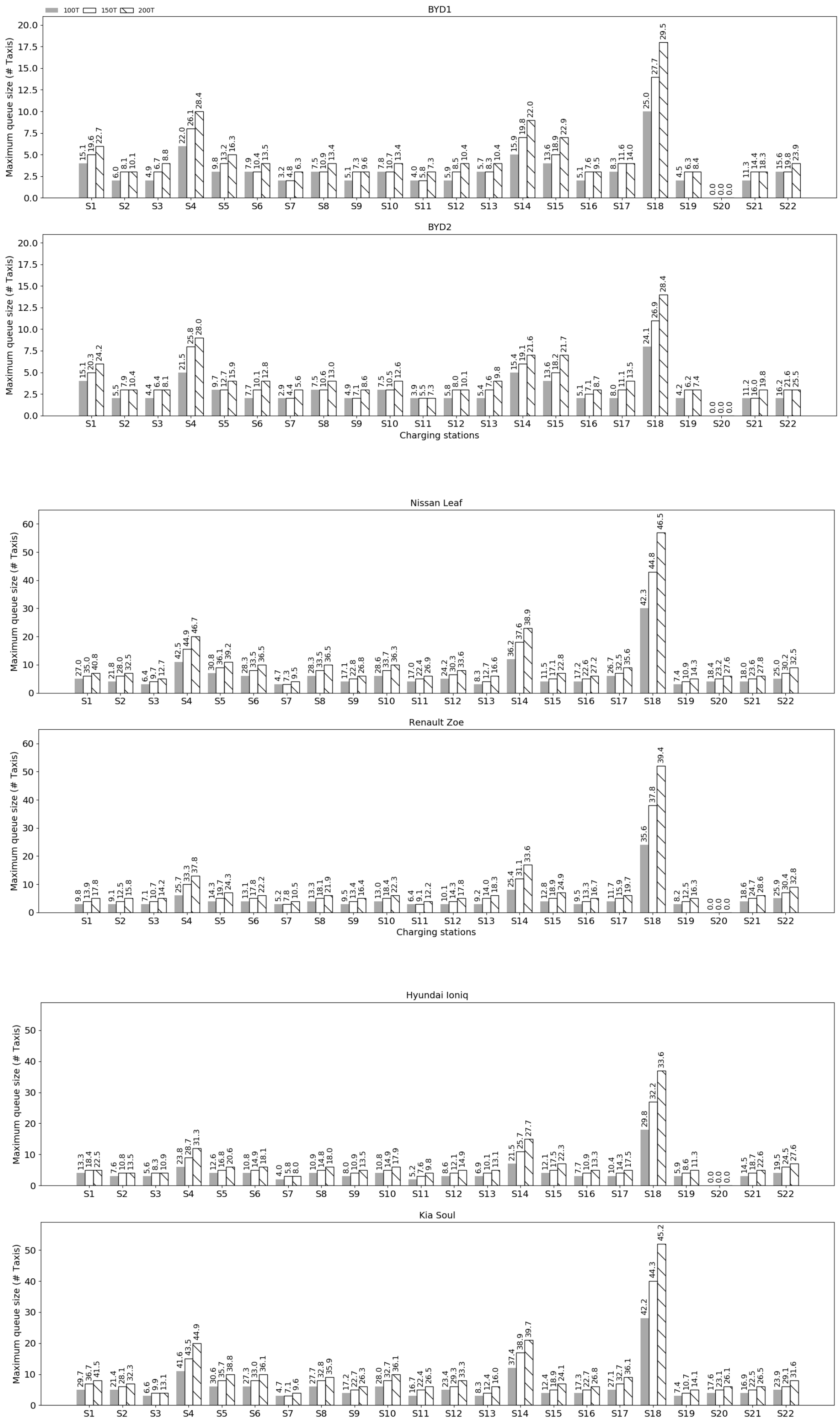


Figure 3.9: Average occupancy and maximum queue size

a fully charged battery. If they have similar behavior, in terms of travel distances during shifts, it is more likely that multiple taxis run out of battery at the same moment and travel to CSs around the same time, generating congestion peaks.

Furthermore, when examining all plots together (from Figure 3.9), some stations tend to reach higher values of occupation and queue size. Particularly, stations 18, 14 and 4. This may be associated with the distribution of trips made by taxis along with the stations' limited capacity (given by the number of plugs or parking spots). Therefore, to emphasize in the aforementioned issue, the travel distribution of the scenario with 200 taxis BYD1, has been closely analyzed. The map in Figure 3.10 indicates the CSs' location in the *Aburrá* Valley and shows in darker tones the most visited regions by taxi trips according to the OD Survey used for the simulation. The number above each station indicates the percentage of time while the station was occupied. When analyzing the trips' distribution, it is clear that stations 4 and 18 have higher charging demand, since they are the only stations that cover a wide area where taxi trips occur the most. Similarly, station 14 is located near to a zone with high trip demand and does not have other stations close enough to share the charging demand. Contrarily with stations 8, 19, 10 and 6, which share the charging demand due to their proximity. Likewise, CS 15 is the only one covering the area around the International Airport located just outside the city.

