Optimization models for the management of the one-way station-based electric car-sharing system integrated with Vehicle-to-Grid technology

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Optimization models for the management of the one-way station-based electric car-sharing system integrated with Vehicle-to-Grid technology

EXTENDED ABSTRACT *(English)*

Electric Vehicle (EV)-sharing systems have attracted large attention in recent years as a new business model for achieving both economic and environmental benefits. Car-Sharing Systems (CSSs) are becoming increasingly popular in urban areas replacing car ownership. The most attractive CSSs give users the opportunity to make one-way trips. This behavior creates an unbalanced status between stations. Hence, some users could leave the system because they may not find a car/parking place available near their origin/destination. In recent years, CSSs are employing Electric Vehicles (EVs). A recent technology applied to EVs, called Vehicle-to-Grid (V2G), has allowed selling energy by transferring it from EV batteries to an electric grid. The Vehicle-to-Grid (V2G) concept is emerging as a possible innovative solution for the energy supply support system. A management system combining Car-Sharing Systems (CSSs) and V2G technology is a recent challenge for academia and industry.

In this thesis, two optimization models are proposed to find the optimal EVs management of the one-way station-based CSS integrated with V2G technology. The proposed models allow finding the start-of-day EVs distribution, maximizing revenues from system users, and V2G profits through daily EVs charging/discharging schedules. These schedules are based on EVs daily users' requests and on electric energy prices. The CSS considered is the one-way station-based. Models' outputs suggest EVs distribution among stations at the beginning of each day, making the most of V2G technology and satisfying CSSs customers' requests simultaneously. These distributions represent the final configurations that should be obtained through overnight vehicle relocation. The proposed models have been formulated as a simulation-based model and a Mixed Integer Linear Programming (MILP) model, respectively.

The simulation-based optimization models include a smart charge/discharge algorithm for the management of the one-way station-based CSS with EVs in a V2G framework. Furthermore, two different day-ahead energy markets (i.e., Italian and Dutch day-ahead energy markets) were used for V2G profits evaluation. Additionally, two cases referred to the non-optimized and the optimized EVs distribution among stations at the beginning of the day have been evaluated. In order to assess the effectiveness of the proposed CSS optimization management, two simulation-based models and a charge/discharge process have been applied to a real-size test case (i.e., the city centre of Bari, Italy). The numerical application has been carried out changing some key parameters of the problem, namely electricity market trend and the demand level of the simulated CSS.
Similarly, the proposed MILP model aims to maximize the CSS revenues and the V2G profits simultaneously, and to provide the optimal start-of-day EVs distribution. As an additional output, it is possible to evaluate the daily amount of energy transferred from/to the smart grid trough the energy sale/purchase phase from/to EV batteries. In order to validate the MILP model, a small-size and a large-size test (i.e., the city of Delft, The Netherlands) were conducted achieving promising results in terms of V2G profitability and energy supply network support. Furthermore, a sensitivity analysis has been carried out through parameters tuning and six different scenarios were analyzed.
The main goal of the proposed thesis is to provide a first-step analysis on a real-size network and to evaluate the applicability and profitability of the proposed smart charging management system combining electric CSSs with V2G technology.

key words

Vehicle-to-Grid; One-Way Electric Car-Sharing; Electric Vehicles; Mixed Integer Linear Programming; Simulation-based optimization; Shared Mobility; Shared Energy.

Modelli di ottimizzazione per la gestione del sistema di car-sharing elettrico one-way station-based integrato con la tecnologia Vehicle-to-Grid

EXTENDED ABSTRACT (Italiano)

I sistemi di condivisione di veicoli elettrici (EV) hanno attirato grande attenzione negli ultimi anni come nuovo modello di business per ottenere vantaggi economici e ambientali. I sistemi di car-sharing (CSS) stanno diventando sempre più popolari nelle aree urbane, sostituendosi alle auto di proprietà. I CSS più attraenti danno agli utenti l'opportunità di fare viaggi di sola andata (one way). Questo comportamento crea uno sbilanciamento tra le stazioni. Pertanto, alcuni utenti potrebbero lasciare il sistema a causa della mancanza di un'auto / parcheggio disponibile vicino alla loro origine / destinazione. Negli ultimi anni, i CSS stanno impiegando veicoli elettrici (EV). Una recente tecnologia applicata ai veicoli elettrici, chiamata Vehicle-to-Grid (V2G), ha consentito di vendere energia trasferendola dalle batterie dei veicoli elettrici a una rete elettrica. Il concetto Vehicle-to-Grid (V2G) sta emergendo come una possibile soluzione innovativa per il sistema di supporto dell'approvvigionamento energetico. Un sistema di gestione che combina i sistemi di car-sharing e la tecnologia V2G è una sfida attuale sia per il mondo accademico che industriale.

In questa tesi, vengono proposti due modelli di ottimizzazione per trovare la gestione ottimale dei veicoli elettrici del sistema di car-sharing basato su stazione unidirezionale integrato con tecnologia V2G. I modelli proposti consentono di trovare la distribuzione di veicoli elettrici a inizio giornata, massimizzando i ricavi dagli utenti del sistema e i profitti V2G attraverso programmi giornalieri di carica / scarica dei veicoli elettrici. Questi programmi si basano sulle richieste quotidiane di veicoli elettrici degli utenti e sui prezzi dell'energia elettrica. Il CSS considerato è quello a senso unico basato sulle stazioni (*one-way station-based*). I risultati dei modelli suggeriscono la distribuzione dei veicoli elettrici tra le stazioni all'inizio di ogni giornata, sfruttando contemporaneamente al massimo la tecnologia V2G e soddisfacendo le richieste dei clienti dei CSS. Queste distribuzioni rappresentano le configurazioni finali che

dovrebbero essere ottenute attraverso la rilocazione notturna dei veicoli. I modelli di ottimizzazione proposti sono stati formulati rispettivamente come modello MILP (Programmazione Lineare Mista Intera) e due modelli basati sulla simulazione (*simulation-based*).

I modelli di ottimizzazione *simulation-based* includono un algoritmo di carica/scarica intelligente per la gestione del CSS con veicoli elettrici abilitati alla tecnologia V2G. Inoltre, per la valutazione dei profitti V2G sono stati utilizzati due diversi mercati dell'energia del giorno prima, ovvero i mercati dell'energia del giorno prima italiano e olandese. Inoltre, sono stati valutati due casi riferiti alla distribuzione di veicoli elettrici non ottimizzata e ottimizzata tra le stazioni a inizio giornata. Al fine di valutare l'efficacia della gestione ottimizzata dei CSS, sono stati applicati due modelli *simulation-based* e il processo di carica/scarica intelligente su un caso studio reale, ovvero il centro città di Bari, Italia. L'applicazione numerica è stata eseguita modificando alcuni parametri chiave del problema, ovvero l'andamento del mercato elettrico del giorno prima e il livello di domanda del CSS simulato.

Allo stesso modo, il modello MILP proposto mira a massimizzare simultaneamente i ricavi CSS e i profitti V2G e a fornire la distribuzione ottimale di veicoli elettrici di inizio giornata tra le stazioni. Come output aggiuntivo, è possibile valutare la quantità giornaliera di energia trasferita da / alla rete intelligente (*smart grid)* attraverso la fase di vendita / acquisto di energia attraverso le batterie dei veicoli elettrici. Per validare il modello MILP, sono stati condotti test numerici su reti di piccole e grandi dimensioni (caso studio della città di Delft, Paesi Bassi) ottenendo risultati promettenti in termini di redditività V2G e di supporto alla rete di approvvigionamento energetico. Inoltre, è stata effettuata un'analisi di sensitività attraverso la messa a punto dei parametri analizzando sei diversi scenari.

L'obiettivo principale del lavoro di tesi proposto è fornire una prima fase di analisi su una rete di dimensioni reali e valutare l'applicabilità e la redditività del sistema di gestione della ricarica intelligente che combina i CSS elettrici con la tecnologia V2G.

key words

Vehicle-to-Grid; Car-sharing elettrico one-way; Veicoli elettrici; Programmazione mista lineare intera; Ottimizzazione simulation-based; Mobilità condivisa; Energia condivisa.

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CHAPTER 1 - INTRODUCTION

1.1 - Overview

Shared mobility is one of the possible solutions for reducing the traffic congestion problem and it offers the potential to enhance the efficiency, competitiveness, social equity, and quality of life in large cities (Machado et al., 2018). Among the different systems of shared mobility, such as bike-sharing, car-pooling, and peer-to-peer ridesharing, car-sharing is the most known and widespread system in urban areas. Recently, Gallo and Marinelli (2020) introduced a review of the main actions and policies that can be implemented to promote sustainable mobility. In the literature, several authors have been studying Car-Sharing Systems (CSSs). Generally, CSSs are classified as station-based (one-way or two-way), free-floating, or hybrid systems. Station-based CSSs allow users to picking-up and dropping-off a car only in stations. In one-way station-based CSSs, the available cars are distributed in predefined parking places and the departure station could differ from the arrival one (Nourinejad and Roorda, 2015, Boyaci, et al., 2015; Correia et al., 2014). In two-way station-based CSSs, the predefined parking places remain, but the departure station and the arrival station must be the same (Nourinejad and Roorda, 2015). No intermediate parking is allowed. Free-floating systems are the most recent ones, and they offer the possibility to park a rented car in any public space of the operational area served by car-sharing companies (Firnkorn and Müller, 2011, Li et al., 2018). Finally, CSSs hybrid systems are the combination of both two-way and one-way. (Jorge et al., 2015a) or the combination of the existing station-based mode with the free-floating systems (Ciari et al., 2014).

In the beginning, CSSs were based on internal combustion engine vehicles, however, CSSs with Electric Vehicles (EVs) have also recently emerged. Indeed, electric mobility has been growing rapidly in recent years. In 2019, the global electric car fleet reached around 7.2 million units, recording a 40% increase year by year (Global EV Outlook 2020, 2020). The concept of shared mobility with EVs is currently one of the main

topics in transportation and a possible expectation for sustainability (Axsen and Sovacool, 2019). If combined with EVs, shared mobility could give another significant contribution to reducing pollution, in terms of GHG reduction (Requia et al., 2018; Martin and Shaheen, 2011, Jung and Koo, 2018).
Considering the EVs increasing and their overall adoption, a forthcoming problem could be the EVs' large-scale energy supply system (Kongjeen and Bhumkittipich, 2018). A large number of EVs could cause several power systems issues, including voltage regulation, peak-load demand, frequency variations, and harmonic contamination. A smart grid system can manage the EVs integration and fleet planning to reduce power system stress to a minimum (Ul-Haq et al., 2016).
According to the Global EV Outlook 2020, a smart EV charging system can improve power systems through the supply of Demand-Side Response (DSR) services by minimizing the electricity demand pattern. In particular, EVs have the potential to provide energy back to the grid when the energy is needed, i.e., during electric energy peak-loads, and to use excess energy from the grid for recharging the EVs battery. The idea is to use EVs battery as a source of energy storage, considering the fast and precise control signals to provide DSR services and to participate in electricity markets. The technology, where EVs supply power to the network, is called Vehicle-to-Grid (V2G). V2G technology aims to involve EV owners in a new "energy sharing" concept by receiving economic benefits. The introduction of V2G technology could be versatile and can be applied to EVs. Applied on a large-scale scenario, V2G technology can have multiple advantages in terms of emissions reduction (Saber and Venayagamoorthy, 2010), electric supply network support (Kempton and Letendre, 1997; Kempton and Tomić, 2005; Guille and Gross, 2009), and economic revenues for EVs owners (Taiebat and Xu, 2019).
To the best of our knowledge, only a few authors have analyzed V2G integration in CSSs in the literature (Freund et al., 2012; Fournier et al., 2014; Kahlen et al., 2018; Mamalis et al., 2019; Zhang et al., 2020).
The aim of this thesis is to propose and test, for the one-way station-based electric CSS with V2G technology, two simulation-based models, and a Mixed Integer Linear

Programming (MILP) formulation determining EVs distribution among stations at the beginning of the day. The objective is to find the optimal daily EVs charging/discharging schedules to maximize revenues from the system users and V2G profits. V2G profits are referred to sale/purchase criterion based on the day-ahead market electric energy price variation. In order to show the effectiveness of the proposed model, numerical applications on small-size and large-size networks have been performed.

1.2 – Outline

With the purpose of describing logical steps between the state-of-the-art and the new models proposed, this thesis is articulated with the following structure.
In chapter 2, an overview of the state-of-the-art of CSSs business models and approaches is reported, followed by a brief introduction of CSSs relocation strategies and KPIs. The goal of this chapter is to provide a background of CSSs highlighting the strengths and weaknesses of all different models.
In chapter 3 the innovative V2G concept and its applicability in shared-vehicle systems is presented. Currently, V2G is a high-potential technology that could provide benefits in terms of economic, environmental, and energy supply network support. Several pilots around the world are testing V2G performance and real-world applicability as a new business model.
In chapter 4 two models that evaluate V2G impact on the one-way station-based CSS are introduced. Specifically, two simulation-based models and a MILP model are presented. In order to test the effectiveness of the proposed models, a set of numerical applications is carried out. In particular, for simulation-based models, a numerical application on the city center of Bari, Italy, including demand perturbation and two cases on initial vehicle distribution among stations at the beginning of the day are tested. Indeed, for the MILP model, two numerical applications on a small-size test network and on a real-size test network in the city of Delft, The Netherlands, are analyzed reaching optimality. Additionally, a sensitivity analysis is carried out for the

best CSS configuration. A summary of conclusions and a proposal for some future research directions are provided in Chapter 5.

CHAPTER 2 – AN OVERVIEW ON CAR-SHARING MODELS

2.1 – Introduction

One of the major current transport challenges is trying to reduce traffic congestion and emission of pollutants, as it was treated in the 2015 United Nations Climate Change Conference in Paris. A possible solution could be improving the practice of vehicle sharing, implementing the "Mobility as a Service" (MaaS) concept, which offers convenient door-to-door transport without the need to own a private vehicle (Kamargianni et al., 2016). Car-Sharing Systems (CSSs) can play an essential role in the MaaS if integrated with other sustainable systems (e.g., public transport, bike-sharing, car-pooling, etc.). A CSS is generally based on a car fleet and on a restricted number of users having access to cars for short-term periods by paying per use (Bardhi and Eckhardt, 2012). There are two types of CSSs: station-based systems and free-floating systems. The reference model is station-based. In this case, a user can pick-up and drop-off a car only within stations. On the other hand, in the free-floating case, more flexibility is allowed. This happens because free-floating systems define a geofence through which the rent and the return of vehicles very close to the demand point is possible, without the necessity to pass by a station before or after the trip (Herrmann, Schulte and Voß, 2014). The most attractive CSSs give users the opportunity to make one-way trips. One-way operations, as well as the imbalance of vehicle demand, could generate some problems both at trip origin (pick-up station) and at trip destination (drop-off station). Among the possible issues, a situation in which vehicles are accumulated to stations where they are not needed may occur, while at the same time there could be vehicle shortage at stations where more vehicles are required (Barth, Todd and Xue, 2004; Kek et al., 2009; Nair and Miller-Hooks, 2011; Di

Febbraro, Sacco and Saeednia, 2012; Boyacı, Zografos, and Geroliminis, 2015; Schmöller et al., 2015; Huang, Correia and An, 2018). Due to this unbalanced status between stations, some users could leave the system (lost users) because they may not find a car/parking place available near their origin/destination.

Vehicle relocation, i.e., the transfer of vehicles from stations with high vehicle accumulation to stations with low vehicle accumulation, is a technique that has been proposed to reduce the imbalance of one-way CSSs (Jorge Correia and Barnhart, 2014). Two different relocation approaches were proposed: user-based and operator-based relocations. User-based strategies offer incentives to customers for changing their travel behavior. In contrast, operator-based strategies provide vehicle redistributions performed by operators: during the night, when the demand is negligible (static relocation), or during the whole day, when the demand changes depending on time (dynamic relocation). For a detailed overview of the different one-way CSSs vehicle relocation problem approaches, see Weikl and Bogenberger (2013) and Illgen and Höck (2019).

According to recent studies, car-sharing could decrease CO_2 and GHG emissions (Crane et al., 2012). In order to reduce pollution, vehicles powered by different cleaner alternative fuels or EVs can be employed. Recently, many researchers are focusing on the development of EVs.