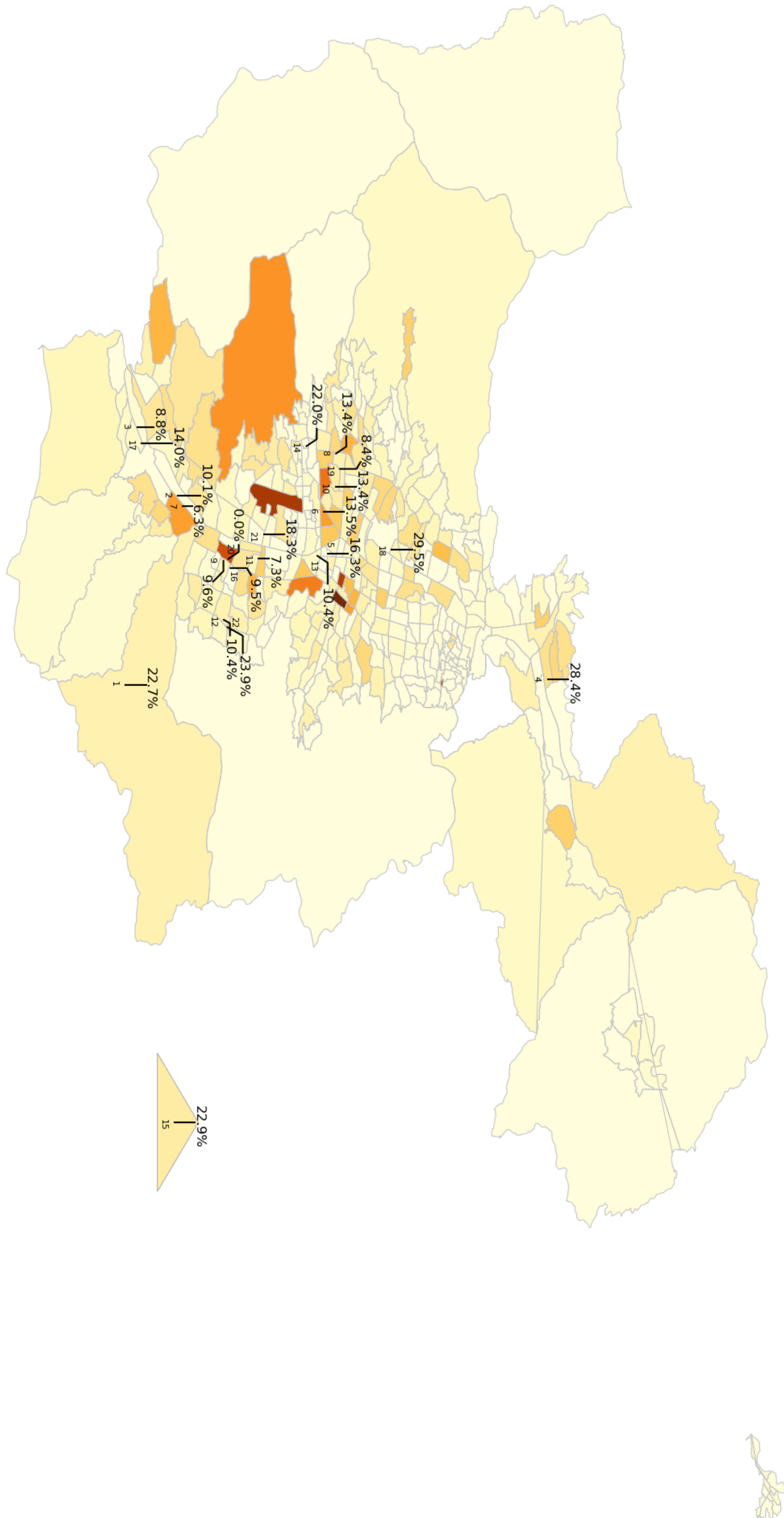


Figure 3.10: Trips distribution and CSs occupancy

Chapter 4

Coordinated Charging Strategy

This chapter contributes to the existing literature by presenting a proposal of a CC strategy based on "reservations" in a network of PVCSs. In comparison with the related works (see Section 2.1.1), this strategy considers the non-linear charging behavior of EV's battery, the integration of PV and the compatibility between EV and CS's charging protocols. Besides, it looks after the interests of both EV users and CSs' operator, enhancing the QoS, which involves the availability, execution duration and execution price of the charging service.

4.1 Scheduling System Description

The purpose of the reservation system is to efficiently manage charging requests on a network of PVCSs. Given a set of EVs users requesting charging services, the goal is to find a schedule for most of the users so that the number of declined services is minimized and the availability of the service is strengthened. Additionally, a percentage of the energy provided to the accepted users must come from the PV source. In this way the operator's profit and the service execution price might improve.

The system controls the reservations of a set C of charging stations that belong to the same operator and are located in a scattered area. Each station $j \in C$ is equipped with Y_j charging points. Given that the stations in the network can work with multiple charging protocols (e.g. CHAdeMO, CCS, Type 1, among others), the compatibility of each charging point with the different protocols available is taken into account. Depending on the charging protocol, the charging point $k \in Y_j$ provides a specific power to charge the vehicle. All CSs are connected to the grid, and some of them have, as well, solar energy generation by integrating a PV array of size f. Assuming that the stations' operator has a forecasted output power of the PV arrays, the reservation system gets the PV energy ϕ_j available at each station $j \in C$.

Each day, the system collects a batch of charging requests from a set V of users that are driving inside a specific area, which is divided in a set of zones Z. The parameter d_{jh} indicates the distance from the station $j \in C$ to the center point of a zone $h \in Z$. Each user $i \in V$ is characterized by its charging information. When an user submits a request, he/she must specify a charging start and finish limit time, a_i and l_i respectively, which determine the time-window available of each user to complete the charging service. The user also specifies the initial and final (target) SoC denoted by SOC_i and $\overline{SOC_i}$. Besides, the system also gets information about the current location of each user and about some attributes of his/her vehicle, such as the battery capacity and the charging protocols admitted. Then, with the battery capacity information and the initial and final SoC, the energy requested by each user for the charging service is calculated.

In addition to the parameters specified by each user, the reservation system must consider two other factors:

i. There is a maximum allowed travelled distance v for the users.

ii. Respecting the total energy charged by accepted users. A minimum percentage (α) must be supplied by the PV source.

The parameter v limits the stations that the user can visit, as he/she can be assigned only to stations that are located inside the travelled distance v. Furthermore, for those CSs that include solar generation, the system requires information about the generated power by the PV arrays. Finally, the system should accurately calculate the charging duration and charged energy that would take each service.

As mentioned in Section 2.1.1, it is important to consider the non-linear charging behavior of EVs' battery. Thus, the piecewise linear function (described in Section 3.2.1) is used to calculate, with more reliability, the time it takes to charge a vehicle from its initial SoC to the desired final SoC. This function returns the time and the energy charged in each linear segment of the piecewise approximation. Hence, for a given SOC_i, $\overline{SOC_i}$, a battery capacity and a charging power, the total charging duration θ_{ijk} and the total energy charged κ_{ijk} by the user $i \in V$ at the charging point $k \in Y_j$ of station $j \in C$ is computed.

Once the system has the previous required information about the charging requests, it may determine the charging schedule for each user, trying to maximize the number of accepted services (i.e. assign a schedule to most of the users requesting a charging service). If the charging request of a user is accepted and a schedule is assigned to him/her, the variable x_{ijk} is equal to 1 indicating that user $i \in V$ is scheduled at the charging point $k \in Y_j$ of station $j \in C$. Otherwise, a zero (0) is assigned to x_{ijk}.

Consequently, the objective function of the scheduling system is expressed as follows:

$$Max \sum_{i \in V} \sum_{j \in C} \sum_{k \in Y_j} x_{ijk} \tag{4.1}$$

The system sets, for each accepted user, his/her charging start time τ_{ijk} and charging finish time ϵ_{ijk}. The distance traveled by the user from his/her current location to the assigned CS is denoted by b_i. According to the amount of energy (kWh) charged by each vehicle, denoted κ_{ijk}, the variable γ_{ijk} indicates the share of energy that comes from the PV source.