Consistently with the scope of this thesis, in this chapter, the main outlines of car-sharing systems will be illustrated. The goal is the description of a common background related to different models and approaches of CSSs in the literature as a basis for a better understanding of the proposed models.

In Par. 2.2, a brief overview of station-based CSSs is illustrated considering two different approaches as the one-way and the round-trip ones, respectively. In Par. 2.3, a brief overview of free-floating CSS is described, while in Par. 2.4 a short introduction of Peer-to-Peer (P2P) CSS is presented. One of the major issues of CSSs is the relocation of vehicles among the stations or parking places within a service area. This issue causes CSSs imbalances and a decrease in performance. In Par. 2.5, a description of relocation strategies and a state-of-the-art approach are illustrated.

Finally, in Par. 2.6 Key Performance Indicators (KPIs) used in the literature for evaluating CSSs performance, and a new set of KPIs applied to the MILP model are introduced.

2.2 – Station-based car-sharing model

Station-based CS business models can be classified into two different trip configurations, such as one-way and round-trip (two-way) as explained in detail in Par. 2.2.1 and 2.2.2.

2.2.1 – *One-way approach*

The one-way station-based CSS is the most worldwide adopted business model by CS owners due to its flexibility and adaptation to customers' needs. It provides the possibility to pick-up and drop-off an available vehicle parked at any designed spaces (i.e., CS stations) across a city or region (Shaheen et al., 2015). Usually, short trips and a fixed fee by the minute of vehicle usage are the most important advantages. Furthermore, a reservation-based system is able to book a vehicle for a specific time window. However, if on the one hand, the one-way approach provides flexible services, on the other it can cause operational management issues. The operators have to guarantee a high level of vehicle availability in different zones within the service area during the whole operating time. Furthermore, coupled with the imbalance of vehicles between stations, it could generate an oversized fleet and an increase in vehicle under-utilization. The above-mentioned issues are due to the fluctuation of demand. Specifically, the unequal travel demand between stations presents an operational problem of imbalances in vehicle availability across stations for unidirectional vehicle-sharing systems (Alfian et al., 2015). When this happens, CS operators can apply rebalancing policies, i.e., redistributing vehicles from where they are not needed considering the expected demand in the near future, with the objective of serving more effectively the travel demands more effectively. Before applying vehicle rebalancing, CS

operators need to know in advance the optimal solution for infrastructure planning according to travel demand. Specifically, the number, size, and location of stations to deploy in a specific service area, as well as the fleet size, has to be evaluated by models and algorithms.
Generally, the need for a comprehensive framework for service planning is required to manage the whole station-based system. Decision support systems can be based on multi-criteria approaches, e.g., the Analytic Hierarchy Process (Xue et al., 2019) and, recently, the fuzzy Delphi method (Liu et al., 2020).
The redistribution strategies, named vehicle relocation strategies, are explained in the remainder of Par. 2.4.
Finally, the station-based one-way scheme is illustrated in Figure 2.1, focusing on the electric CSS.

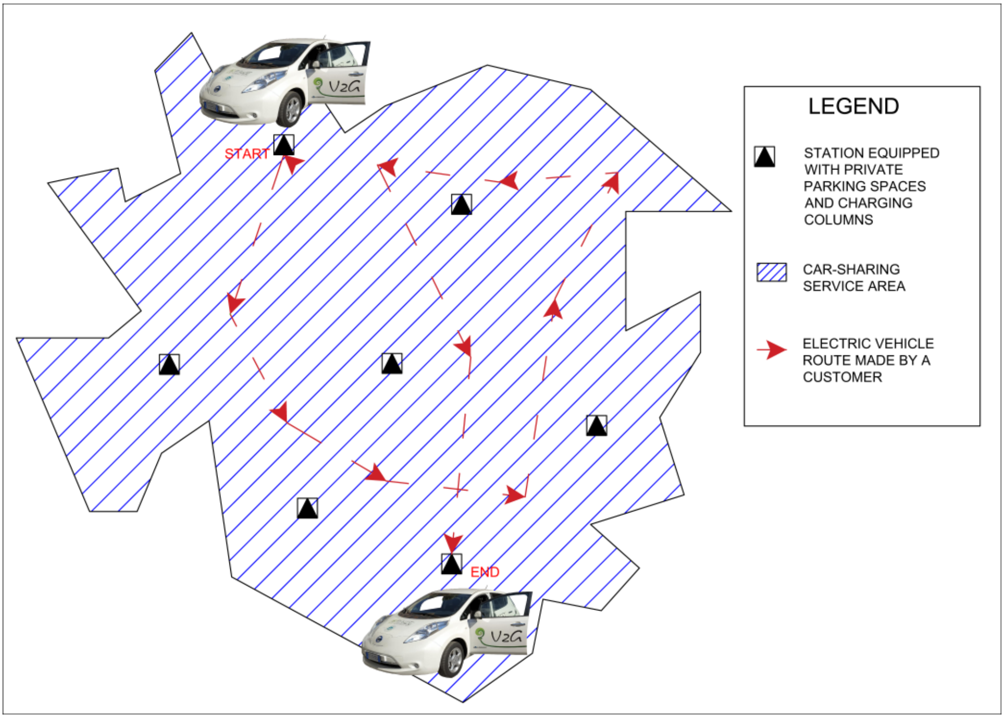

Figure 2.1. One-way electric car-sharing scheme.

2.2.2 – Round-trip approach

The round-trip station-based CSS is a two-way service where customers pick-up an available vehicle at a station and return it to the same place. Typically, an hourly fee basis is the pay-per-use model, but also miles/kilometers fee is adopted by CS providers (Shaheen et al., 2015).

This service allows picking-up the available vehicles within stations equipped with pre-defined parking spaces owned by the service provider or reserved by the local authority. Customers' private intermediate stops during the trip are not considered. Thus, this includes both the travel to and from one or more destinations including intermediate stops. In general, customers need to reserve an available vehicle in advance, especially when utilization is low through short notice (Heilig et al., 2018; Le Vine et al., 2014).

From the customers' perspective, round-trip services could not be attractive from an economic point of view if a vehicle is parked for a long time during the trip. Therefore, this kind of carsharing is mostly used for short trips requiring short-term parking, i.e., for leisure, shopping, and occasional trips (Jorge et al., 2015a).

According to Lee et al. (2016) in round-trip service, there is a close relationship between vehicles traveled during the peak hours and yearly subscriptions. Furthermore, according to Wu et al. (2020), there is a close relationship between vehicle usage frequency and some trip purposes, e.g., commuting and education. Finally, according to Hui et al. (2017), there is an interesting characteristic of round-trip service in trip chaining considering different usage patterns that can be useful for better service management.

Figure 2.2 illustrates the round-trip station-based scheme considering the electric CSS.

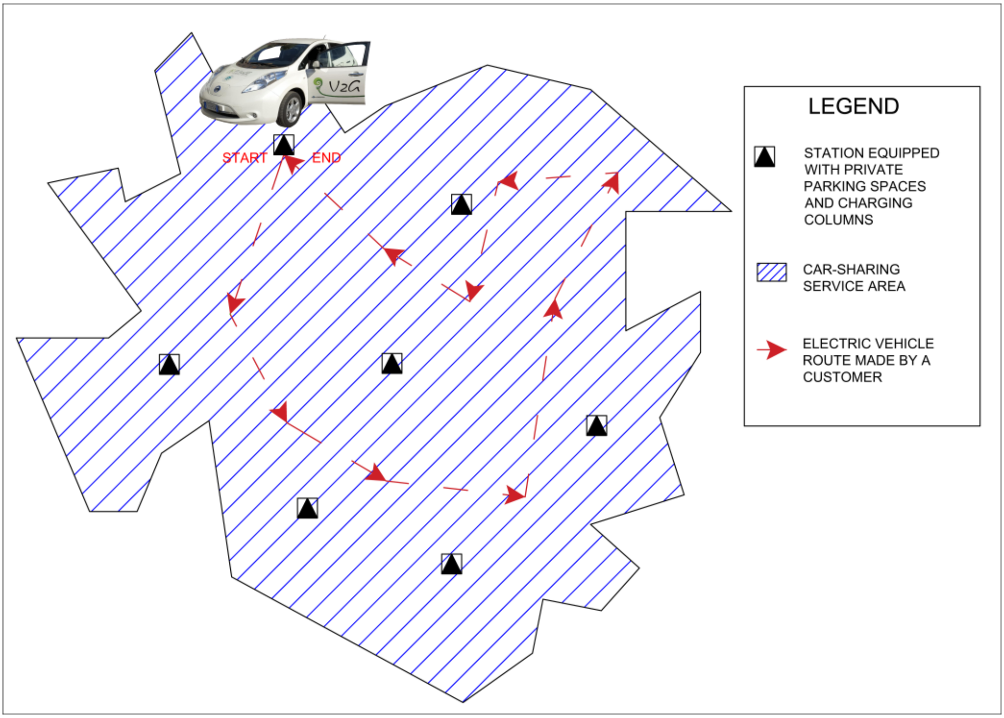

Figure 2.2. Round-trip electric car-sharing scheme.

2.3 –Free-floating car-sharing model

The free-floating CSS allows the picking-up and dropping-off of vehicles anywhere within a predefined service area. Compared to station-based models, no private stations are needed for parking vehicles, given that they can be parked in every free public parking places within the service area. Often, local authorities provide reserved CS roadside and parking places for promoting a shared-use mode of transport. In free-floating CS services, customers can check vehicles' availability and location in real-time by using dedicated online platforms, e.g., smartphones, personal computers, or tablets, for the reservation process. Additionally, via smartphone, it is possible to unlock and lock the shared vehicle for starting and ending the rental period, respectively. This information is elaborated by CS operators and allows them to make available a shared vehicle available to other customers in a short time. Due to advancement in technology and public policies that enable private firms to reserve on-street parking, free-floating one-way carsharing services are largely expanding. The introduction of these services, e.g., mobile applications, smartcards, positioning systems, and vehicle access technologies, has removed some of the restrictions faced by users in conventional round-trip services. Therefore, it is gradually replacing round-trip systems because of the freedom that this system offers (Namazu et al., 2018; Shaheen et al., 2015; Vasconcelos et al., 2017). Figure 2.3 illustrates the free-floating one-way scheme adopting EVs.

According to Heilig et al. (2018), the number of CS users and vehicles used in shared systems has increased during the last few years and is going to follow the increasing trend using forecast models. Recently, Jochem et al. (2020) conducted a survey that included more than 10,000 survey participants across 11 European cities stating that if the floating CS service is implemented, it can decrease car ownership more than twice. Several CS companies are investing in new shared vehicles and new CS companies are emerging to provide this service in urban areas worldwide. In Europe, the number of CS users has grown from 200,000 in 2006 to 6.76 million in 2018 (Shaheen and Cohen, 2020). Accordingly, also free-floating CSSs are growing rapidly. In January 2018, car2go collected over 3 million members over 26 cities in 8 different countries (car2go, 2018). In 2018, DriveNow and car2go companies merged to SHARE NOW becoming the largest free-floating CS service provider worldwide. Recently, due to the COVID-19 pandemic situation, SHARE NOW announced to withdraw consistently its fleet from all North American and European cities (SHARE NOW, 2020).

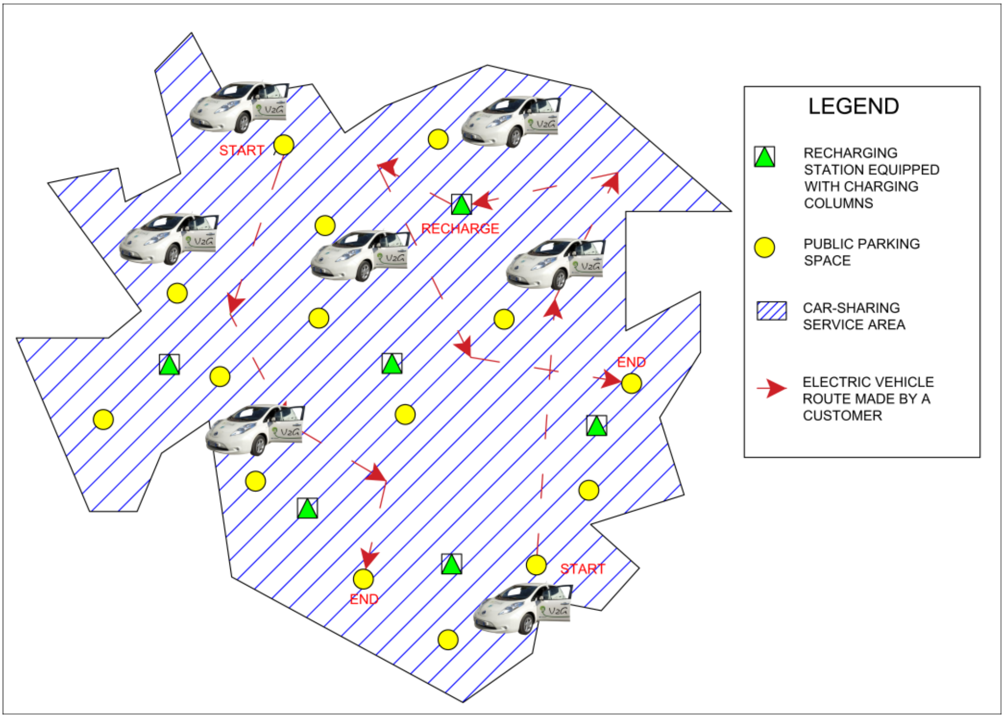

Figure 2.3. Free-floating electric car-sharing scheme.

2.4 – Peer-to-Peer car-sharing model

The peer-to-peer (P2P) CS business model is a recent CSS where private vehicle owners offer the temporary usage of their vehicle to others by using an internet platform provided by P2P operator service (Shaheen et al., 2019). The rental procedure of a vehicle sharing by an individual or members of a P2P CS company is intermediate by P2P operators. In exchange for providing the service and insurance, operators keep a percentage of the rent transactions. Generally, the operator provides the rental procedure by scheduling vehicle availability and confirming or denying members' requests for P2P CS service, typically in a station-based round-trip mode. The P2P CSS can offer a wide choice of locations, vehicle types, and daily/hourly rental prices when compared with the other CSSs (Shaheen et al., 2018a, 2018b; Ballùs-Armet et al., 2014). According to Shaheen et al. (2018b), the P2P model can reduce costs for the renter, operating costs for CS companies, and promote profits for vehicle owners. In the literature, a simulation-based model has been proposed by Hampshire and Sinha, (2011) with the aim to improve and analyze P2P service. Shaheen et al. (2019) analyzed the P2P impact in the USA including automated vehicles. Furthermore, Dill et al. (2019) analyzed P2P service travel behavior with the tendency for car owners to decrease distance travel and to move throughout other modes. Finally, Saranti et al. (2019) studied the use of blockchain technology in future application for P2P CS service for accelerate economic transactions bypassing many bureaucratic steps.

2.5 – Relocation strategies

The most attractive CSSs give users the opportunity to make one-way trips. However, one-way operations, as well as the imbalance of vehicle demand, could generate some problems both at the trip's origin (pick-up station) and at the trip's destination (drop-off station). Among the possible problems, a situation in which vehicles are accumulated to stations where they are not needed may occur, while at the same time there could be vehicle shortage at stations where more vehicles are needed (Barth et al., 2004). Due to this imbalanced status among stations, some users could leave the system because they may not find a car/parking place available near their origin/destination.

Vehicle relocation, i.e., transfer of vehicles from stations with high vehicle accumulation to stations with low vehicle stock is a technique that has been proposed to reduce the imbalance of one-way CSSs (Jorge et al., 2014). Thus, the relocation activities allow to rebalance the CSS to satisfy as many customers as possible.

The high flexibility of one-way mode, present in the one-way station-based and free-floating business models, may generate an important task in point-to-point service management due to vehicle relocation operation. This task could affect the performance and effectiveness of the overall CSS negatively. In the literature, the relocation problem has been conducted widely. Currently, solving the vehicle relocation problem is a challenge for both one-way station-based and free-floating CSSs. This latter resulted to be more complex due to higher degrees of freedom compared with the one-way station-based service. In order to test the effectiveness of one-way CS service, simulation tools have been implemented by using dicrete-events models (Alfian et al., 2015; Alfian et al., 2017) and object-oriented approaches (Cepolina et al., 2015).