Accordingly, the schedule parameters must satisfy the following conditions:

$$\tau_{ijk} \geq a_i \tag{4.2}$$

$$\epsilon_{ijk} \leq l_i \tag{4.3}$$

$$\epsilon_{ijk} - \tau_{ijk} = \theta_{ijk} \tag{4.4}$$

$$b_i \leq v \tag{4.5}$$

$$\frac{\sum_{i \in V} \sum_{j \in C} \sum_{k \in Y_j} \gamma_{ijk}}{\sum_{i \in V} \sum_{j \in C} \sum_{k \in Y_j} \kappa_{ijk}} \geq \alpha \tag{4.6}$$

$$\sum_{i \in V} \sum_{j \in C} \sum_{k \in Y_j} \gamma_{ijk} \leq \phi_j \qquad \forall j \in C \tag{4.7}$$

Equations 4.2-4.4 ensure that the charging times remain within the available time-windows specified by users and that the times are consistent with the charging duration. Since the execution duration of the charging service is related with the QoS, it is of special interests to take care of the time variable and the availability of users. Equation 4.5 ensures that the CS assigned to an user is within the allowed travel distance. Equation 4.6 is used to guarantee that an α percent of the energy charged is PV. And, by last, equation 4.7 ensures that the consumed PV energy at each station is not greater than the generated PV energy.

4.2 Coordinated Charging Strategy Description

A GRASP[1] based heuristic algorithm was developed to address the scheduling problem as contribution towards a coordinated charging strategy.

The scheduling problem handled in the coordinated charging strategy can be reduced to a Multidimensional Knapsack Problem (MKP). The MKP can be described as follows: there is a given set of m resources with capacities c_i and a set of n items, where each item j has a profit p_j and consumes an amount w_{ij} from each resource i. The goal is to select a subset of items with maximum total profit, but chosen items must not exceed resource capacities (Puchinger et al., 2006). Suppose that the problem studied in this research is simplified by relaxing the constraints related to charging protocols compatibility, maximum traveled distance, and users' available time-windows. In this way, all the charging points from all stations could work with the whole set of available charging protocols, and all the vehicles would admit, as well, all the charging protocols. Thus, as the users could drive to any station independently from the travel distance, all users would be able to charge at all charging points. However, the charging points have a limited capacity to attend users in a specific clock-hours. On these terms, the simplified problem becomes where and which charging request to assign to each of the charging points, so that the number of assignments is maximized. If each charging point is seen as a resource m, where its capacity dimension is time, and each charging request is seen as an item n, that consumes a certain charging time and has a utility of 1; then, the current problem simplified, by relaxing the above constraints, can be seen as a MKP, which has been proved to be NP-hard (Magazine and Chern, 1984). Therefore, the current problem with its original constraints could also be considered as an NP-hard problem. Besides, the scheduling problem of EVs has been considered to be a NP-hard problem in some studies; thus, a wide diversity of applications implementing heuristics and metaheuristics methods can be found in the literature. Accordingly, in the present research, a GRASP-based heuristic algorithm is developed. This method has been implemented in a wide variety of applications, including fields such as scheduling, routing, location, assignment, transportation, among others (Festa and Resende, 2009). And it has shown, as well, promising results in solving the MKP (de Almeida Dantas and Cáceres, 2015).

The GRASP is a iterative process, where each iteration consists in two phases: i) a randomized constructive phase and ii) an improvement phase. The best solution found after the iterative process finishes, is kept as the final solution. The GRASP method, either with its basic components or with some modifications, has been implemented in some scientific works concerning EVs charging strategies. As described in the literature review from Section 2.1.2, García-Álvarez et al. (2018) developed a scheduling algorithm based on the GRASP method to minimize the total tardiness experienced by users at a CS. Authors in Arias et al. (2017) proposed a hybrid method, that uses the construction

[1]Greedy Randomized Adaptive Search Procedure (GRASP)

phase of the GRASP and the short-term memory of TS for the LS phase, to mitigate the operational costs of the electrical distribution system when coordinating the charging of EVs. For the admission control mechanism proposed in Wei et al. (2018), where both profit and QoS are of main interest, authors presented a scheduling model, combining a greedy-based and a price-oriented algorithm. Likewise, Wang and Yang (2018) employed a greedy algorithm to determine which charging requests are declined and a deadline-based algorithm to schedule the admitted services. They compare their proposal with FCFS and LLF algorithms.

4.2.1 Constructive Phase

The output of the GRASP' constructive phase is an initial solution that is iteratively built, as presented in Algorithm 1. The process initialize once the whole information of the available CSs from an operator and the batch of charging requests from EV users is available. The process begins by sorting CSs in a list according to their PV generation capacity, and by sorting users' requests in another list according to the energy demand (lines 2-3, Alg. 1). Then, the iteratively construction of the initial solution begins.

A set of n CSs containing the highest PV generation capacity are selected for the Restrict Candidates List (RCL) (line 5, Alg. 1) and one of them is randomly chosen (line 6, Alg. 1). For the chosen station, the algorithm seeks to schedule the EVs that are compatible with this CS, at the charging points that work with the charging protocol admitted by each vehicle. The algorithm selects, if possible, the time interval to schedule an EV (lines 7-25, Alg. 1), according to the:

- charging times available at the charging points of the station
- time submitted by the EV user in the charging request,
- charging duration (i.e. calculated with the piecewise linear function)
- PV energy generation during those times.

The algorithm seeks to schedule the vehicle at the time with the highest share of energy obtained from PV (lines 12-18, Alg. 1). Thus, at each iteration of the constructive algorithm, an EV might be scheduled. The constructive loop stops when it is not possible to schedule the missing charging requests due to feasibility issues, or at the best scenario, it stops when all charging requests have been accepted and have a schedule assigned. Only the initial solutions that are feasible, are considered for the improvement phase.

4.2.2 Improvement Phase

This phase, as its name suggests, looks to improve the initial solution obtained in the previous phase. It consists on a LS with a Variable Neighborhood Descent (VND) structure and a best improving

Algorithm 1: Constructive phase

Initialization
Sort the set of stations C
Sort the set of users V
while *stop condition is False* **do**
    RCL $\leftarrow$ {n stations $\in C$}
    Choose one station $j \in C$ randomly from RCL
    for *each user* $i \in V$ *able to charge at station* j **do**
        Choose the charging point $k \in Y_j$, $j \in C$ that works with charging protocol admitted by the vehicle of user i
        Get the set of available time intervals I_k at charging point k, that match with the time-window of user i and have a duration $\geq$ the charging duration θ_{ijk} of user i
        if $I_k \neq \{\}$ **then**
            $maxP \leftarrow 0$
            for *each time interval in* I_k **do**
                Get the available PV energy
                Compute the share of energy γ_{ijk} charged from PV if user i is scheduled in this time interval
                if $\gamma_{ijk} > maxP$ **then**
                    $maxP \leftarrow \gamma_{ijk}$
                    $sch_{interval} \leftarrow$ current time interval
                end
            end
            Assign schedule parameters to user i:
            $\tau_{ijk} \leftarrow$ lower limit of $sch_{interval}$
            $\epsilon_{ijk} \leftarrow$ upper limit of $sch_{interval}$
            $x_{ijk} \leftarrow 1$
        end
    end
    if *there are not more EVs to schedule or there are not more CSs available* **then**
        stop condition = True
    end
end

strategy, where the whole neighborhood N_k is analyzed and the best solution replaces the current one. The algorithm for implementing the improvement phase is summarized in Algorithm 2.

There are two neighborhoods, $k = \{1, 2\}$. The move that defines the first neighborhood consists of inserting a non-assigned EV user in a charging point, of some compatible station, and shifting to a new feasible schedule the already assigned EVs that intersect with the new vehicle. At each iteration the reached solution is evaluated according to Eq. 4.1 and in terms of β (i.e. the total share of energy obtained from PV). After exploring the first neighborhood, the best reached solution replaces the current solution (line 20, Alg. 2) and the search process begins again in N_1. However, when no improvements are found in N_1, the k index is increased (line 22, Alg. 2) and the search process continues in N_2. The second neighborhood is defined by removing an assigned EV and inserting a non-assigned EV in the time interval that gets free with the previous removal. When improvements are found in N_2, the best option is chosen replacing the current solution and the search loop starts again in N_1. The algorithm terminates when reaching a solution that is a local optimum with respect to all neighborhoods.

4.3 Computational experiments

This section presents the computational studies conducted to evaluate the performance of the proposed charging strategy.

4.3.1 Input Data: Case Study of Medellín

As introduced in Chapter 3, the city of Medellín, Colombia, has been working in mobility alternatives that contributes to reduce air pollution. Due to the high interest in electrifying the taxis transport sector, the type of EV users involved in the case study are electric taxis' drivers. The Case Study presented in Section 3.3 provides inputs for the current case.

The information about the charging requests, required to evaluate the strategy, comes from the traveling profiles of ETs from the last Case Study, which were generated through the simulation model described also in Chapter 3. These profiles were created based on the travel patterns of conventional taxis drawn from the OD Survey of the *Aburrá* Valley of 2012 (Área Metropolitana del Valle de Aburrá, 2012). From the traveling profiles it is possible to track, for each user V_i, the behaviour of the SoC, the distances and times traveled in each trip, allowing to identify the clock-times and locations (zone) at which taxi drivers must need to go charging ($SOC_i \leq 30\%$). Then, this data is used to establish the sets of charging requests. An example of how charging requests would look like is shown in Table 4.1. Since the total number of EVs rolling out in a city might affect the congestion level at public CSs, three different amount of taxis (100, 150, 200) are considered for the simulation. Besides,

Algorithm 2: Improvement phase

```
Initialization
y ← initial solution
k ← 1
best_sol ← y
while stop condition is False do
    if k ← 1 then
        for each non-assigned user r, r ∈ V of the solution y do
            Assign a schedule to user r
            Evaluate if the schedule of an assigned user a, a ∈ V of the solution y
              intersects with the schedule of r
            for each user a that intersects with user r do
                Shift user a to a new time interval
            end
            y' ← new solution reached
            Calculate value of Eq.4.1 and β(y')
            if value(Eq.4.1) improved and β(y') > β(y) then
                best_sol ← y'
            end
        end
        if best_sol ≠ y then
            Update current solution, y = best_sol
        else
            k ← 2
        end
    end
    if k ← 2 then
        for each assigned user a, a ∈ V of the solution y do
            Remove the schedule of user a from the solution y
            for each non-assigned user r, r ∈ V of the solution y do
                Evaluate if user r can be schedule at the new free time interval
            end
            y' ← new solution reached
            Calculate value of Eq.4.1 and β(y')
            if value(Eq.4.1) improved and β(y') > β(y) then
                best_sol ← y'
            end
        end
        if best_sol ≠ y then
            Update current solution, y = best_sol
            k ← 1
        else
            stop condition = True
        end
    end
end
```

these taxis can belong to one of the six different types of vehicles specified in Table 3.2.

$\mathbf{V_i}$	$\mathbf{a_i}$	$\mathbf{l_i}$	$\mathbf{SOC_i}$	$\overline{\mathbf{SOC_i}}$	**Location (zone)**	**Vehicle type**
V1	17.26	20.12	0.29	0.91	Z203	BYD1
V2	17.79	20.65	0.28	0.88	Z203	BYD1
V3	17.35	20.21	0.25	0.99	Z338	BYD1
V4	17.52	20.38	0.30	0.89	Z293	BYD1
V5	18.12	20.98	0.25	0.98	Z394	BYD1

Table 4.1: Example of charging requests, taken from instance number 4 of the group with the charging requests from 100 taxis

In addition to the information about the charging requests, it is necessary to have the charging infrastructure's data. The case study considers a subset of 19 stations from the network of public CSs described in Table 3.1, specifically from CS1 to CS19, which are managed by the same operator. This set of stations are installed either at an indoor parking lot, at an outdoor parking lot or at a gas service station. The last two with the possibility of having a roof-mounted PV array.

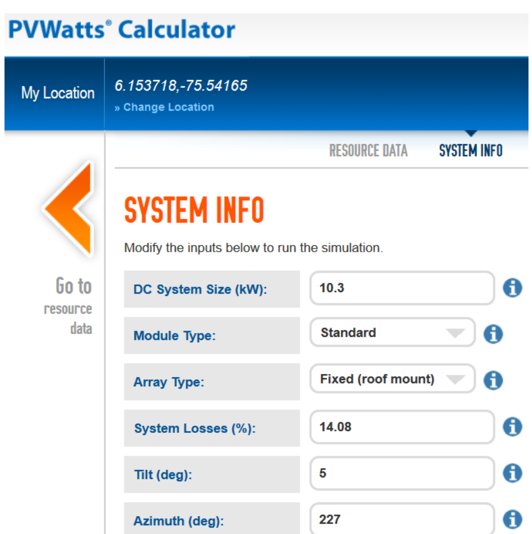
Although some CSs could have PV generation, currently none of them have one of these systems installed. Hence, there is no access to historical data about solar energy generation at the stations. Therefore, assuming that PV modules were installed at stations that are located outdoors, the software PVWatts developed by the National Renewable Energy Laboratory (NREL), is used to compute the output power of the PV array. By using this software, it is possible to estimate the total amount of electricity generated by the PV system monthly and hour-by-hour. Furthermore, the power generation is affected, among other parameters, by the azimuth and tilt angles at which the PV modules are installed. Thus, the Photovoltaic Geographical Information System (PVGIS), from the European Commission Joint Research Center, is used to calculate the optimal angles for each CS according to their coordinates. Table 4.2 shows the optimal angles obtained for each CS able to have a PV array installed[2]. In addition to these angles, the parameters required include: *location, DC System Size, Module type, Array type* and *System losses*. The array type is set to "fixed (roof mount)" for all CSs, and the DC System Size (shown in Table 4.2) is calculated according to the roof-mounted area available for each station. The values for module type and system losses are set as default. Fig. 4.1 shows an example of the inputs parameters and the corresponding hourly PV energy generation data provided by PVWatts for CS1.