Zakaria et al. (2018) proposed an Integer Linear Programming (ILP) model including the minimization of three terms in the objective function, i.e., the number of rejected requests, operators' staff, and relocation operations.

Two main relocation approaches were proposed in the literature: user-based and operator-based. Generally, user-based strategies offer incentives to customers for changing their travel behavior, while operator-based strategies provide vehicle redistributions performed by operators: during the night, when the demand is negligible (static relocation) or during the whole day when the demand changes depending on time (dynamic relocation).

Di Febbraio et al. (2019) proposed a user-based relocation methodology in which the users may accept to leave the car in a different location in exchange for fare discounts. They provided a two-stage optimization problem for optimizing the alternative destinations proposed to users and for maximizing the profit of CS operators. Finally, they stated that with the proposed user-based relocation strategy and without the operator-based relocation, the number of rejected reservations can be significantly reduced.

Kim et al. (2017) analyzed the maximization of demand satisfaction including and excluding vehicle relocation, highlighting the high impact of relocation operations in meeting customer demand in a one-way CSS.

Focusing on the station-based mode, the scientific literature is mainly directed on the relocation problem of electric vehicles. Boyac. et al. (2017) proposed an optimization strategy for CS profit maximization of user-based vehicle relocation considering both electric vehicles and personnel distribution among stations.

Gambella et al. (2018) introduced an operation-based vehicle relocation optimization model for electric CS considering consumption and recharge processes at stations.

Recently, Lemme et al. (2020) presented an optimization model in station-based CSS with the aim to assess the impact of electric vehicles' adoption on fleet composition, including hybrid and internal combustion engine vehicles.

2.6 – Key performance indicators

In the literature, several one-way car-sharing relocation models are introduced, and a recent and exhaustive literature review has been introduced by Illgen and Hock, (2019). In order to define the optimal distribution of the vehicles among the different locations, these models define several Key Performance Indicators (KPIs). Among the first indicators proposed are those related to time, i.e., 'zero-vehicle-time' and 'full-port-time'. The 'zero-vehicle-time' (Barth and Todd, 1999; Kek et al., 2006; Kek et al., 2009) occurs when a station has no parked vehicles, while the full-port-time (Kek et al., 2006; Kek et al., 2009) occurs when a station is full of parked vehicles reserved by other users. Both 'zero-vehicle-time' and 'full-port-time' reduce the attractiveness of a CSS and can imply a loss of revenues for CSS operators. Other KPIs presented in the literature are the 'vehicle-to-trip ratio', the 'number of relocations', and the 'number of trips' indicators.

The 'vehicle-to-trip ratio' (Barth and Todd, 1999) or 'vehicle-to-trip station ratio' (Kek et al., 2009) evaluates the CSS performance by adding/removing vehicles and/or stations in the system. The 'number of relocations' evaluates the CSS performance by applying different relocation policies or strategies (Barth et al., 2004; Jorge et al., 2014; Kek et al., 2009; Nourinejad and Roorda, 2015). Finally, the 'number of trips' indicator provides basic information related to the percentage of satisfied demand (Jorge et al., 2014; Nair and Miller-Hooks, 2014) by counting all completed trips made by customers. Additionally, the 'number of trips' indicator can be applied to evaluate the level of service (Alfian et al., 2014; Fink and Reiners, 2006; Nair and Miller-Hooks, 2010) or the actual vehicle utilization (Alfian et al., 2014).

In the MILP model proposed, one of the KPIs used is related to the ‘number of trips’. It is defined as ‘CSS revenues’ KPI namely the sum of revenues obtained from the CSS users paid fee. However, this KPI is not enough for evaluating the fleet management performance in a V2G framework. As explained in the next section, V2G technology requires EVs charging (purchasing electric energy) and discharging (selling electric energy) phases management in order to maximize profits balancing the electricity supply and demand.

CHAPTER 3: THE VEHICLE-TO-GRID (V2G) TECHNOLOGY

3.1 – V2G concept

V2G concept consists of enabling EVs to share the energy from and to the power grid bidirectionally, according to demand-response services. The batteries of plug-in electric vehicles act as a form of distributed energy storage and can be used to transfer electricity from EVs to the power grid and vice versa. Therefore, V2G allows to charge EVs batteries during low demand times and to send electricity back to the grid during periods of high demand (Kempton and Tomić, 2005a, 2005b). Before the introduction of V2G technology, the electric energy transfer between the power grid and EVs batteries was only unidirectional, named grid-to-vehicle (G2V), and smart charging management was not necessary. Successively, the bidirectional energy flow was implemented by providing energy and ancillary services to the electric grid from EVs. Smart charging systems and aggregators are required for EVs participating in V2G, where multiple EVs are able to be dispatched as a single unit (Han et al., 2010; Kempton and Tomić, 2005).
V2G concept was firstly proposed by Kempton and Letendre (1997). Furthermore, in order to demonstrate V2G benefits, several authors have analyzed the interconnection between EVs energy storage and the power grid (Kempton and Kubo, 2000, Kempton and Tomic, 2005, 2005a, 2005b, Williams et al., 2006, Tomic and Kempton, 2007). According to Kaur et al. (2019) and Liu et al. (2019), V2G technology has the potential to transform EVs into a distributed energy resource with multiple benefits for the smart grid integration. According to Noel et al. (2019), V2G technology implemented on EVs can provide several advantages in terms of technical benefits, economic benefits, and environmental benefits. Technical benefits are related to the power grid operators and include voltage regulation (Rogers et al., 2010), spinning reserve (Pavic et al., 2015), load peak shifting (Dallinger et al., 2011), and frequency regulation (Kolawole and Al-Anbagi, 2019). Among the environmental benefits, V2G technology can incentivize the decarbonization of the electricity sector if it is combined with renewable power sources

(i.e., solar photovoltaic and wind energy) in terms of higher flexibility and backup storage (Noel et al., 2019; Saber and Venayagamoorthy, 2010). Finally, the economic benefits obtained by V2G technology can be classified in terms of EV owners, grid operator, and society: EV owners can open a new revenue source by selling/purchasing electric energy stored in EV batteries with different prices during the day to the distributed systems operator while for grid operators and society, V2G can provide cheaper electricity market alternatives. Profits obtained from the purchase and sale of electric energy may be managed by a smart charging system aiming at identifying the most favorable time intervals with the most profitable tariffs during the day in order to maximize profits. Therefore, the energy demand response from the power grid is higher during the daytime (daily peaks) and, consequently, the energy tariff is higher. In contrast, the energy demand response from the power grid is lower during the night (off-peak hours, overnight), thus the energy tariff is lower. This process could allow small profits per vehicle per day, but considering EVs fleet large-scale, the aggregation of all EVs energy transfer, in terms of profits/kWh, could be relevant. Yilmaz et al. (2013) and Arfeen et al. (2019) have analyzed all differences between uncoordinated and coordinated smart charging/discharging systems highlighting strengths and weaknesses of both methodologies in terms of requirements and costs, and impact on power distribution networks. The uncoordinated charging system allows the EVs charging at any time when plugged into charging columns while the coordinated charging/discharging system allows the bidirectional energy transfer between EV batteries and the power grid in a specific time interval managed by a smart system. Several authors have treated the smart charging/discharging system in the literature, focusing on power daily load curve (Zhang et al., 2012; Lassila et al., 2012), economic benefits of EV owners (Fan, 2012), operating costs (Rotering and Illic, 2011) and power losses (Dallinger et al., 2011). Recently, Cai et al., (2018) have proposed a day-ahead optimal charging/discharging scheduling for EVs considering a random initial EV batteries SoC.

In recent years, V2G implementation is a challenge, and several pilot programs are presenting encouraging results through the usage of the bidirectional flow of electricity between EVs and the power grid. Companies involved in the processes of generation, transmission, distribution, and consumption of energy can take advantage of this new functionality given that V2G may prove to be effective in balancing the grid while bringing economic benefits (Modumudi, 2019). Recently, several pilot projects concerning V2G implementation are in progress, e.g., Enel and Nissan projects (Enel, 2017), Smart Solar Charging (de Brey, 2017), WeDriveSolar project (WeDriveSolar, 2020), and Engie eps and FCA project 2020 (Engie-FCA project, 2020).

3.2 – The potential benefits of V2G

In this paragraph, V2G benefits are classified and summarized into three main themes: economic, technical, and environmental. These three themes have different sociotechnical dimensions and depends on different factors and levels of society. It is important to highlight the interconnection between the concept of V2G and EVs. Since the application of EVs is antecedent to V2G, the benefits derived from V2G technology could be considered as a subset of EVs benefits. On the contrary, V2G implementation could help the diffusion of EVs adoption by economic incentives for EV owners. Furthermore, V2G technology could not only generate direct benefits for EV owners but also indirect benefits for society. It is important to contextualize the potential benefits of V2G that can be implemented considering temporal aspects. For example, economic benefits through EV participating in frequency regulation are ready to be implemented in a short term period in most arear while the electricity supply network decarbonization needs a long term period before its transaction through renewable power sources full adoption.

3.2.1 – Energy supply support benefits

The primary benefit that V2G may offer is the potential energy to the power grid through EV battery power capacity storage. Since EV power capacity is potentially low cost and with a quick response, it is able to serve multiple types of power markets. Theoretically, if all vehicles in the USA were converted to V2G-enabled EVs and assuming that each EV has 30 kWh of battery electric energy capacity (the minimum value), the total capacity of USA EV fleet would be 2.7 terawatts (TW) and 8.1 TWh (U.S. Highway Statistics, 2016). This capacity resulted to be substantially comparable with the USA electricity capacity that is around 1 TW (EIA, 2017), demonstrating that V2G application on a large scale would be a high storage resource. This energy storage capacity could be realized by other technologies, such as hydrogen, purpose-built batteries, flywheels, power-to-gas, compressed air energy storage, and pumped hydroelectric, but these technologies would generate a significantly higher cost (quantifiable in trillions of dollars). On the other side, V2G has some disadvantages if compared to the above-mentioned technologies due to obstacles in the future developments. The biggest obstacle is the dependency from EV owners in allowing their EVs to participate in a V2G aggregator system. For example, to reach 1 MW of energy capacity storage the number of EV owners that should allow V2G participating is around 100 units. Thus, the uncertainty of EV owners to participate in the "energy sharing" process is high, but it could be overcome by using incentives.

3.2.2 – Economic benefits

V2G technology can generate economic savings on three different actors on different scales, i.e., EV owners (consumers), grid operators, and society. Specifically, for consumers, V2G can generate a new profit source from participating in ancillary markets providing frequency regulation support. Practically, the frequency regulation is the amount of energy capacity, usually in the order of some MW over the period of one hour (MWh), that can compensate energy demand from the grid. This amount of energy is sold to energy markets in exchange of an energy unit price, generally expressed in \$/MWh, that varies along a time unit. Besides frequency regulation service, V2G can support the power grid in specific period with high power demand within a day, named peak hours. During peak hours, the amount of energy taken from V2G can help power grid to slightly decrease load demand with a higher energy price unit. This process is named “peak shaving”. Additionally, during low demand period, the energy stored from power grid could be used for charge EV batteries and contribute for a better balance of energy. This process is named “load balancing”. Figure 3.1 shows a scheme of the peak shaving and load balancing processes.

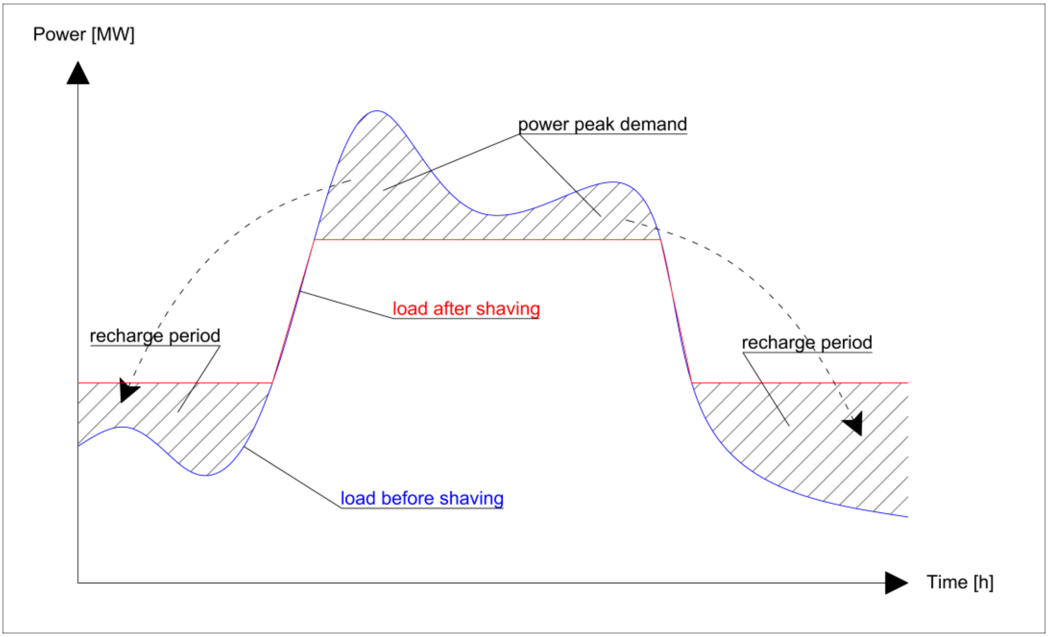

Figure 3.1. Power grid peak-shaving and load balancing processes by adopting V2G smart charging system.

Noel et al. (2019) introduced an equation for estimating V2G economic revenues from US energy markets, as shown in eq. (3.1)

$$R = Pr_{FREQ} \cdot P_{MW} \cdot A \tag{3.1}$$

Where R is the annual revenues, Pr_{FREQ} is the frequency regulation price, express in \$/MWh, P_{MW} is the power capacity, express in MW, and A is the availability to provide V2G, expressed in hours. The authors calculated, by a numerical example, how frequency regulation participation could benefit an EV owner. They assumed a Nissan Leaf EV model with P_{MW} equal to 10 kW of energy capacity, a charger type L2, A equal to 15 hours during weekdays and 23 hours during weekends, Pr_{FREQ} equal to 34 \$/MWh (average value of May 2018 of PJM electricity grid). The final value obtained from eq. (2.1) is 2,140\$/year, and 600\$/year including charger cost. These values are estimated, and no models are used for a real evaluation of EV owners' economic revenues. In this thesis, one of the outputs of proposed models is V2G profits evaluation by using two different approaches, further explained in chapter 4. Furthermore, due to the lack of business models and other social barriers to EV diffusion, EV owner may have some difficulties to evaluate carefully future savings. For this reason, fleet managers (e.g., CS companies) could be more cost-sensitive for V2G revenues evaluation and EV aggregation (Sovacool et al., 2018; Markel et al., 2015). Nonetheless, V2G economic benefits could incentivize EV fleet adoption in several uses, e.g., buses, vans, and garbage trucks (Noel et al., 2014; Zhao et al., 2016; Park et al., 2016).

For grid operators and society, V2G economic benefits are quantifiable also increasing the cost-effectiveness of ancillary services by operating costs reduction. Furthermore, V2G can reduce electricity grid costs if merged with renewable power sources integration in ancillary markets.

3.2.3 – Environmental benefits

On a large scale, V2G adoption could provide environmental benefits in both the electricity and transportation sectors. From the electricity point of view, V2G can play an important role in environmental benefits through participation in the ancillary services markets. According to (Noori et al., 2016), the most relevant ancillary service market that may compete with V2G is natural gas. Therefore, V2G integrated with renewable sources (wind and solar) as a business model could decrease carbon-based energy production systems and, consequently, decrease emissions. As concern transportation sector benefits, V2G can help the decarbonization process and the public health improvement through the transaction from internal combustion engine vehicles (ICVs) to EVs.