Finally, the value for the parameter v is set to 8km. It is similar to the service radius of 7km for

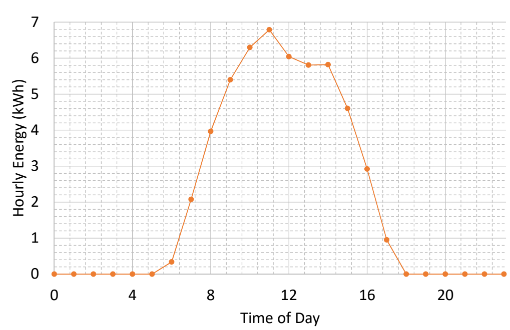
[2]PVWatts defines the azimuth angle as "the angle clockwise from true north describing the direction that the array faces"

Station	Azimuth (deg)	Tilt (deg)	DC System Size (kW)
CS1	227	5	10.3
CS2	178	5	10.3
CS3	153	5	16.3
CS7	179	5	43.1
CS8	172	5	10.3
CS10	171	5	5.1
CS11	177	5	10.3
CS12	200	5	10.3
CS13	167	5	5.1
CS15	159	5	5.1
CS16	178	5	10.3
CS19	171	5	5.1

Table 4.2: Values for parameters required by PVWatts



(a) Input parameters



(b) Hourly PV energy generation (Month: June, Day: 10th)

Figure 4.1: Software PVWatts, CS1's data

a charging station mentioned in Jia et al. (2019). It should be noted that v takes into account the route traveled distance, it is not an euclidean distance between two points. The value of α, is derived from an estimation of the PV percent that can be supplied to vehicles according to the total energy demanded in the charging requests and the PV generation data.

4.3.2 Experimental Environment and Test Instances

The instances used in the experiment were built using the traveling profiles mentioned in the above section. Three types of instances were considered: the first type is made up of 100 charging requests; the second consists of 150; and the third includes 200 requests. For each of the three types, 10 instances were built, having a total of 30 test instances. Each intances has the information of $N = \{100, 150, 200\}$ number of charging requests, depending on the type of instances to which they belong. Each charging request includes the parameters specified in Section 4.1 for a taxi when it needed to charge (SoC $\leq 30\%$) according to its traveling profile.

To assess the charging strategy, a comparisson between two scenarios is conducted. The two considered scenarios are the non-coordinated charging and the coordinated charging (i.e. using the proposed charging strategy). For both scenarios, it is assumed that:

- Taxi drivers will go charging when they have the SoC $\leq 30\%$.
- At the beginning of the day, the system receives all the charging requests and the forecasted PV generation for the day.
- The taxis shift hours are from 7:00 AM to 7:00 PM.
- Taxi drivers have access to domestic charge. Thus, the last time to start charging is 8:00PM (i.e. 20 in military time); otherwise, taxis are supposed to go charging at home. Although charging requests can have higher values for l_i, the charging time is limited to 8:00PM.
- The final SoC required by users is in the range of 80% to 100% of the vehicle's battery capacity, and it is (for simulation purposes) randomly generated for the charging requests.

The non-coordinated charging scenario follows the same charging process defined in the Case Study of Section 3.3, where users drive to the closest charging station and once there, they are scheduled with a FCFS scheme.

The algorithms were implemented in Python. All experiments were computed with High Performance Computing (HPC), available by the *Centro de Computación Científica* APOLO[3] at Universidad EAFIT. This supercomputing resource have a Intel Xeon E5-2683 processor (with 32 cores at 2.10 GHz) and 32 GB of RAM running on Linux CentOS 6.6. The number of iterations for the GRASP

[3] `http://www.eafit.edu.co/apolo`

was set to 50 and the size of the restricted candidate list to 3. Each instance was executed 10 times, each with a different random number generator seed.

4.3.3 Analysis and Comparison of the Results

To indicate the performance of the proposed GRASP-based algorithm, Table 4.3 presents the detailed results of the 30 instances. Each instance was computed 10 times. Column 1 indicates the instance type and column 2 lists the instances number. Columns 3, 4 and 6 detail the best, average and worst values obtained for the objective function, respectively. Column 8 presents the CPU time, which represent the total time for solving the whole problem. Column 5 and 7 show performance gap in percent of the average and worst values, respectively, of the objective function found in each instance against the best value of the objective function found in each case. The last row of the table shows the average and maximum results for all instances.

The results suggests that the proposed method is stable according to the average and maximum gaps. As expected, the CPU time increase with higher instance sizes. The average CPU time is 1440.44s and the maximum value 5069.85s. This maximum value corresponds to the instance type with highest size. Thus, taking into account that the method shows to be stable, the parameter of the GRASP concerning the number of iterations could be smaller for this kind of instance.
Two key performance indicators were compared between the scenarios:

i. Number of users accepted, or with a successful charging service

ii. Percentage of energy charged from the PV source.

Although the objective function of the system is oriented to increase the number of services accepted, enhancing the service availability, the operator's profits (directly related with the service's execution price) is also a main concern. Consequently, a higher percentage of energy charged from PV is desirable. The results obtained for each sample in all scenarios are presented in Table 4.4

Figure 4.2 illustrates the results obtained for the first indicator in each scenario. By analyzing the results for each group with the same number of vehicles, it can be seen that the coordinated charging strategy always reached a higher percentage of accepted services, i.e., users whose charging requests obtained a successful response (Coordinated), or users who arrived at the station and were able to charge (Non-Coordinated). When examining in detail the non-coordinated charging scenarios, it can be noticed that as the number of vehicles increases, the percentage of accepted services is smaller. Since in this case users always go to the closest CS and the schedule is done under the FCFS scheme, the decrease in the percentage of accepted users may be due to higher congestion at certain stations. This issue may lead to longer queues, increasing thus the probability that the time limit (waiting up to 8PM) will be exceeded. In contrast, the percentage in the coordinated scenario is not highly affected by a greater number of vehicles.

Instance type	Instance number	Objective function Best value	Objective function Average value	GAP (%) Average value	Objective function Worst value	GAP (%) Worst value	CPU time (seconds)
N=100	1	97.00	97.00	0.00	97.00	0.00	155.32
	2	97.00	96.70	0.00	96.00	0.01	286.79
	3	94.00	94.00	0.00	94.00	0.00	121.51
	4	95.00	95.00	0.00	95.00	0.00	145.99
	5	92.00	92.00	0.00	92.00	0.00	133.76
	6	93.00	93.00	0.00	93.00	0.00	132.44
	7	94.00	94.00	0.00	94.00	0.00	155.41
	8	92.00	92.00	0.00	92.00	0.00	153.52
	9	89.00	89.00	0.00	89.00	0.00	137.10
	10	94.00	94.00	0.00	94.00	0.00	135.21
N=150	1	92.67	92.67	0.00	92.67	0.00	525.48
	2	88.67	88.67	0.00	88.67	0.00	448.94
	3	91.33	91.33	0.00	91.33	0.00	340.64
	4	92.00	92.00	0.00	92.00	0.00	698.69
	5	87.33	87.33	0.00	87.33	0.00	534.74
	6	90.67	90.67	0.00	90.67	0.00	761.11
	7	90.00	90.00	0.00	90.00	0.00	479.28
	8	93.33	93.33	0.00	93.33	0.00	689.77
	9	93.33	93.33	0.00	93.33	0.00	540.17
	10	94.67	94.67	0.00	94.67	0.00	565.45
N=200	1	90.10	90.10	0.00	90.10	0.00	3741.18
	2	97.03	96.93	0.00	96.53	0.01	2749.45
	3	90.10	89.85	0.00	89.60	0.01	2044.15
	4	90.10	90.10	0.00	90.10	0.00	2480.43
	5	93.56	93.47	0.00	93.07	0.01	3986.20
	6	94.06	94.06	0.00	94.06	0.00	4787.79
	7	90.59	90.59	0.00	90.59	0.00	3817.95
	8	92.08	92.08	0.00	92.08	0.00	5069.85
	9	90.10	90.10	0.00	90.10	0.00	4779.44
	10	91.09	91.09	0.00	91.09	0.00	2615.35
Average results				**0.00**		**0.00**	**1440.44**
Maximum results				**0.00**		**0.01**	**5069.85**

Table 4.3: Performance of GRASP-based algorithm

	Results Coordinated Charging				Results Non-Coordinated Charging			
	Instance Number	**Accepted Services (%)**	**Energy from PV (%)**	**Services rejected (%) (cause 1)**	**Instance Number**	**Accepted Services (%)**	**Energy from PV (%)**	**Services rejected (%) (cause 1)**
N=100	1	97.00	6.58	100.00	1	83.00	3.15	0.00
	2	96.70	6.56	90.91	2	84.00	2.34	0.00
	3	94.00	6.38	100.00	3	89.00	2.96	0.00
	4	95.00	6.01	100.00	4	83.00	2.80	0.00
	5	92.00	6.61	100.00	5	83.00	2.14	0.00
	6	93.00	5.45	100.00	6	87.00	1.90	7.69
	7	94.00	7.96	100.00	7	84.00	3.14	0.00
	8	92.00	5.77	87.50	8	82.00	2.87	0.00
	9	89.00	8.27	100.00	9	92.00	3.13	0.00
	10	94.00	7.45	100.00	10	83.00	2.58	0.00
N=150	1	92.67	5.57	90.91	1	84.00	2.34	0.00
	2	88.67	6.73	88.24	2	80.67	2.30	0.00
	3	91.33	6.65	100.00	3	85.33	2.53	0.00
	4	92.00	6.96	91.67	4	80.67	2.95	3.45
	5	87.33	6.06	84.21	5	77.33	2.29	2.94
	6	90.67	7.05	85.71	6	84.00	2.81	0.00
	7	90.00	5.95	93.33	7	79.33	2.48	0.00
	8	93.33	5.35	100.00	8	72.00	2.94	0.00
	9	93.33	6.58	90.00	9	73.33	2.78	2.50
	10	94.67	6.34	100.00	10	82.00	3.00	0.00
N=200	1	90.10	3.85	65.00	1	70.30	1.72	0.00
	2	96.93	4.37	64.52	2	74.75	1.95	0.00
	3	89.85	5.29	78.05	3	70.79	2.18	1.69
	4	90.10	5.11	60.00	4	71.78	3.18	0.00
	5	93.47	4.37	60.61	5	67.82	2.03	1.54
	6	94.06	4.82	100.00	6	70.79	2.40	0.00
	7	90.59	5.36	73.68	7	66.34	3.27	0.00
	8	92.08	4.65	93.75	8	72.77	1.84	1.82
	9	90.10	4.16	65.00	9	66.34	1.26	0.00
	10	91.09	5.60	100.00	10	80.69	2.37	0.00

Table 4.4: Results Computational Experiment

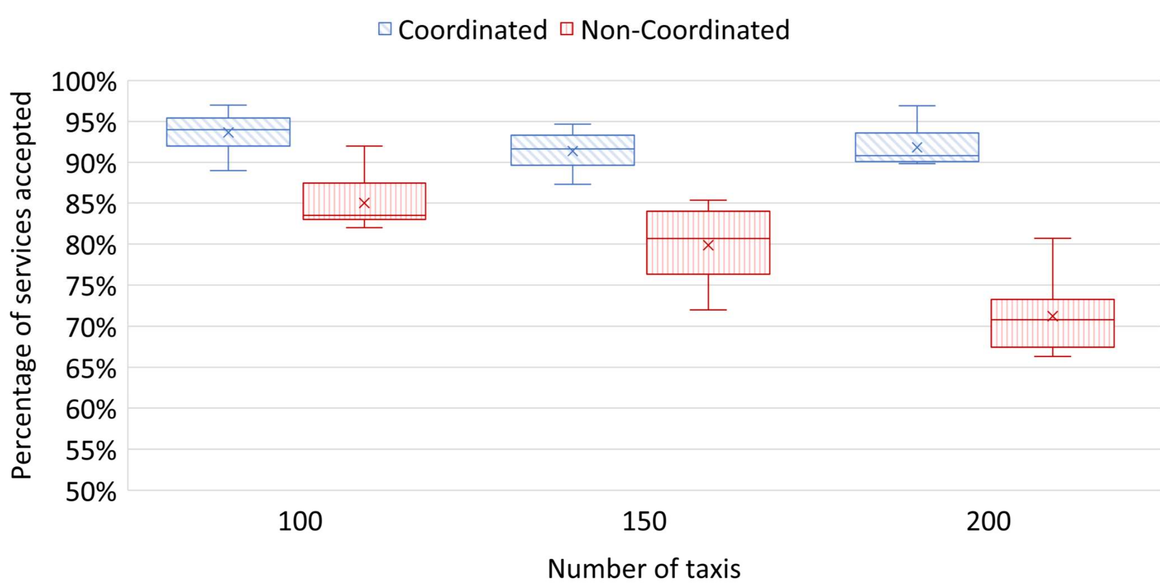


Figure 4.2: Percentage of services accepted in each scenario

In both scenarios, there are two reasons why users do not get a successful charging service. In the coordinated, charging requests are rejected because:

- Cause 1: CSs are outside the maximum allowed travel distance v from the location specified by the user.
- Cause 2: it is not possible to assign a reservation due to the lack of availability at the stations.