3.3 – Technical challenges to V2G

V2G adoption may face in some technical challenges in the short and long term. One of the most challenge is the battery degradation issue which can decrease EV range over the time. Hence, considering the existence of range anxiety for EV owners (Schuitema et al., 2013; Egbue and Long, 2012; Hidrue et al., 2011), further EV battery degradation due to V2G service may decrease EV owner participation in sharing their EVs. Calculating EV battery degradation is complex due to aging degradation, known as calendar and cycling aging, that depend on temperature, time, number of charge/discharge cycles, charge and discharge power rates, depth of discharge (DOD), the battery SoC, capacity, C-rate, and previous degradation rate. (Thompson, 2018; Bishop et al., 2013; Rezvanizaniani et al., 2014). Temperature, SoC, DoD, and C-rate are called stress factors (Thompson, 2018) because they are directly dependent on battery usage, while the number of charge/discharge cycles, time, and previous degradation rate are dependent on battery usage. Furthermore, battery degradation depends on the type of battery in terms of chemical composition. The most popular battery chemistries are NCA (Nickle Cobalt Aluminum), LPF (Lithium Iron Phosphate), NMC (Nickel Cobalt Manganese), and LMO (Lithium Manganese Oxide). In the literature, several battery degradation models were proposed (Wang et al., 2014; Smith et al., 59; Millner, 2010; Uddin et al., 2017; Dubarry et al., 2017; Fernández et al., 2013; Redondo-Iglesias et al., 2018; Schmalstieg et al., 2014; Wright et al., 2002; Xu et al., 2016;Ecker et al., 2012; Petit et al., 2016). Nonetheless, EV battery degradation is dependent on EV driving usage, as well as weather conditions under which the EV is used. According to (Wang et al., 2016), the battery degradation of a typical EV has been estimated to be about 31% over 10 years with a non-linear path. Additionally, the authors estimated V2G impact on battery degradation, as reported in Figure 3.2, assuming different participation rates (everyday for 10 years and 20 times per year) V2G can generate further battery degradation about 3.6% over 10 years in the extreme case for frequency regulation.

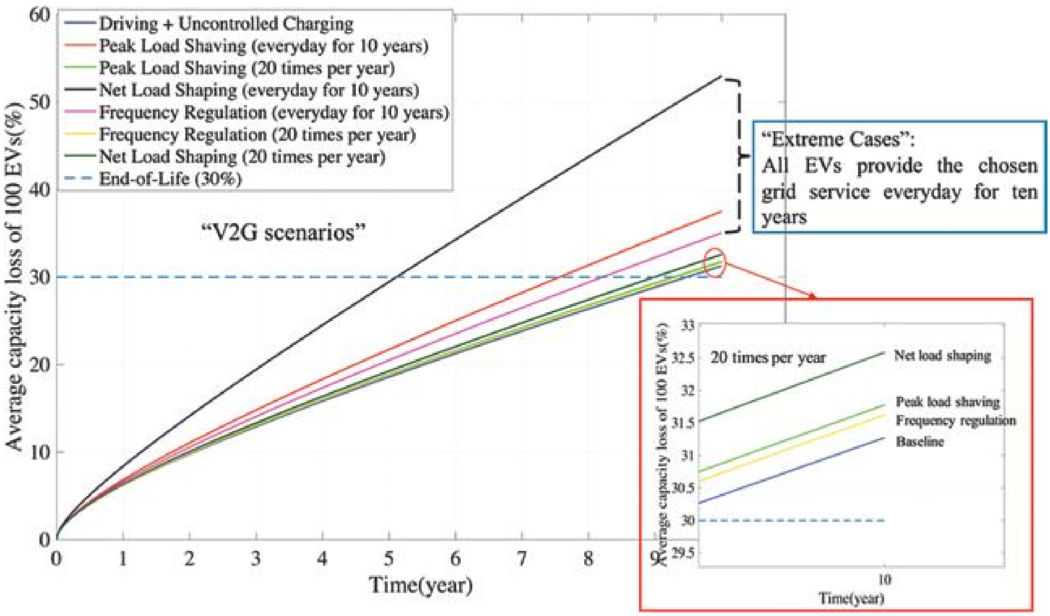

Figure 3.2 Average battery capacity losses over 10 years with V2G services, providing three different services (peak shaving, frequency regulation, net load shaping) in two usage scenarios (everyday for 10 years and 20 times per year) (Source from Neil et al., (2019)).

On the contrary, (Uddin et al., 2017) demonstrated that using a smart grid algorithm to control charge/discharge cycles and the DOD, V2G service can reduce overall battery degradation by 9.1%.

Finally, battery degradation is a still open important technical challenge for academia and pilot that may move V2G towards a business challenge for consumers. However, according to Neil et al. (2019), V2G profits will need to be enough to compensate for potential battery degradation or at least replacing the cost of the battery with a new one at least.

Another challenge for V2G adoption is the charger efficiency. The amount of energy losses during charge/discharge phases that may influence the cost-effectiveness of both EV ownership and V2G participation. Apostolaki-Iosifidou et al. (2017) estimated the amount of energy losses using V2G system that varies through the amount of current and the charge/discharge phase. The authors tested two different current levels, i.e., 10A and 40A, including transformer and breakers losses with, in the worst case, energy efficiency is around 83% and 62% for charging and discharging phases, respectively. On the contrary, Kwon et al. (2015), and Bodo et al. (2017) estimated that applying technical improvements to the charger could increase discharging efficiency up to 94.5% in practice.

3.4 – Literature review on car-sharing with V2G models

A first step addressed to the EV charge algorithm in a one-way station-based electric CSSs has been presented by Gambardella et al., (2018), Brendel et al., (2018), and Illgen and Hock, (2018). However, these models do not consider the possibility of selling energy to the power grid but only G2V optimization, that is, from the power grid to the vehicle.

In the literature, V2G technology implemented to CSSs was introduced by Freund et al. (2012) and by Fournier et al., (2014). Freund et al. (2012) introduced a software agent control architecture considering distribution system operators, micro smart grid operators, and car-sharing operators in order to maximize the EVs charging through the utilization of renewable energy sources. Fournier et al. (2014) analyzed the integration of electric car-sharing fleets implemented with V2G technology into a grid and estimated the potential profit using a Monte Carlo simulation model with real car-sharing data.

Khalen et al., (2018) developed a mixed rental-trading strategy that predicts the day-ahead electricity prices and demand for each district of a city including uncertainties. The authors provided the optimal EV SoC management for maximizing V2G profit for fleet owners.

Mamalis et al., (2019) developed a queuing-theoretic model and computational tools for coordinating EVs in car-sharing service platforms. The authors have assumed that an EV battery can be divided into two distinct parts as the car-sharing service and the grid service part, respectively. The model provides an algorithm to optimize the transportation price and the EV battery split percentage for dual-use.

Shuyun et al., (2019) introduced a dynamic pricing scheme for the EV-sharing network. The authors formulated the dynamic pricing scheme as an optimization problem that maximizes the system profit considering EVs relocation and Vehicle-Grid integration.

Finally, Zhang et al., (2020) introduced a two-stage mathematical formulation that evaluates CSS design and EVs profitability integrating V2G technology. They applied a linear-decision-rule-based approximation approach for solving dynamic operations considering the minimization of overall costs as the main objective function.

No study has focused on a vehicle-by-vehicle EV fleet management optimization model that provides the optimal start-of-day EVs distribution among stations and the optimal charging/discharging EVs scheduling for maximizing CSSs performance. These two aspects are closely related to each other. If an EV is used to sell energy to the power grid, it reduces its State-of-Charge (SoC) and could be unavailable to users if the SoC falls below a threshold level. On the other hand, if an EV is expected to remain unused, it could be worthwhile to sell the energy stored in its battery if the selling price is higher than its purchase price.

For this reason, in this work a model that aims to find the optimal energy sale/purchase scheduling for each EV and the optimal start-of-day EVs distribution to maximize revenues from CSS users have been proposed. Therefore, in addition to the ‘CSS revenues’ KPI, is introduced the ‘V2G profits’ KPI resulting from smart charging depending on customers' demand and electric energy prices.

In order to test the effectiveness of the proposed model, it has been applied on a small-size and on a real-size networks (i.e., Delft network, The Netherlands) for evaluating the V2G impact and profitability in terms of customer satisfaction (revenues derived from CSS) and V2G profits. In addition, a sensitivity analysis is carried out tuning up different parameters. As a result of the proposed model, it is possible to provide the optimal day-ahead assignment of EVs at each station at the beginning of the day considering a fixed EV fleet and a fixed demand.

CHAPTER 4: THE PROPOSED OPTIMIZATION MODELS

4.1 – Simulation-based models

4.1.1 – Notation

All symbols and mathematical notations adopted in the remainder of this paragraph are resumed as follows. They are listed in the order of mention.

v_{tot}	total number of EVs.
n_c	number of charging connectors in the depot.
p_d	total number of parking places in the depot.
n_s	total number of charging stations.
i	progressive number of service area stations: $i \in \{1,2, \dots, n_s\}$.
ps_i	total number of parking places of the station i.
n_{sa}	total number of EVs distributed in the service area.
n_d	total number of EVs in the depot.
n_{pd}	total number of EVs plugged to charging columns and parked in the depot.
c	average loss of revenue per lost user.
$\mathbf{ep}$	vector of the expected energy price.
$\mathbf{S}$	subset of the steps of the day from which a charging or a discharging phase of the EV battery take place.
s_w	an element of the set $\boldsymbol{S}$: $w \in \{2, \dots, \lvert\mathbf{S}\rvert\}$.
d_{char}	number of steps necessary for fully charge/discharge an EV battery.
D	profit gained from a generic EV plugged to charging column and parked in the depot.
D_k	profit gained from the EV k plugged to charging columns and parked in the depot: $k \in \{1,2, \dots, n_{dp}\}$.

$p(v_i)$ V2G profits obtained from the EVs belonging to the station *i* allocated in the service area: $i \in \{1,2,\dots,n_s\}$.

$\boldsymbol{v}$ vector of the number of EVs parked at the beginning of the day at each station i of the system.

v_i an element of the vector $\boldsymbol{v}$: $i \in \{1,2,\dots,n_s\}$.

$l_u(\boldsymbol{v})$ number of users who cannot find an EV available near their origin depending on the vector $\boldsymbol{v}$.

$l_p(\boldsymbol{v})$ number of users who cannot be able to reserve a parking space in their chosen destination depending on the vector $\boldsymbol{v}$.

Z total number of steps in a day.

z step of the day: $z \in \{1,2,\dots,Z\}$.

t_c step of the day from which EVs in the system area start to charge.

t_s step of the day from which EVs in the system area can sell energy.

SoC_{min} minimum value of the State of Charge below which the sale of energy is not allowed.

j progressive number of an EV in the service area: $j \in \{1,2,\dots,n_{sa}\}$

SoC_j battery State of Charge of an EV j in the service area: $j \in \{1,2,\dots,n_{sa}\}$

4.1.2 – Model description

It is assumed a CSS with a total number of EVs equal to v_{tot} and a depot with a number of charging columns and parking places equal to n_c and p_d respectively. The system has an amount of charging stations n_s allocated in the service area. Each station i has several parking places ps_i and charging columns that can satisfy all the EVs parked in it. Every EV parked in a station must be connected to charging columns in order to end the rental period. The system provides a static EVs relocation during the night. Some EVs may be distributed in the service area (n_{sa}) and some other in the depot (n_d) depending on the expected demand. The EVs plugged to charging columns and parked in the depot (n_{pd}) are used for V2G throughout the day. The depot may also contain unplugged EVs because they are in excess compared to the daily demand of EVs/parking places, as no other depot charging connectors are available. All the EVs parked in the depot (plugged and unplugged ones) cannot be reserved by users. EVs in the service area can be used both by users and for selling/purchasing energy. Depending on EVs distribution at the beginning of each day (i.e., at the end of the relocation process), it is possible to obtain V2G profits at the end of the day (resulting from the EVs plugged to charging columns in the service area and in the depot) and to satisfy a certain number of users.

V2G profits is defined as the difference between the revenues from the sale of energy stored in the EV batteries (generated during the batteries discharging phases at the charging columns) and the costs for the purchase of energy (incurred during the charging phases).

It is considered the potential car-sharing demand which is that of travelers willing to use CSS as their primary mode of transportation. In other words, in the demand it is taken into account the travelers who first check the CSS smartphone/web application looking for a car/parking place. A part of this potential car-sharing demand may not be satisfied (named lost users the unsatisfied demand) because some stations may be empty or full during the day due to one-way trips. The number of users who cannot find an EV available near their origin (named $l_u(\boldsymbol{v})$) or cannot be able to reserve a parking place in their chosen destination (named $l_p(\boldsymbol{v})$) will change transport service. These users generate a loss of revenues in CSS, and an average loss of revenue per lost user equal to c is assumed. The aim of our research is to find an EVs distribution among stations and depot simultaneously, making the most of V2G technology and satisfying CSS customers' requests. In order to achieve this goal, two optimization models and an EV charge/discharge process to be applied to each operating day are proposed. The first model refers to the EVs in the depot, while the second one to the EVs allocated in the service area.

Real-time demand and CSS functioning are obtained through a modified version of the bike-sharing simulator proposed by Caggiani and Ottomanelli (2012). In this simulator, the operating day is divided into Z steps. For each step z and each station i, given the pick-up vehicle demand, the model simulates the destination choice to assess the arrival time for each user. The destinations are randomly chosen according to the relative origin/destination attractiveness and the nature of the trip (one-way or round trip). At the begin of each interval z, the number of vehicles and the available parking places are updated by considering in-out user's flow. For further information and a comprehensive description of the bike-sharing simulator see Caggiani and Ottomanelli (2012). This simulator has been modified to consider the constraints imposed by a station-based one-way CSS and the charge/discharge of EV batteries. In particular, the proposed charge/discharge process flowchart is shown in Figure 4.1. Additionally, a detailed charge / discharge process flowchart is shown in Figure 4.2 which describes all steps of the algorithm process.

In summary, the night charging of EVs parked in the service area starts with the step t_c. Once the EVs are full-charged, after the step t_s, it is allowed to sell the energy stored in their batteries. For each step and each EV, the sale of energy can only take place if the State of Charge (SoC) of EV battery is higher than a pre-established minimum level (SoC_{min}) and if the energy previously accumulated has been purchased at a price lower than the price expected for that step. In order to evaluate the difference between the selling price and the purchase price, all the energy prices and the purchased quantities are stored in a matrix for each step and each EV. The total value of V2G profits will be the sum of these differences. If the sale of energy does not happen, and if the EV is in a station, the battery will be charged. If the EV is hired by a user, the battery will be discharged along the trip path.

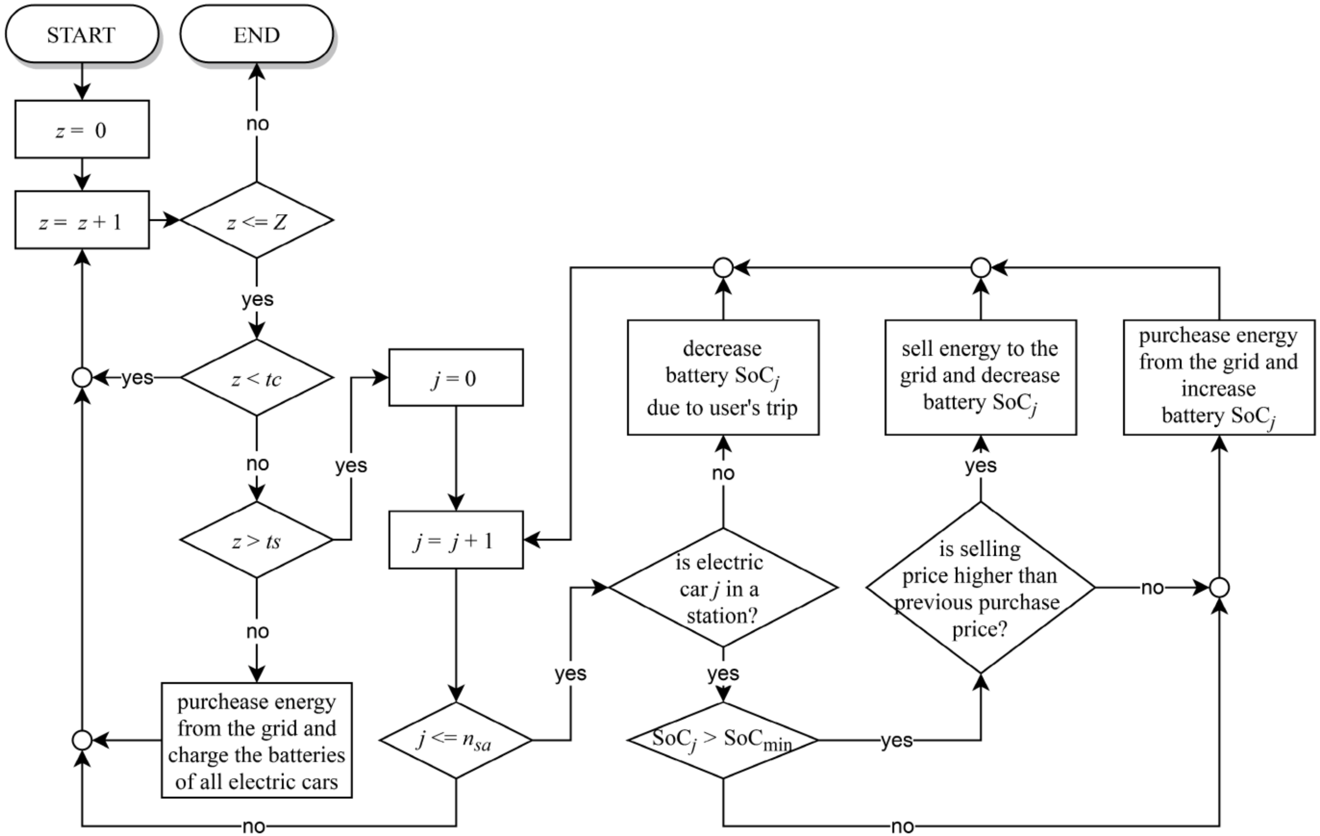

Figure 4.1. EVs charge/discharge proposed process flowchart.