And in the non-coordinated case, charging services fail due to:

- Cause 1: the remaining SoC of the vehicle is not enough to travel to the closest CS.
- Cause 2: the user reaches the time limit to charge at the station.

Figure 4.3 shows the percentage of declined services due to each cause in every scenario. It can be noticed that, for coordinated charging, always the major cause of rejections is related to not having stations within the allowed travel distance. However, as the number of vehicles increases, the percentage due to cause 2 also grows. This could be associated with certain aspects such as higher station occupancy, or that users' charging requests have similar times available, so it is difficult to schedule all, or that the scheduling of these remaining vehicles involves violating the restriction of PV energy charged. On the other hand, for non-coordinated charging, about 100% of the charging services failed due to the time limit issues, which, as mentioned, can be associated with congestion in a station. The fact that the percentage of rejections for not having enough SoC to reach the closest CS is close to 0%, in contrast with the grow on declined services due to cause 2 in the coordinated case, leads to consider that the value assigned to v could be higher or even different for each user according to their preference. Since the distribution of stations is not homogeneous throughout the city area, it may happen that certain users are in locations far from the stations.

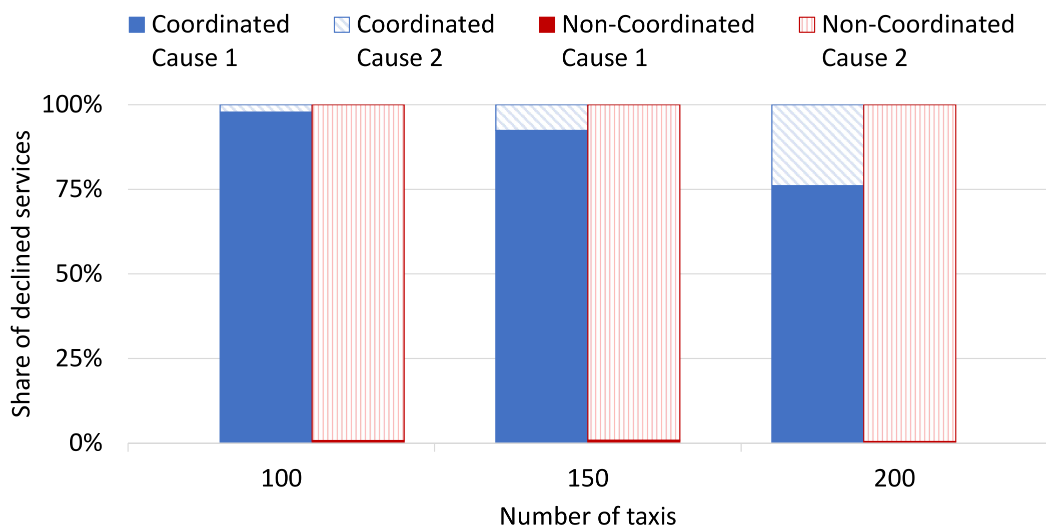


Figure 4.3: Distribution of the total percentage of declined services by cause of rejection

Regarding the indicator for the PV energy consumed, the results are shown in Figure 4.4. The CC strategy also showed a better performance for this indicator in all scenarios. Nevertheless, the highest percentage obtained was only about 7%. This issue may be caused by a low installed capacity of PV generation concerning the energy demand from vehicles or by a lack of coordination between peak charging hours and highest generation moments. For which it would be convenient to consider the installation of ESS or the possibility of selling PV energy to the power grid, so that the PV energy generated is not wasted, enabling an improvement to the operator's profit.

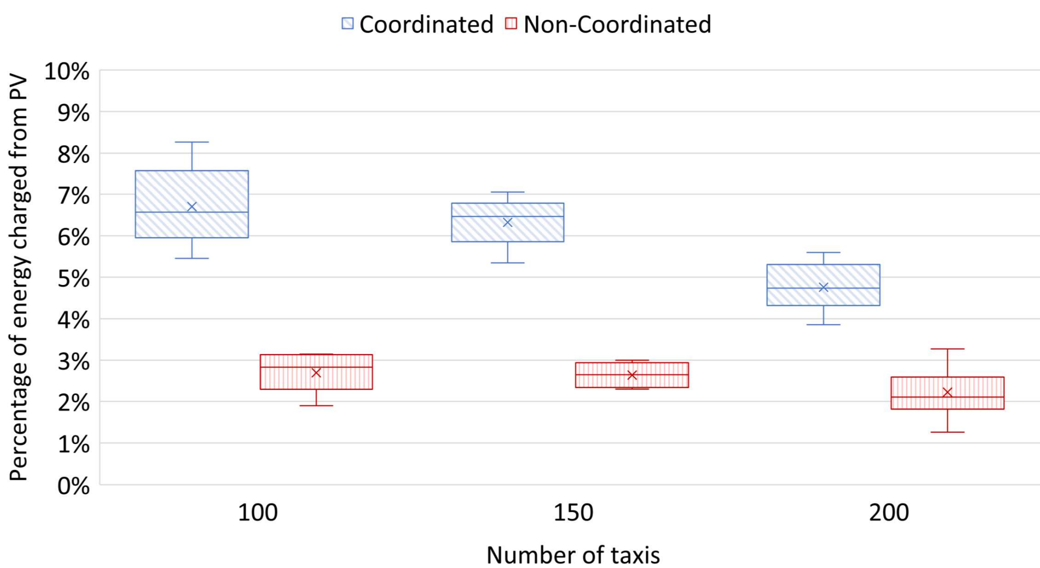


Figure 4.4: Percentage of energy charged from the PV source in each scenario

Chapter 5

Conclusions and Future Research

The increasing adoption of electric vehicles, as a mobility alternative, draws in some challenges related with the charging process and, also, with the charging infrastructure required to support a proper operation of this technology. This research has presented the development of a discrete-event simulation and a coordinated charging strategy, both tested through a case study. This section summarizes the conclusions regarding each evaluation.

According to the literature review (See Chapter 2) it can be concluded that the existing coordinated charging strategies are mainly focused on improving either users, operators or the electric grid, but few of them looks for combined benefits (among those actors) to analyze. Mainly, three types of strategies can be identified: i) those that include price mechanisms, ii) those that work with techniques related to energy management between the subsystems and iii) those that use reservations or admission mechanisms. Despite the existence of several coordinated charging strategies, most of them do not consider the operation of networks of charging stations, but rather the operation at an individual station.

The discrete-event simulation (See Chapter 3) allowed to simulate the daily operation of an ETs fleet for the particular case of Medellín, Colombia. Five main indicators were extracted from simulation results: average waiting time, percentage of waiting events, percentage of failed events, CSs occupancy and maximum queue size. The major findings of this phase were:

- Even if vehicles share similar battery capacity, the power admitted by the charging protocol of each vehicle highly affects the operation at stations. For an ET fleet of 200 taxis, the Kia Soul (27kWh, Type1 and CHAdeMO) scenario showed a percentage of charging failures around 1.5 times compared to a fleet of Hyundai Ioniq (28kWh, Type2 and CCS) and the average waiting time is around 76% above. The only simulation parameter that differs between these scenarios is the charger protocol admitted by each vehicle, evidencing the importance of this variable.

- For an ET fleet deployment, the planning of charging infrastructure must consider travel patterns of current taxis operation, to prevent saturation of specific stations and consistently distribute the charging demand. Regardless of the vehicle type, the group of the most occupied stations in the simulation was always the same, due to locations and trips distribution. These stations have shown queue sizes that can hardly be accommodated by the system. Proper public charging infrastructure is one of the enablers for the correct operation of an ET fleet.

- The current public charging infrastructure of Medellín is not sufficient to satisfy the charging demand of a large-scale ET fleet operating, under an uncontrolled charging scheme. For 200 ETs, as set in the initial phase of the city government project, approximately 50% of charging services would require some waiting time, at least of 1.0 hour, even when domestic charge is considered.

- An uncontrolled charging strategy, may result in a charging infrastructure imbalance. Whereas, in the simulation, some stations reported occupation levels above 40%, others never raised over 20%.

A case study using this discrete-event simulation may be implemented in other cities, where a goal of ETs is set and a given charging infrastructure exists. However, as there is no real data available, the analysis is limited in some aspects. The assumptions made for the simulation, may exclude important considerations, such as dwell times, precise energy consumption of the particular traveled routes during services, taxi-drivers charging decisions, (i.e. which CS to go, how long drivers are willing to wait and SoC level until they charge taxis), and specific service arrival rates. Thus, the possibility of combining the initial travel patterns drawn from the OD survey with real data obtained during operation, is of main interest for the present authors for future work, since the real time monitoring of taxis fleet could enrich the simulation and its corresponding analysis.

This research presents also a novel charging strategy in order to coordinate multiple charging requests in a network of PVCSs. The charging strategy looks for the welfare of both EV users and stations operator, through providing charging reservations to as many users as possible in a way that the PV energy generated can be suitably used. The system considers the variety of charging protocols and the non-linear charging behavior of EVs' battery. In order to evaluate the proposed strategy, a simulation considering the same case study of electric taxis in Medellín, Colombia was performed with two different charging scenarios: Coordinated and Non-Coordinated (See Chapter 4). The major findings of this analysis were:

- The CC strategy leads to a better QoS by increasing the service availability (reduction of percentage of declined services around 10% for 100 and 150 ET, and around 20% for 200 ET), by improving the service execution price with a higher use of the energy generated from the PV (around 3.5% more), and by taking into consideration users' time availability to provide the charging service.

- A higher number of EVs may lead to a collapsed infrastructure if non-coordinated scheme is adopted, because the rate of accepted services is reduced from 85% for 100 ET to 70% for 200 ET. Extrapolating this value for more vehicles may lead to a low level of accepted services, decreasing the QoS. Thus, implementing charging strategies is necessary to promote the adoption and facilitate the implementation of this technology, as the rate of accepted services remains around 93%.

- Defining a maximum travel distance for each user and not for the whole system, might prevent the rejection of some services. Let's recall that in the coordinated charging scenario, almost all rejected requests (from 100% for 100 ET to 75% for 200 ET) were because the CSs are outside the maximum allowed travel distance from the location specified by the user.

- The PV energy generation is a good contribution to the environment and to the cost model for the CS operator. However, as the maximum reached value for the energy obtained from PV generation was lower than 7%, the synchronization with demand is relevant and operators may consider to install ESSs in the CSs (or selling the energy surplus to the power grid), for a better exploitation of the PV energy.

In addition to the interests in obtaining real data during operation of EVs, future work would consider the management of CSs with energy storage devices and a model to forecast PV generation in order to have a more accurate data in real time. Thus, the monitoring of such stations is also a direction considered in future research. Additionally, it would be interest to include a comparison with other scheduling schemes. Due to the technical challenges involved in the implementation of a coordinated charging strategy in real time, an analysis of communication protocols and the communication architecture required to implement the proposed strategy could be conducted.

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Acronyms

ABC Artificial Bee Colony. 15

ACO Ant Colony Optimization. 15

ALNS Adaptive Large Neighborhood Search. 16

BEV Battery Electric Vehicle. 1, 7

CC Coordinated Charging. 4–6, 8, 9, 11, 39, 54, 58

CS Charging Station. ix, xi, xiii, 1–7, 9–19, 21–26, 28–32, 34, 35, 37–45, 47, 50, 53, 57–59

EA Evolutionary Algorithm. 15

EDF Earliest Deadline First. 16

ESS Energy Storage System. 2, 4, 54, 59

ET Electric Taxi. 21–25, 28, 29, 45, 57–59

EV Electric Vehicle. i, 1–19, 21, 22, 24, 25, 28, 29, 39, 40, 42–45, 58, 59

FCEV Full Cell Electric Vehicle. 1

FCFS First Come First Serve. 11, 15, 16, 43, 49, 50

FCS Fast Charging Station. 11

GA Genetic Algorithm. 16

GHG Greenhouse Gas. 19

GRASP Greedy Randomized Adaptive Search Procedures. 15, 42, 43

HEV Hybrid Electric Vehicle. 1

HI Hyundai Ioniq. 33, 34

KS Kia Soul. 33, 34

LLF Least Laxity First. 16, 43

LS Local Search. 15, 43

NL Nissan Leaf. 33, 34

NREL National Renewable Energy Laboratory. 19

OD Origin-Destination. 29, 37, 45, 58

PHEV Plug-in Hybrid Electric Vehicle. 1, 7

PSO Particle Swarm Optimization. 15

PV Photovoltaic. ix, xiv, 3, 7, 10, 12, 14, 19, 39–41, 43–45, 47, 49, 50, 53–55, 58, 59

PVCS Photovoltaic Charging Station. i, 3, 4, 6, 7, 10, 39, 58

QoS Quality of Service. 2, 5–7, 9, 12, 13, 15, 17–19, 39, 41, 43, 58, 59

RCL Restrict Candidates List. 43

RE Renewable Energy. ix, 2–5, 19

RES Renewable Energy Source. 2, 13, 14

RZ Renault Zoe. 34, 35

SA Simulated Annealing. 15

SoC State of Charge. ix, xiii, xiv, 17, 23, 24, 26, 28, 32, 35, 40, 45, 49, 53, 58

SS Scatter Search. 15

TS Tabu Search. 15, 43

VND Variable Neighborhood Descent. 43

VNS Variable Neighborhood Search. 15