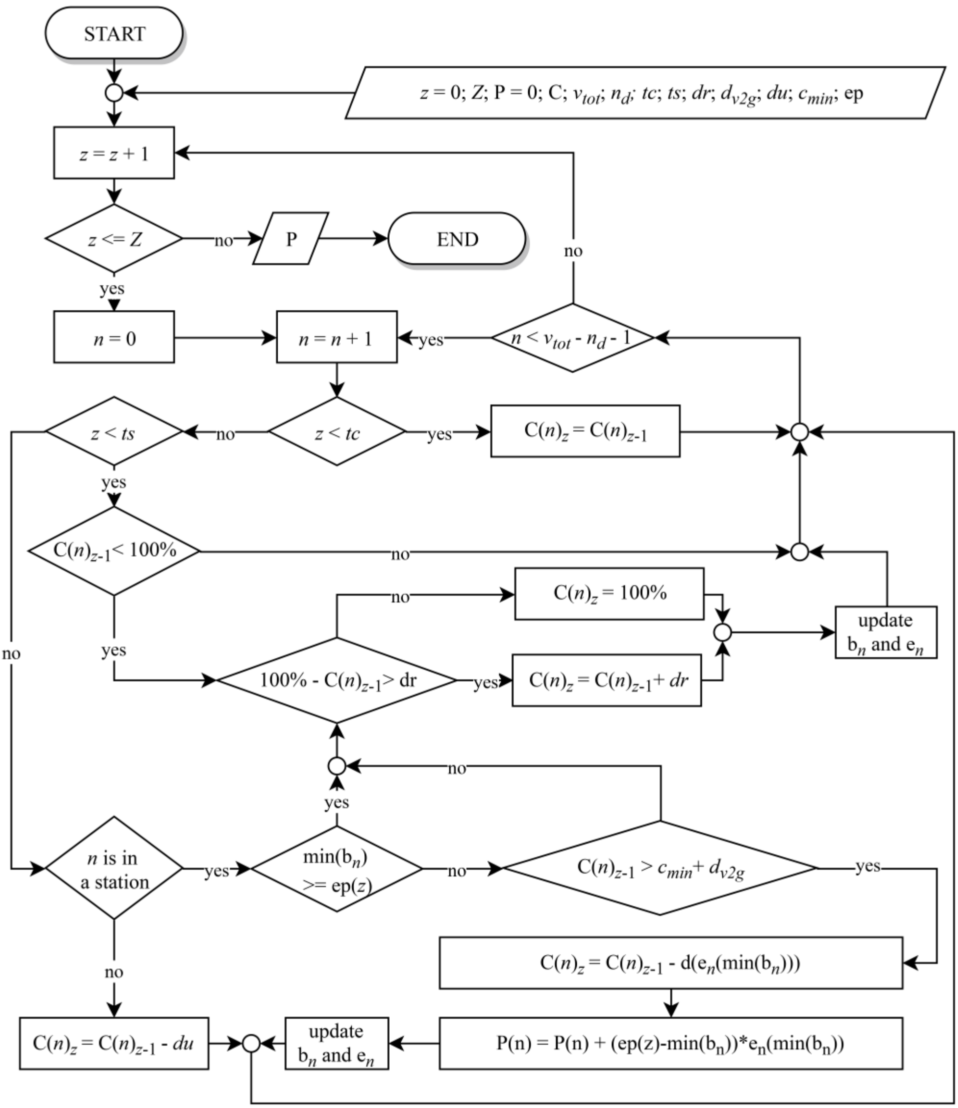

Figure 4.2. Detailed step-by-step EVs charge/discharge proposed process flowchart.

4.1.3 – Mathematical formulation

For the first model, it is assumed that the EVs batteries follow a repeated sequence of charging and successive discharging phases throughout the day. They can occur one immediately after the other or maybe spaced out in time. Since the EVs plugged to charging columns of the depot cannot be reserved by users, it is possible to find, for each EV, the sequence of charging/discharging phases during a day in order to maximize V2G profits, without considering users satisfaction. Therefore, the aim of the first model (4.1)-(4.4) is to maximize the profit D due to the purchase/sale of energy of one EV parked in the depot and connected to a charging column, considering the vector of the expected energy price $\boldsymbol{ep}$.

$$\max D(\mathbf{S}, \mathbf{ep}) \tag{4.1}$$

subject to

$$\mathbf{S} \subset \{1,2, \dots, Z\} \tag{4.2}$$

$$s_w \in \mathbf{S} \tag{4.3}$$

$$s_{w+1} - s_w \geq d_{char}\,, \qquad \forall w \in \{2, \dots, |\mathbf{S}|\} \tag{4.4}$$

Assuming the whole day divided into a number of steps Z, the decision variable of this problem is a subset of the steps of the day **S** (4.2), from which a charging or a discharging phase of the EV battery take place. If s_w is an element of the set **S** (4.3), two consecutive elements must be spaced out at least by a number of steps, equal to d_{char}, necessary for fully charge/discharge the EV battery (4.4).

In the second model (4.5)-(4.11), the objective function (4.5) is the maximization of the algebraic sum of three terms.

$$\max\left[\sum_{k=1}^{n_{dp}} D_k + \sum_{i=1}^{n_s} p(v_i) - \left(l_u(\mathbf{v}) + l_p(\mathbf{v})\right)\cdot c\right] \tag{4.5}$$

subject to

$$v_i \geq 0, \qquad \forall i \in \{1,2,\dots,n_s\} \tag{4.6}$$

$$v_i \leq ps_i, \qquad \forall i \in \{1,2,\dots,n_s\} \tag{4.7}$$

$$n_d = v_{tot} - \sum_{i=1}^{n_s} v_i \tag{4.8}$$

$$n_d \leq pd \tag{4.9}$$

$$n_{dp} = n_c \quad if \quad n_d \geq n_c \tag{4.10}$$

$$n_{dp} = n_d \quad if \quad n_d < n_c \tag{4.11}$$

The first term is the total V2G profit obtained from EVs parked in the depot. This value is a function of the maximum profit gained from an EV in the depot (D_k), according to the problem (4.1)-(4.4), and to the total number of the EVs connected to the charging columns of the depot (n_{dp}). The second term is the sum of V2G profits obtained from the EVs belonging to the station i allocated in the service area ($p(v_i)$) and the third term is the lost revenue due to lost users ($l_u(\boldsymbol{v})$ and $l_p(\boldsymbol{v})$), where the parameter c is the average loss of revenue per lost user. The decision variables v_i of this problem (elements of the vector $\boldsymbol{v}$) are the number of EVs parked at the beginning of the day at each station i of the system. Each v_i is a positive integer number (4.6) and must be lower or equal to the parking places (ps_i) (4.7). The number of EVs in the depot (n_d) can be calculated as the difference between the total number of EVs of the system and the total number of EVs in the service area (4.8). In particular, n_d must be at most equal to the number of parking places available in the depot (p_d) (4.9). The number of

plugged EVs parked in the depot, n_{pd}, is evaluated through constraints (4.10) and (4.11).
The solution of this proposed optimization (4.5)-(4.11) suggests the spatial EVs distribution in the service area and in the depot that has to be achieved through a static relocation carried out by the operator during the night. The results of problems (4.1)-(4.4) and (4.5)-(4.11) are a compromise solution between the maximization of profits deriving from V2G system and the minimization of lost revenues due to lost users. Indeed, both problems consider the point of view of the car-sharing operator who has the objective of getting as many earnings as possible using the same amount of available resources (EVs). In this way, the operator makes the most of the EVs whether they are parked or used by customers.
Profits and lost users are evaluable from CSS demand data. The problem can be solved by knowing EVs and parking places forecast demand. In literature, several car-sharing demand prediction methods have been proposed. In general, neural networks appear to be one of the most used methods. They allow predicting the demand starting from historical data such as the past choices of users, station and user characteristic data, daily weather condition, GPS data, etc. (Wang, Zhong and Ma, 2018; Luo Y. et al., 2019; Luo M. et al., 2019; Moein and Awasthi, 2020; Wang L. et al., 2020; Wang N. et al., 2020). The forecasting methods proposed for other shared vehicle systems, such as bike-sharing systems (Lin et al. 2018; Zhang et al., 2017), could also be applied to the CSSs with appropriate modifications. In our problem the forecasted demand could be estimated, after a period of demand observation to obtain historical data on user choices, using the Nonlinear Autoregressive Neural Network with eXogenous inputs (NARX) as described in the work of Caggiani et al. (2018).

4.1.4 – Numerical applications

In order to evaluate the effectiveness of the proposed simulation-based models and the charge/discharge algorithm, a set of numerical applications has been conducted. In Par. 4.1.4.1

4.1.4.1 – Assumptions and parameters settings

The proposed model has been applied to the city centre of Bari (Italy), considering ns = 15 stations, as shown in Figure 4.3. The service area has been divided into a number of zones equal to the number of stations. Furthermore, it has been assumed a CSS user's willingness to walk to reach a station equal to 500 m (Herrmann, Schulte and Voß, 2014). For this reason, it must be ensured that, from any point of a zone, each related station is reachable on foot via a path no longer than 500 m. Since this area of the city shows a grid configuration of its road network, the distance between two points cannot be measured along the direct path (Euclidean distance) but along the grid. For these configurations, the distances between two points can be calculated according to the Taxicab geometry (Kraus, 1973). In order to assure a walking path up to 500 meters long, from a user's origin to the nearest CSS station and vice versa, the borders of every district have been defined making sure that each one of them falls within a taxicab circle centred in its station and having a radius of 500 m. In particular, a taxicab circle with a radius of 500 m is equivalent to a square with semi-diagonals parallel to the grid and 500 m long (Çolakoğlu, and Kaya, 2007).

The number of parking places for each station psi varies between 8 and 12. In the depot, there are pd = 60 parking places and nc = 15 charging connectors.

The total number of EVs has been set equal to $v_{tot} = 100$. The EV model chosen is the Nissan Leaf 2019 with a battery capacity of 40 kWh and it is enabled to V2G technology with CHAdeMO plug-in fast charge. It is considered for this vehicle a maximum covered distance, with a fully charged battery, equal to 270 km. The selected charging columns have a maximum DC output power of 50 kW, compatible with the fast charging CHAdeMO connection and V2G technology (see for example Enel charger, 2019).

Nissan (2020) claims that the Nissan Leaf 2019 (40 kWh) battery can be charged from 20% to 80% in about an hour with a CHAdeMO (50 kW) rapid charger. Some factors such as the charger type and condition, battery/ambient temperature can change the duration of the charge.

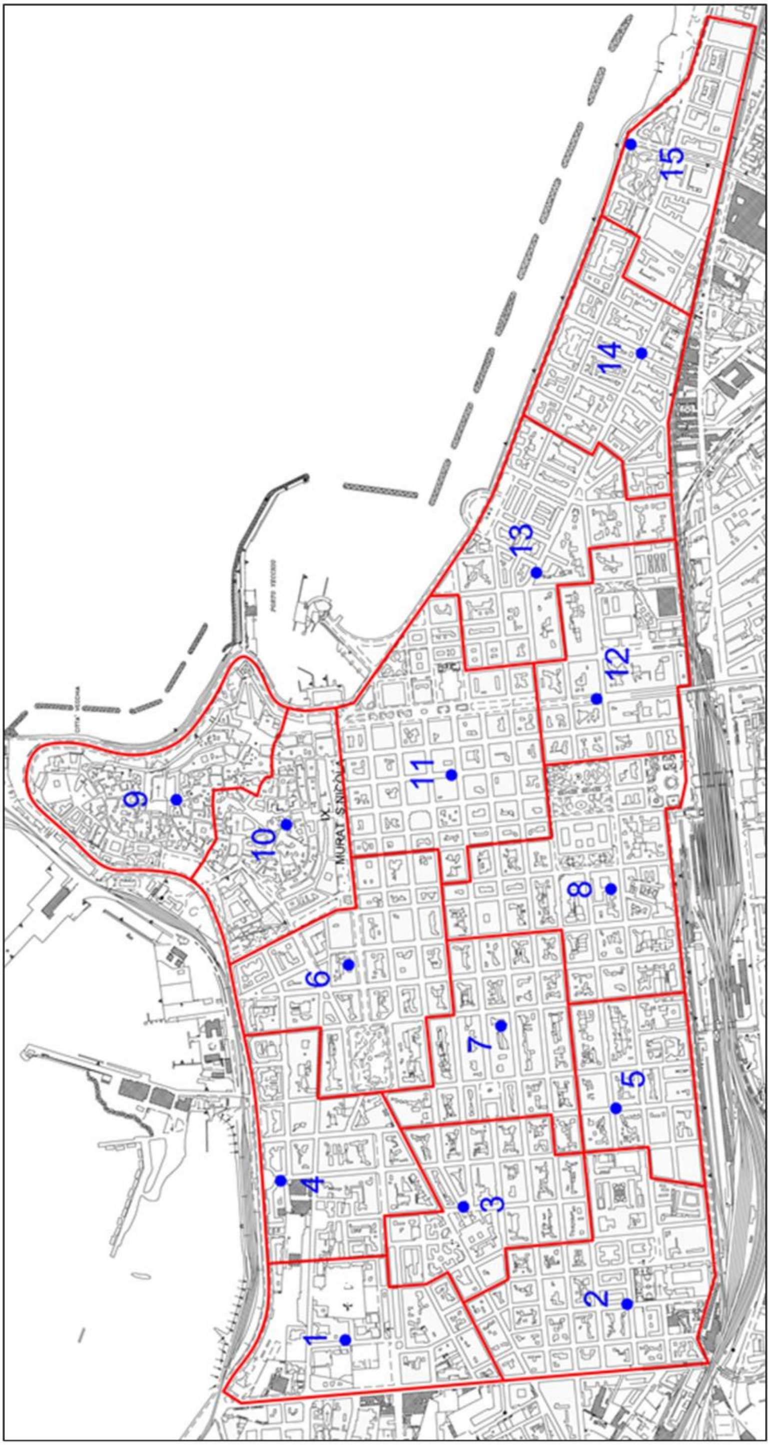

Figure 4.3. The city center of Bari – zones and stations.

According to Fastned (2020), a Dutch company of charging stations, the charging speed of this model starts to decrease from a SoC equal to 60%. In this application, a linear battery charge/discharge pattern has been assumed. To also consider this speed reduction and other factors that can influence the speed of charging/discharging, an average battery charging or discharging time at stations/depot has been set equal to 2 hours and 15 minutes.

During the charging and the discharging phases, energy losses occur both in the EV and the at the grid connection. These losses depend on different variable factors such as the battery SoC, the temperature and the current; furthermore, the amount of losses depends on whether the system is in the charging or discharging phase (Noel et al., 2019). In literature, the charging, the discharging or the round-trip (whole cycle) efficiency values are debated (Apostolaki-Iosifidou, Codani and Kempton, 2017; Shirazi and Sachs, 2018; Apostolaki-Iosifidou, Kempton and Codani, 2018). Indeed, there is some ambiguity in the round-trip efficiency values used in literature ranging from 55% up to 100% (Schram et al., 2020). Recently, Schram et al. (2020), through an empirical evaluation, show that the maximum round-trip efficiency at maximum current and with a SoC between 25% and 70% was equal to 87.0% ($\pm$1%). They found these results for a Nissan LEAF (MY2018) with a DC V2G 10 kW charging station. To the best of our knowledge, there are no empirical tests on more recent V2G-enabled cars and fast-charge DC charging columns such as the Nissan Leaf and charging columns considered in this application. However, EV components technologies (batteries and power electronics units), as well as electric vehicle supply equipment (i.e., charging stations), are continually evolving. Additionally, the use of some charging/discharging management algorithms can improve the V2G efficiency. For example, the algorithm proposed by Apostolaki-Iosifidou, Codani and Kempton (2017) can reduce global losses by 8.5%. For these reasons, any charge/discharge efficiency values have been fixed. However, to take into account globally energy losses, the sum of V2G profits in the objective function (4.5) has been reduced by 10%.

According to the simulator, the day has been divided into steps of 5 minutes each. The following step of the day values were also set: $t_c = 25$ (corresponding to 2:05 a.m.)

and $t_s = 73$ (corresponding to 6:05 a.m.). Considering an average speed of EVs equal to 15 km/h, an EV can travel 1.25 km for each step with a battery consumption equals to 0.46% of its energy capacity. This average speed has been considered for the intrinsic characteristics of the case study. The city center of Bari includes a historic area with very narrow streets with a speed limit of 20 km/h. Furthermore, almost all the city center zones are subject to a speed limit of 30 km/h due to the mixed presence along the streets of cars and electric scooters. Furthermore, the traffic congestion during peak hours on some main network arcs has been taken into account.

When the EVs are in the stations or in the depot, the EVs batteries can be charged or discharged (by 3.7% of their capacity for each step) depending on the expected trend of energy price. For each EV in the stations, the energy is sold only if the autonomy of the EV is more than 35 km and if in that time step the cost of energy is higher than the amount paid to charge the battery.

Modelling the open market of electricity trade is very complex. Different predicting models of energy price have been proposed in the literature (Szkuta, Sanabria and Dillon, 1999; Contreras et al., 2003; Shuman and Yang, 2019) and Jiang and Hu (2018) have written a review recently. Choosing the best one, in a V2G framework, is beyond the scope of this first study. Therefore, the expected price of electric energy has been assumed as the average prices of one year. In particular, the price of electric energy evaluating the average hourly value of each Wednesday of 2018 of the Italian and of the Dutch electricity market (GSE, 2018; SMARD, 2019) has been estimated. Figure 4.4 shows these average trends.

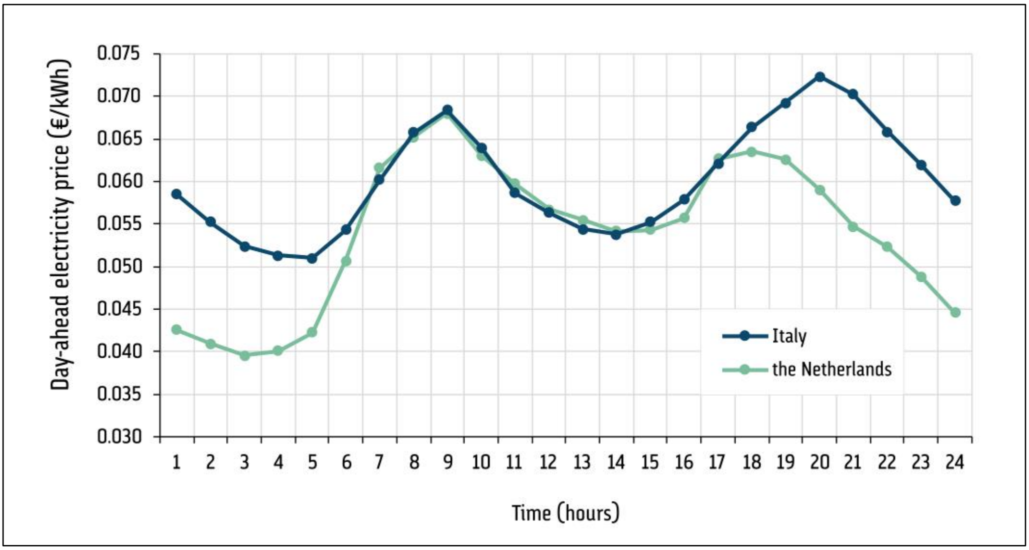

Figure 4.4. Day-ahead electricity market - average annual daily price (the year 2018 – Wednesday).

these two markets have been chosen in order to evaluate the effects on V2G profits, relating to a market that presents a low daily energy price variation (Italy - "Case 1") compared to a market with more significant hourly price differences (the Netherlands - "Case 2").

Assuming a lost user corresponds to a lost trip between two stations, the average loss of revenue per lost user is set equal to $c = 2.8036$ €. This value derives from the average distance between two stations (in an attempt not to overestimate or underestimate losses) and a rental cost per minute of 0.25 €.

For this application, it has been chosen to identify the EVs configuration at the beginning of a single day using the proposed models and charge/discharge process. The SoC of each EV battery has been set, at the beginning of that single day, equal to a random value between 10% and 30%. Furthermore, to evaluate the effects of the CSS congestion on the values of the objective function (4.5), three different demand levels have been set: "LEV 1" with total daily EV requests equal to 111, "LEV 2" with 230 requests and "LEV 3" with 480 requests. LEV 1 is a low demand level compared to the 100 EVs available, while a very high level of demand has been set for the LEV 3 case to reproduce a congested and unbalanced state of the system.

4.1.4.2 – Simulation results

The problems (4.1)-(4.4) and (4.5)-(4.11) have been solved by using a Genetic Algorithm (GA) repeating the optimizations 30 times for each electricity market trend and also for each demand level, related to the model (4.5)-(4.11). In particular, the solution of the problem (GA chromosome) consists of an integer vector, having a length equal to the number of stations (15 in this study). The unitary elements in the vector correspond to the number of EVs parked at the beginning of the day at each station of the system. The fitness function to maximize has been defined equal to the equation (4.5). After some empirical tests carried out to optimize GA parameters, it has been set the population size equal to 200 and the maximum number of generations equal to 3600; the algorithm stops, before reaching the maximum generation number, if the average relative change in the best fitness function value over 50 generations is less than or equal to 10E-12. The genetic operators used to generate offspring are the tournament selection, the scattered crossover, and the gaussian mutation. Note that in this study a GA metaheuristic algorithm has been used for solving the problem. However, further solution methods/parameters could be explored and compared in future works in order to understand which one is the most suitable in solving the proposed optimization and finding even better results. Moreover, the formalization of mathematical programming models based on the presented problems and released from the simulation of CSS operations has been proposed in Par.4.2.
In order to verify the effectiveness of our proposal, for each combination, it was carried out 30 runs starting from a random distribution of the EVs at the beginning of the day, without optimizing their position. The mean and the variance values of the objective function and the average values of the other key variables obtained with EV random distribution (non-opt) and with optimizations (opt) are summarized in Table 4.1. It is possible to state that, in any combination, the optimizations allow getting lower losses with lower variance compared to the non-optimized case. This is more evident for the greatest demand level. For example, for the most congested case (LEV 3), considering the Italian electricity market (Case 1), the mean objective function value is equal to -

273.3 € against a non-optimized value equal to -375.1 €. On the contrary, the objective function assumes positive values only for less congested cases for which the profits from V2G exceed the lost revenue due to the loss of users.
As far as concern the profits, the mean profits of V2G for the entire fleet is higher for medium-low demand levels and for Case 2. In particular, the highest average profit (76.94 €) is obtained for Case 2 with LEV 1. These results are obtained due to EVs less use for low demand levels and to the higher energy prices of the Dutch electricity market compared to the Italian one during the day.
V2G profits obtained in this numerical application refer to a single day. Profits resulting from more extended periods will depend on several factors including demand fluctuation, energy prices over time and on a possible batteries degradation. Indeed, V2G could reduce battery lifetime by adding to EVs regular use capacity losses a further degradation. In the literature, the impact of V2G on batteries has been studied mainly through battery degradation models. For a discussion on literature relating to V2G batteries capacity losses see Noel et al. (2019). In summary, the obtained results are variable. They show that V2G can cause significant capacity losses (Wang et al., 2016), minimal losses (Shinzaki et al., 2015) or even can reduce EV battery degradation (Lunz et al., 2012) for example through the use of a smart grid algorithm (Uddin et al., 2017). In this thesis, battery degradation has not been considered. A smart grid algorithm for optimal battery management of a CSS fleet, in the framework of the proposed relocation strategy, will be presented in a future study.
The best EVs distributions among stations at the beginning of the day, over 30 runs, are shown in Table 4.2. These distributions represent the final configurations that should be obtained through overnight EVs relocation in order to maximize the objective function (4.5). The number of EVs in the depot is almost always greater or equal to the number of charging columns, that is 15, to maximize profits (for a single EV of the depot, the profit deriving from the optimization (4.1)-(4.4) is equal to 1.29 € for Case 1 and equal to 1.39 € for Case 2). The greater the demand level, the greater the number of EVs in the depot. This is evident in LEV 3 of Case 1 and of Case 2, which, on average, show the highest values. In these cases, in fact, the presence of many EVs in the depot

indicates that it is better to remove them from the system, to avoid an increase in the number of lost users due to lack of free parking places. In fact, lost users are increasing more and more from LEV 1 (about 12) to LEV 3 (about 113) regardless of the electricity market.

		Case 1						Case 2					
		LEV 1		LEV 2		LEV 3		LEV 1		LEV 2		LEV 3	
		non-opt	opt	non-opt	opt	non-opt	opt	non-opt	opt	non-opt	opt	non-opt	opt
obj. fun.	mean	-13.3	18.2	-121.3	-73.2	-375.1	-273.3	5.9	43.9	-94.58	-47.2	-344.6	-248.6
(€)	variance	377.5	44.8	582.4	30.7	2806.9	106.3	339.6	29.5	1482.2	50.4	2469.9	71.4
V2G	stations	28.47	32.12	28.74	32.34	29.49	27.61	49.53	58.14	48.89	58.06	52.75	49.68
profits	depot	15.82	17.44	15.66	17.44	15.27	17.44	16.75	18.80	17.92	18.43	16.67	18.80
(€)	total	44.28	49.57	44.40	49.79	44.77	45.05	66.28	76.94	66.81	76.48	69.42	68.48
number	stations	75.17	84.97	74.70	84.10	75.90	70.43	72.37	85.00	71.17	84.50	76.53	72.03
of EVs	depot	24.83	15.03	25.30	15.90	24.10	29.57	27.63	15.00	28.83	15.50	23.47	27.97
lost	l_u	9.20	1.40	32.33	16.93	54.67	52.83	11.20	1.67	34.30	17.23	52.63	49.73
users	l_p	11.33	9.80	26.77	26.93	95.10	60.70	10.33	10.13	23.27	26.87	95.03	63.37

Table 4.1. Mean values (over 30 runs) of the main results.

				stations															
		obj. fun.		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	depot
	LEV 1	29.9	EVs	8	10	0	8	3	6	4	9	0	2	6	7	2	10	10	15
Case 1	LEV 2	- 60.3	EVs	9	9	6	4	3	6	3	3	1	7	3	7	2	7	12	18
	LEV 3	- 246.7	EVs	3	3	6	2	3	5	0	4	1	8	5	6	0	12	12	30
	LEV 1	57.3	EVs	7	7	2	9	6	5	3	8	0	4	5	7	2	10	10	15
Case 2	LEV 2	- 34.8	EVs	9	6	6	3	3	7	3	3	0	8	3	7	3	10	10	19
	LEV 3	- 232.2	EVs	6	4	3	2	3	5	0	6	0	7	5	6	0	12	12	29

Table 4.2. Best EV distribution among stations at the beginning of the day.

4.1.4.3 – Demand perturbation

The optimizations results have been obtained assuming that the expected demand is the same as the real one. Actually, even if reliable, forecasting models are unlikely to predict future demand accurately. For this reason, it has been verified how the proposed model behaves when the Real Demand (RD) is different from that used to define the best EVs distribution among stations at the beginning of the day (Predicted Demand, PD). In order to set a RD different from the PD, the demands used for the optimizations (PD) have been modified through two perturbation procedures. As far as concern the time and the place of the trip origins, in the first procedure, named “PERT 1”, a part of the PD has been randomly shifted over time (from the predicted step to another one) without changing the origin stations. In the second procedure, named “PERT 2”, a part of the PD has been randomly shifted not only in time but also in space (from the predicted origin station to another one). The amount of shifted PD in the origins has been extracted randomly from 10% to 40% of the total daily EVs requests (AM = 10%, 20%, 30% and 40%). Both perturbation procedures do not change the demand level. Therefore, to add further forecast errors, some increase in the demand level, from 0% to 20% has been assumed (EXTRA = 0%, 10% and 20%). The steps/stations of origins of this added demand were chosen randomly. For all cases, the destination stations of the RD have been randomly selected according to the CSS simulator that is to the relative origin/destination attractiveness and the nature of the trip.

The CSS has been simulated considering the best solution found with the PD (best EVs distribution at the beginning of the day) and the RD for each case (Case 1 and Case 2) and each demand level (LEV 1, LEV 2 and LEV3). The differences (percentage deviations) between the objective function values found assuming perfect knowledge of the demand and those obtained with the perturbed demand, are shown in Table 3. In this table, deviations not lower than -10% have been highlighted in bold.

Negative deviations are obtained when the objective function values are lower than those found considering perfect knowledge of the demand. It can be noted that most of the best percentage deviations (positive deviations) are those belonging to the less perturbed demands with EXTRA = 0% and PERT 1 regardless of the AM value and the demand level. On the other hand, on average, the deviations become worse the more the real demand RD differs from the predicted one PD.

However, there are also positive/negative deviations scattered throughout the combinations and also belonging to very perturbed demands. This seems to occur because the more the RD differs from the PD, the more the solution space of the problem changes. Excluding the combinations PERT 1 with EXTRA = 0%, the random perturbation can therefore lead to an unpredictable further increase/decrease of the objective function values starting from the same EV distribution at the beginning of the day. This analysis thus suggests that it is essential to correctly predict the overall demand level (total daily EV requests) and to predict with accuracy the starting station of users' trips. According to the CSS simulation, if the forecast of these two aggregated data is correct, it is possible to obtain good values of the proposed objective function also without the need to predict the starting step of users' trips accurately.

It is important to underline that the objective function deviations are entirely due to the decrease/increase in the number of lost users. Indeed, for all the combinations of Table 4.3, the percentage deviations of V2G profits range between -0.77% and 0.95%. Small increases in the total daily demand or variations of origin/destination stations/time steps do not appear to have affected the total time in which the EVs are in the stations selling/purchasing energy. More evident V2G profits differences occur if medium-low congested cases (LEV 1 and LEV 2) with the most congested ones (LEV 3) are compared, as shown in Table 4.1.

	EXTRA	AM	Case 1			Case 2		
			LEV 1	LEV 2	LEV 3	LEV 1	LEV 2	LEV 3
PERT 1	0%	10%	**0%**	**56%**	**-7%**	**0%**	**72%**	**-5%**
		20%	**0%**	**23%**	**9%**	**-10%**	**137%**	**7%**
		30%	**10%**	**14%**	**7%**	**-10%**	**88%**	**10%**
		40%	**0%**	**32%**	**24%**	**-10%**	**80%**	**5%**
		60%	-19%	**74%**	**26%**	-44%	**113%**	**13%**
	10%	10%	**10%**	**0%**	-20%	-15%	**81%**	-31%
		20%	-75%	-23%	**-3%**	-29%	**56%**	-40%
		30%	-38%	**33%**	-31%	-20%	**137%**	**6%**
		40%	**19%**	**9%**	-23%	-24%	**97%**	-23%
		60%	-37%	-33%	-25%	-39%	**-9%**	**-4%**
	20%	10%	**47%**	**14%**	-58%	-20%	**48%**	-28%
		20%	**19%**	-56%	-37%	-34%	-32%	-40%
		30%	-94%	**47%**	-68%	-25%	**97%**	-37%
		40%	-84%	**97%**	-73%	-54%	-33%	-69%
		60%	-37%	**56%**	-29%	-78%	-73%	-16%
PERT 2	0%	10%	-122%	**18%**	**-6%**	-20%	-32%	**29%**
		20%	-47%	**-9%**	**-5%**	-29%	**64%**	**12%**
		30%	-84%	**46%**	**11%**	**-5%**	-41%	**16%**
		40%	**0%**	**55%**	-33%	**5%**	**24%**	-23%
		60%	-93%	**-9%**	-37%	-44%	**129%**	-35%
	10%	10%	-103%	**33%**	-34%	**-10%**	**0%**	-40%
		20%	**28%**	**0%**	-34%	-20%	**16%**	-14%
		30%	-93%	-51%	**-9%**	**-5%**	-194%	-37%
		40%	-131%	**28%**	-32%	-44%	-81%	-44%
		60%	-178%	-19%	-49%	-29%	-97%	-31%
	20%	10%	-18%	**0%**	-18%	-54%	-137%	-91%
		20%	**0%**	**10%**	-65%	**5%**	**40%**	-35%
		30%	-37%	-37%	-56%	-64%	-73%	-56%
		40%	-121%	-61%	-72%	-39%	-194%	-75%

Table 4.3. Percentage deviations of the objective function obtained with RD.

4.1.4.4 – Results discussion

In this Paragraph, two optimization models and a charge/discharge process for one-way station-based Car-Sharing Systems (CSSs) with Electric Vehicles (EVs), implemented with Vehicle-to-Grid (V2G) technology, are proposed. The output of the proposed models suggests EVs distributions among stations at the beginning of each day, simultaneously maximizing V2G profits and keeping revenue losses, due to lost users, as low as possible. In order to assess the effectiveness of the proposed models and the charge/discharge process, a numerical application on a real-size test case have been needed. The numerical application has been carried out changing some key parameters of the problem, namely electricity market trend and the demand level of the simulated CSS. The results have been compared with non-optimized cases. The analyses show that this approach to the problem of CSS relocation in a V2G framework is promising. The optimizations allow getting higher profits from V2G and lower revenue losses with a lower variance of the objective function compared to the non-optimized case. The higher the daily change in the price of energy, the better the obtained results. The proposal seems to be effective, although to a lesser extent, even for the congested case with a high demand level. The impacts on the objective function values due to demand prediction accuracy have also been assessed. The simulations have been shown that V2G profits seem to not be affected by the correctness of the forecasted demand but depend primarily on the overall demand level. On the other hand, the number of lost users is more sensitive to the accuracy of the prediction and, in particular, to the accuracy of the total daily EVs requests of the entire operating area and of each station.

Different solution methods and parameters could be explored and compared in future works to understand which one is the most suitable to solve the proposed models. The formalization of mathematical programming models based on the presented problems and released from the simulation of CSS operations is presented in the next paragraph 4.3.

4.2 – Mixed Integer Linear Programming model

In this section, the proposed Mixed Integer Linear Programming (MILP) model for optimal fleet and smart charging/discharging management of a one-way electric CSS is introduced. The optimal management is achieved by maximizing CSS revenues and V2G profits. Par. 4.2.2 introduces the basic assumptions of the model, Par. 4.2.3 shows in detail the MILP mathematical formulation and Par. 4.2.4 describes a small-size application of the proposed MILP.

4.2.1 – Notation

This section summarizes all the mathematical notations and symbols adopted to the MILP model. They are grouped into three main categories: sets and matrices, decision variables, and parameters used for solving the proposed model.

Sets, matrices, and vectors

$\boldsymbol{S}$ stations set, where $\boldsymbol{S} = \{1, \dots, i, \dots, S\}$

$\boldsymbol{T}$ time steps in a day set, where $\boldsymbol{T} = \{1, \dots, t_s, \dots, t_e, \dots, T\}$

$\boldsymbol{V}$ electric vehicles set, where $\boldsymbol{V} = \{1, \dots, v, \dots, V\}$

$\boldsymbol{A}$ time-space network nodes set obtained combining set $\boldsymbol{S}$ with set $\boldsymbol{T}$ with i_t elements representing station i at time step t, where $\boldsymbol{A} = \{1_1, \dots, i_{t-1}, i_t, i_{t+1} \dots, S_T\}$

$\boldsymbol{C}$ time-space customer demand matrix with $c_{i_t j}$ elements representing the number of customers leaving from origin i at time step t headed toward destination j, $i_t \in \boldsymbol{A}, j \in \boldsymbol{S}$.

$\boldsymbol{Z}$ parking places matrix with z_i elements representing the number of parking places for each station $i \in \boldsymbol{S}$.

$\boldsymbol{\Delta}$ time-distance matrix with δ_{ij} elements representing the time steps t required to travel from origin i to destination j.

$\boldsymbol{e}$ electric energy unit price vector with e_t elements representing the unit price at time step t.

Decision variables

$b_{i_t}^{v}$ charging phase (electric energy purchase) binary decision variable which is 1 when vehicle $v \in \boldsymbol{V}$ parked at station $i \in \boldsymbol{S}$ is charging during time step $t \in \boldsymbol{T}$, and 0 otherwise.

$s_{i_t}^{v}$ discharging phase (electric energy sale) binary decision variable which is 1 when vehicle $v \in \boldsymbol{V}$ parked at station $i \in \boldsymbol{S}$ is discharging during time step $t \in \boldsymbol{T}$, and 0 otherwise.

$w_{i_t}^{v}$ stand-by phase binary decision variable which is 1 when vehicle $v \in \boldsymbol{V}$ parked at station $i \in \boldsymbol{S}$ is in stand-by, and 0 otherwise.

$x_{i_t j}^{v}$ vehicle displacement binary decision variable in a time-space network from station $i \in \boldsymbol{S}$ at time step t to station $j, i_t \in \boldsymbol{A}$, $v \in \boldsymbol{V}$; $x_{i_t j}^{v} = 1$ if v goes through the arc $a = (i_t, j)$, $x_{i_t j}^{v} = 0$ otherwise.

SoC_t^v battery State-of-Charge dependent decision variable of vehicle $v \in \boldsymbol{V}$ at time step $t \in \boldsymbol{T}$.

Parameters

Q battery energy capacity.

β charge/discharge energy rate that is the amount of SoC increase/decrease per time step of the charging/discharging phase.

ε energy transfer efficiency.

k transferred energy per time step that is the amount of electric energy transferred between EV battery and power grid during a time step of the charging/discharging phase, with $k = Q \cdot \beta \cdot \varepsilon$.

α en-route battery discharging rate that is the amount of the battery SoC decrease during a time step t of a user trip.

p EV usage fee per time step t.

t_s beginning of operation time step.

t_e ending operating time step.

SoC_{min} battery State-of-Charge minimum value.

SoC_{max} battery State-of-Charge maximum value.

4.2.2 – Model description

In this paragraph, the charge/discharge EVs phases, CSS operations, and the main problem parameters are presented. The one-way station-based electric CSS consists of a set of CSS stations $\boldsymbol{S}$ and a set of electric vehicles $\boldsymbol{V}$. Each station $i \in \boldsymbol{S}$ has z_i parking places and is equipped with V2G-enabled charging columns so that one EV per parking place can be plugged in. It has been applied a time discretization by dividing the whole day into T time steps considering $\boldsymbol{T}$ as the set of all time steps t included in a day. Each electric vehicle $v \in \boldsymbol{V}$ has a battery energy capacity Q and can be picked-up or returned by a customer to one of the $S = |\boldsymbol{S}|$ stations through a reservation-based system. All customers' requests must be scheduled in advance within a specific time window of the day (from $t = t_s$ to $t = t_e$) named operating time. Customers' trips start when an EV is unplugged and end when it is plugged in again at a reserved parking place. During the operating time, the status of each vehicle v can be active or inactive, as represented in Figure 4.5.

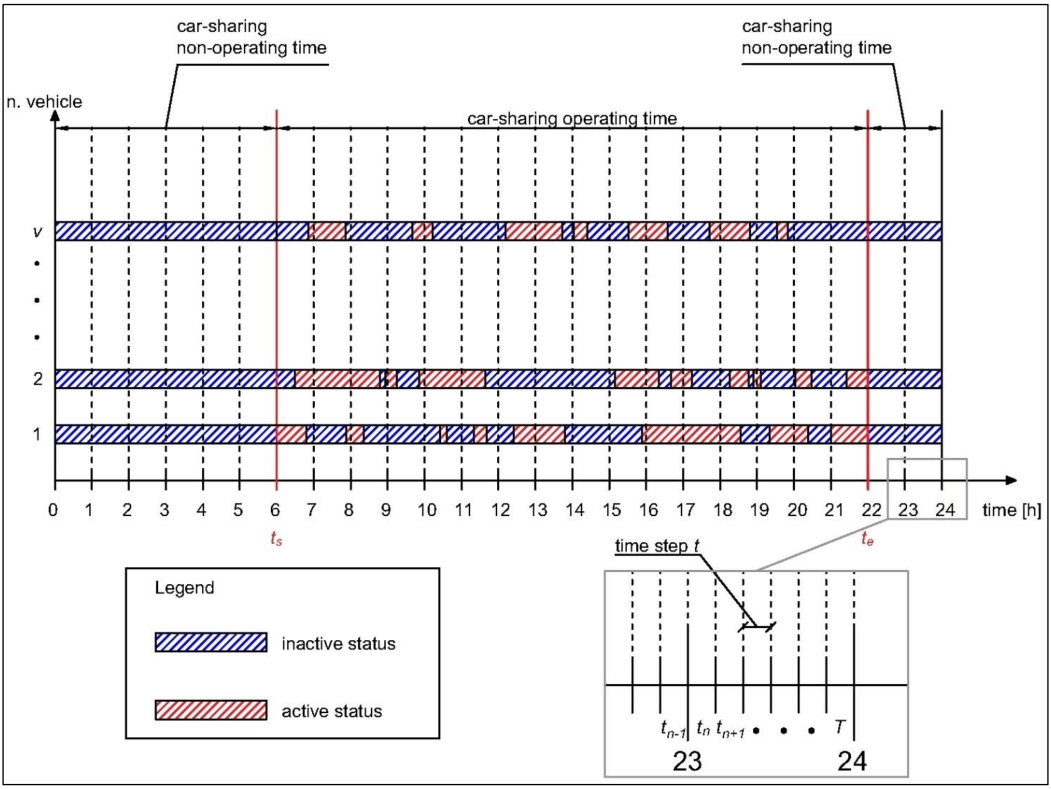

Figure 4.5. The CSS operating scheme applied to the proposed model.

During the inactive status, i.e., when EVs remain plugged into charging columns and are unused by customers, the batteries may be in one of the following phases: charging, discharging, and stand-by phases. In the charging phase, the battery State-of-Charge (SoC_t^v) is increased by a rate β for each vehicle v and time step t. Considering a charging/discharging energy transfer efficiency equal to ε, electric energy k (with $k = Q \cdot \beta \cdot \varepsilon$) is purchased from the smart grid, during time step t, at the energy unit price e_t. In the discharging phase, the reverse process occurs. The battery SoC_t^v is decreased by a rate β for each vehicle v and time step t. The energy k is sold during the time step t, at an electric energy unit price e_t and transferred from the battery to the smart grid. In the stand-by phase, there is no energy transfer (no purchase/sale occurs), and the SoC remains unchanged. The proposed optimization model acts as a smart EVs charging/discharging management system and these three phases, related to CSS EVs during the day, represent the first of the two model outputs. Therefore, for each vehicle v, station i and time step t, charging, discharging, and stand-by phases are represented by binary decision variables named $b_{i_t}^{v}$, $s_{i_t}^{v}$ and $w_{i_t}^{v}$, respectively. These variables assume a value equal to one if the corresponding phase is in progress or equal to zero otherwise. Furthermore, the SoC for each vehicle v at the start of the day is represented by the decision variables SoC_1^v.

During the active status, i.e., when EVs are unplugged from charging columns and are used by customers, a time-space network $\boldsymbol{A}$ and a time-space matrix of customer demand $\boldsymbol{C}$ for evaluating EVs trips between origin/destination stations have been considered. The time-space network is an oriented graph where $\boldsymbol{A}$ is the set of all time-space nodes i_t obtained by combining the stations of the set $\boldsymbol{S}$ with the time steps of the set $\boldsymbol{T}$. In order to make a trip, the required information from the proposed model is related to customer demand. The time-space matrix of customer demand has been set as a tridimensional matrix $\boldsymbol{C}$ with $C_{i_t j}$ elements containing time and space information (origin station i, destination station j, and time step t where an EV parked in station i is reserved). In particular, during a trip made by a customer, an EV is moving in the time-space network through arcs $a = (i_t, j)$. An EV v traverses an arc a according to the value of the decision variables $x_{i_t j}^{v}$. These variables assume a value equal to one if the arc a is traversed or equal to zero otherwise. The optimal configuration of the EVs at the beginning of the day ($t = 1$) is the second output of the proposed model. Additionally, it is necessary to set the origin/destination time-distance matrix Δ between two nodes with δ_{ij} elements. They represent the number of time steps needed to traverse arc $a = (i_t, j)$. Finally, it is considered the *en-route* battery discharging rate α that represents the amount of energy consumption during a time step t of driving. CSS revenues are evaluated by multiplying the CSS fee p for each time step t.

The proposed model presents some assumptions related to the network design of a CSS, the forecast of electric energy unit price and car-sharing demand trends, the battery behavior/degradation, and the relocation processes. Concerning the network design, the proposed model assumes the stations' locations and the number of stations, parking places, and EVs as known. It has been assumed to know the electric energy unit price and car-sharing demand trends. Generally, the electric energy price is a time and day dependent variable due to the energy demand response trade. In the literature, several authors have introduced predicting models of electric energy prices (Contreras et al., 2003; Shuman and Yang, 2019), and Jiang and Hu (2018) have written a review paper recently. As a simplification, it has been assumed that the next-day expected electric energy prices are obtained from a day-ahead electricity market database estimation. Similarly, in the proposed model, it is necessary to use car-sharing demand forecasts. The more accurate the forecasts, the better the model works. Note that the EVs relocation was not directly evaluated in the model. Therefore, an overnight relocation strategy between two consecutive days has been assumed.

The EV battery charge/discharge process follows a non-linear pattern. In the MILP model, both charge and discharge processes are considered linear. Therefore, the EV battery SoC rate is charged or discharged by the same average amount β. In addition, the energy losses during the charging/discharging phase as a fixed parameter ε have been taken into account. The battery lifetime degradation may depend on several factors including the battery SoC charging/discharging range and the number of charge/discharge cycles (see Pelletier et al., 2017). Recently, Koustopolous et al. (2020) have studied the optimal Li-ion battery SoC range by demonstrating through a real test application that it is between 20% and 80%. In the MILP model, EV battery SoC range (i.e., SoC_{min} and SoC_{max}) should be optimized according to the overall profits, including those from V2G. V2G increases the number of battery charge/discharge cycles and could accelerate EV battery degradation (Dubarry et al., 2017). However, there are conflicting opinions on this aspect (Uddin et al., 2018). Contrary to Dubarry et al. (2017), Uddin et al. (2017) have demonstrated that it is possible to extend the lifetime of EV Li-ion batteries through an optimal V2G smart charging system. Nevertheless, the comparison between battery degradation costs and V2G profits would be an interesting research topic for further studies.

4.2.3 – Mathematical formulation

In this section, the mathematical formulation of the proposed MILP model for the daily EVs charging/discharging schedules and the start-of-day EVs distribution of a one-way station-based V2G electric CSS is presented. The MILP formulation is introduced as follows:

$$\max \sum_{v \in \boldsymbol{V}} \sum_{i_t \in \boldsymbol{A}} \left(-e_t \cdot k \cdot b_{i_t}^v + e_t \cdot k \cdot s_{i_t}^v\right) + p \sum_{v \in \boldsymbol{V}} \sum_{i_t \in \boldsymbol{A}} \sum_{j \in \boldsymbol{S}} x_{i_t j}^v \cdot \delta_{ij} \tag{4.12}$$

Subject to

$$\sum_{i \in \boldsymbol{S}} \sum_{j \in \boldsymbol{S}, i \neq j} x_{i_1 j}^v + \sum_{i \in \boldsymbol{S}} x_{i_1 i}^v = 1, \forall v \in \boldsymbol{V} \tag{4.13}$$

$$\sum_{v \in \boldsymbol{V}} x_{i_t j}^v \leq c_{i_t j}, \forall\, i_t \in \boldsymbol{A}, \forall j \in \boldsymbol{S}, i \neq j \tag{4.14}$$

$$\sum_{j \in \boldsymbol{S}} x_{i_t j}^v + x_{i_t i}^v = \sum_{j_{t-\delta_{ij}} \in \boldsymbol{A}, i \neq j} x_{j_{t-\delta_{ij}} i}^v + x_{i_{t-1} i}^v, \forall v \in \boldsymbol{V}, \forall i_t \in \boldsymbol{A}, \forall i \in \boldsymbol{S} \tag{4.15}$$

$$\sum_{v \in \boldsymbol{V}, i \neq j} x_{i_t j}^v + \sum_{v \in \boldsymbol{V}} x_{i_t i}^v \leq z_i, \forall i_t \in \boldsymbol{A}, \forall i, j \in \boldsymbol{S} \tag{4.16}$$

$$SoC_t^v = SoC_{t-1}^v + \varepsilon \cdot \beta \sum_{i_t \in \boldsymbol{A}} b_{i_t}^v - \varepsilon \cdot \beta \sum_{i_t \in \boldsymbol{A}} s_{i_t}^v - \alpha \sum_{i_t \in \boldsymbol{A}} \sum_{j \in \boldsymbol{S}, i \neq j} x_{i_t j}^v \cdot \delta_{ij},$$
$$\forall v \in \boldsymbol{V}, \forall t \in \boldsymbol{T} \tag{4.17}$$

$$b_{i_t}^v + s_{i_t}^v + w_{i_t}^v = x_{i_t i}^v, \forall i_t \in \boldsymbol{A}, \forall v \in \boldsymbol{V}, \forall i \in \boldsymbol{S} \tag{4.18}$$

$$SoC_1^v \leq SoC_T^v, \forall v \in \boldsymbol{V}, \tag{4.19}$$

$$SoC_{min} \leq SoC_t^v \leq SoC_{max}, \forall v \in \boldsymbol{V}, \forall t \in \boldsymbol{T} \quad (4.20)$$

$$b_{i_t}^v \in \{0,1\}, \forall v \in \boldsymbol{V}, \forall i_t \in \boldsymbol{A} \quad (4.21)$$

$$s_{i_t}^v \in \{0,1\}, \forall v \in \boldsymbol{V}, \forall i_t \in \boldsymbol{A} \quad (4.22)$$

$$w_{i_t}^v \in \{0,1\}, \forall v \in \boldsymbol{V}, \forall i_t \in \boldsymbol{A} \quad (4.23)$$

$$x_{i_t j}^v \in \{0,1\}, \forall i_t \in \boldsymbol{A}, \forall j \in \boldsymbol{S}, v \in \boldsymbol{V} \quad (4.24)$$

The aim of the proposed model is the maximization of the objective function (4.12) that is the sum of two terms. The first one (i.e., 'V2G profits' KPI) is the sum of the profits resulting from the energy sale/purchase between EVs batteries and the power grid. V2G profits depend on the energy unit price e_t which is a function of the time step t. The second one (i.e., 'CSS revenues' KPI) is the sum of the revenues obtained from the CSS customers' trips fee p.
The independent decision variables of the problem define the charging, discharging, and stand-by phases for each vehicle v and each time step t during the EVs inactive status ($b_{i_t}^v$, $s_{i_t}^v$ and $w_{i_t}^v$, respectively), the battery SoC for each vehicle v at the beginning of the day (SoC_1^v) and the vehicle displacement in a time-space network from station i at time step t to station j ($x_{i_t j}^v$). The dependent decision variables are the battery SoC for each vehicle v and each time step t excluding $t = 1$ ($SoC_t^v, t \neq 1$).
The objective function is subject to the following constraints. Constraints (4.13) guarantee that, at the start of the day ($t = 1$), each vehicle v can choose only one arc $a = (i_1, j)$ from station i to station j. It allows the start-of-day EV assignment at each station i. These constraints make no distinction between operating time and non-operating time. For this reason, it is necessary to introduce Constraints (4.14). These constraints allow the EV assignment according to the requests of customers $c_{i_t j}$ that leave from station i at time step t to reach destination j. To set the operating time range, the reservation system allows customers' requests $c_{i_t j}$ only within two fixed time steps i.e., the starting operating time step t_s and the ending operating time step t_e. Furthermore, it has been set i not equal to j to avoid the wrong assignment of

decision variables $x_{i_tj}^v$ due to the null value of c_{i_ti}. Constraints (4.15) represent the continuity flow constraints at each time-space node i_t. Constraints (4.16) define the capacity limit of each station i. Thus, the sum of all EVs cannot exceed the maximum number of parking places z_i at station i. Constraints (4.17)-(4.20) define the dependent variables SoC_t^v which represent the EV battery State-of-Charge of vehicle v at time step t. Specifically, Constraints (4.17) allow calculating the EV battery SoC by the residual SoC at the previous time step ($t - 1$) and the sum of three terms. The first and the second term refer to the inactive status while the first term refers to the active status i.e., the electric energy consumption due to EVs displacement during CSS use. In particular, the first term provides the energy purchase from the power grid to EVs batteries while the second term provides the energy sale from EVs batteries to the power grid. Constraints (4.18) ensure that only one of the charging, discharging, and stand-by phases is chosen during the inactive status of a vehicle v. If $x_{i_ti}^v = 1$, i.e., the vehicle v is plugged into a charging column of station i during time step t, only one of the three decision variables, $s_{i_t}^v$, $b_{i_t}^v$and $w_{i_t}^v$ can be equal to one. Constraints (4.19) define the initial SoC of each vehicle v at time step $t = 1$. It must be lower than or equal to the SoC of the same vehicle v at the end of the day ($t = T$). These constraints allow the SoC continuity within two consecutive days. Without SoC continuity constraints, the model would assign SoC_1^v as the maximum value allowed while SoC_T^v as the minimum value allowed, according to the objective function (4.12). Constraints (4.20) define the SoC lower bound and upper bound of all EVs for each step t. Finally, constraints (4.21)-(4.24) define the domain of all independent decision variables.

Solving of the solution to problem (4.12)-(4.24) represents two outputs, namely the daily EVs charging/discharging schedule, expressed by the optimal values of $b_{i_t}^v$, $s_{i_t}^v$ and $w_{i_t}^v$, including the SoC at the start of the operating time (SoC_1^v), and the start-of-day EVs distribution among stations according to the value of decision variables $x_{i_tj}^v$ at time step $t = 1$.

4.2.4 – Numerical applications

4.2.4.1 – Small-size test: toy network

To test the proposed model, it has been applied to a small-size test network. The proposed MILP formulations were solved on a personal computer equipped with an Intel i7 2.4 GHz CPU and 8 Gb of RAM using the CPLEX MILP exact solver by IBM ILOG.

4.2.4.1.1 – Parameter settings

The test network considered has the following characteristics: the total number of stations is set to 5 ($S = 5$) with 5 parking places each ($z_i = 5$ for each station $i \in \boldsymbol{S}$). The EV fleet consists of 10 EVs ($V = 10$) and the operating time is set to 10 hours ($T = 10$). In this test, the non-operating time is not considered, that is $t_s = 1$ and $t_e = T$. The operating time has been discretized into 10 equal intervals each one equal to 1 hour. Electric energy unit price e_t varies between 0.05 €/kWh and 0.25 €/kWh, following the typical day-ahead electricity market trend (see Figure 4.8). The car-sharing usage fee per time step is set equal to $p = 15$ €/h (i.e., 0.25 € per minute). All the stations are equipped with fast-charging columns with CHAdeMO connectors enabled with V2G technology. The EV model chosen for the numerical application is the Nissan Leaf 2019 with a battery energy capacity of $Q = 40$ kWh enabled with bidirectional charging and CHAdeMO connector type. Considering the data provided by Nissan carmaker (Nissan Leaf, 2019), it is assumed the following parameters that have been applied to the simulation, such as the maximum covered distance set equal to 270 km and the full-charge time (from 0% to 100% of EV battery SoC) set equal to 135 minutes. Therefore, the average charged/discharged energy rate per time step is considered equal to $\beta = 44.4\%$. The transferred energy per time step k is the product of EV battery energy capacity Q, the charging/discharging energy rate β, and the energy transfer efficiency ε. Considering $\varepsilon = 90\%$, the transferred energy per time step is $k = 16$ kWh/t. the EV average travel speed is set equal to 25 km/h. The *en-route* battery discharging rate is equal to $\alpha = 9.26\%$ This value is calculated considering the ratio between EV maximum covered distance and the EV average travel speed for each time step. Finally, the time-distance matrix Δ and the time-space aggregate demand matrix $\boldsymbol{C}$ have been shown in Table 4.4 and Table 4.5, respectively.

Origin station i	Destination station j				
	1	2	3	4	5
1	0	1	2	3	2
2	1	0	1	2	3
3	2	1	0	1	3
4	3	2	1	0	2
5	2	3	3	2	0

Table 4.4. Time-distance matrix Δ expressed as the number of time steps t needed to travel from station i to station j.

No. Customer	*Origin i*	*Destination j*	*Origin of the trip time step t*
1	1	2	2
2	2	5	5
3	3	4	7
4	3	5	7
5	3	1	7
6	4	5	1
7	2	1	4
8	5	1	5

Table 4.5. Time-space aggregate demand matrix $\boldsymbol{C}$.

4.2.4.1.2 – Results discussion

The results obtained by solving the problem (4.12)-(4.24) are shown as follows. The sum of V2G profits and CSS revenues (the optimal value of the objective function) is equal to 277.6 € obtained in a CPU time equal to 5.6 s. In particular, the 'V2G profits' KPI is equal to 37.6 € (i.e., 13.5% of the objective function) namely the difference between V2G revenues and V2G costs (69.6 € and 32 €, respectively). The 'CSS revenues' KPI is equal to 240 € (86.5% of the objective function). Furthermore, the whole customers' demand is satisfied (the 'number of trips' KPI is equal to 100%). The problem solution can be depicted on a time-space network (see Figure 4.6).

Each time-space node i_t is represented by a circle where the number of EVs parked at station i at time step t is contained inside the i_t node. According to constraints (4.13), (4.15), and (4.16), each vehicle v must move between time-space nodes depending on the values of $x^v_{i_t i}$ or $x^v_{i_t j}$. If $x^v_{i_t i} = 1$ it means that the EV is moving only through time and not through space, i.e., the EV remains parked at the same station between two consecutive time steps. On the contrary, if $x^v_{i_t j} = 1$, the EV is moving through the time-space arc $a = (i_t, j)$, and is used by a customer. As shown in Figure 4.5, the EVs movements between time-space nodes are represented by two types of arrows. The blue and the red arrows display the decision variables $x^v_{i_t i}$ and $x^v_{i_t j}$, respectively. Additionally, results of the EVs battery SoC management for each time step and the initial EVs assignment among stations at the beginning of the day are shown in Table 4.6 and Figure 4.7. For more details, in Table 4.6 it is possible to observe the vehicle-by-vehicle EV battery SoC for each time step t considered in the small-size numerical application. The higher the number of EVs and time steps t considered, the higher the computation time needed for solving the model to optimality.

Furthermore, it is possible to evaluate the amount of electric energy transferred to the power grid during the day. As depicted in Figure 4.8, 348 kWh are purchased from the power grid to charge the EVs batteries against 432 kWh sold from EVs batteries to the power grid, according to electric energy prices trend $\boldsymbol{e}$.

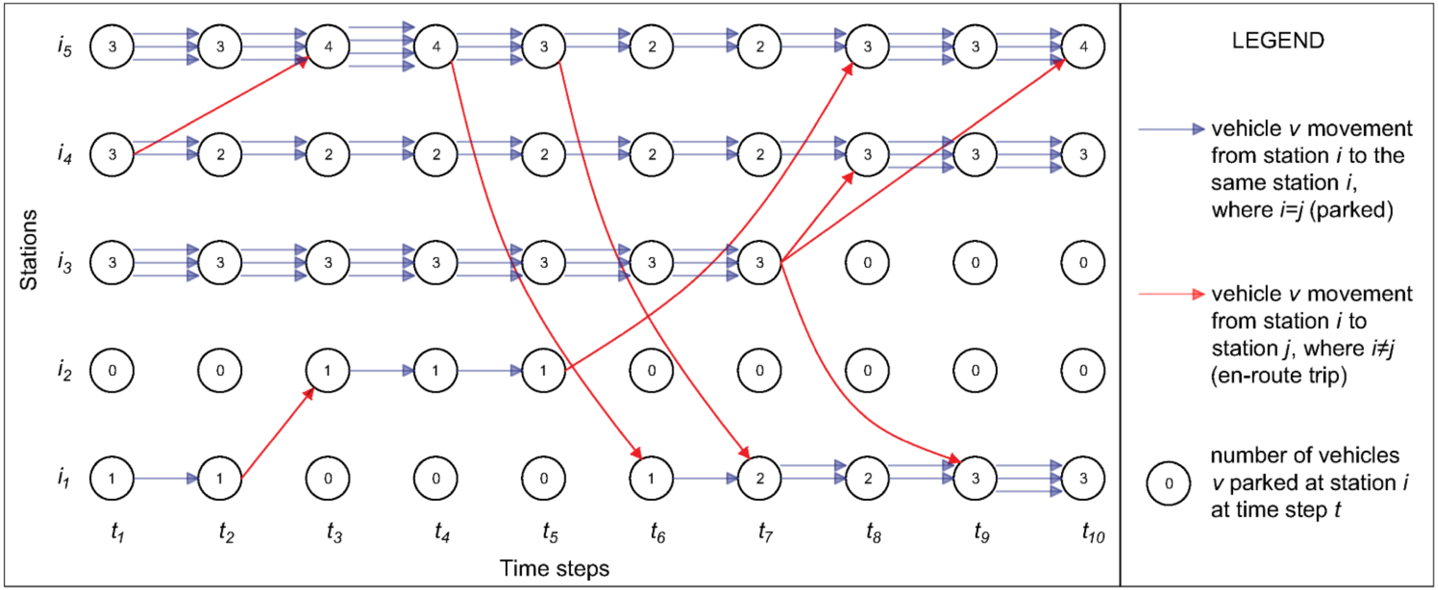

Figure 4.6. Test network results: Time-space network functioning scheme.

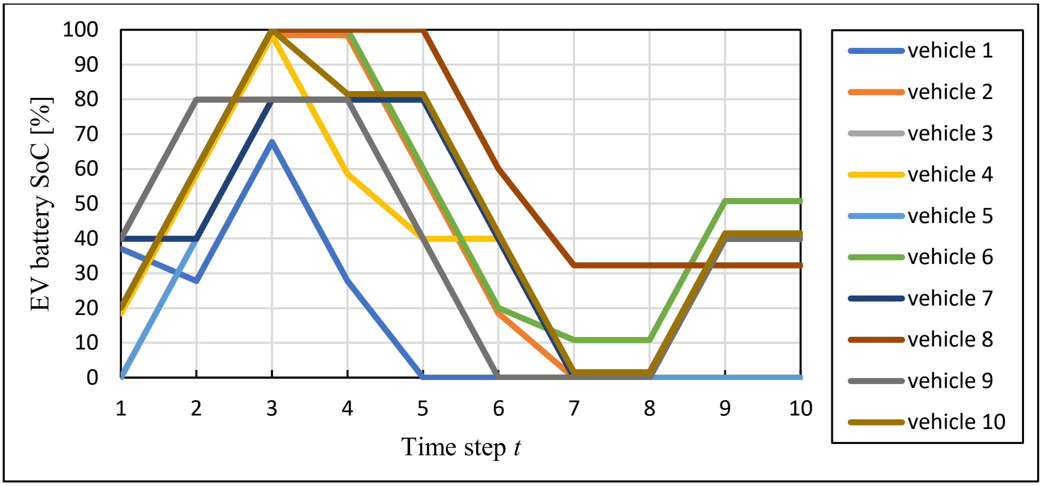

Figure 4.7. Test network results: EV battery SoC variation for each time step t.

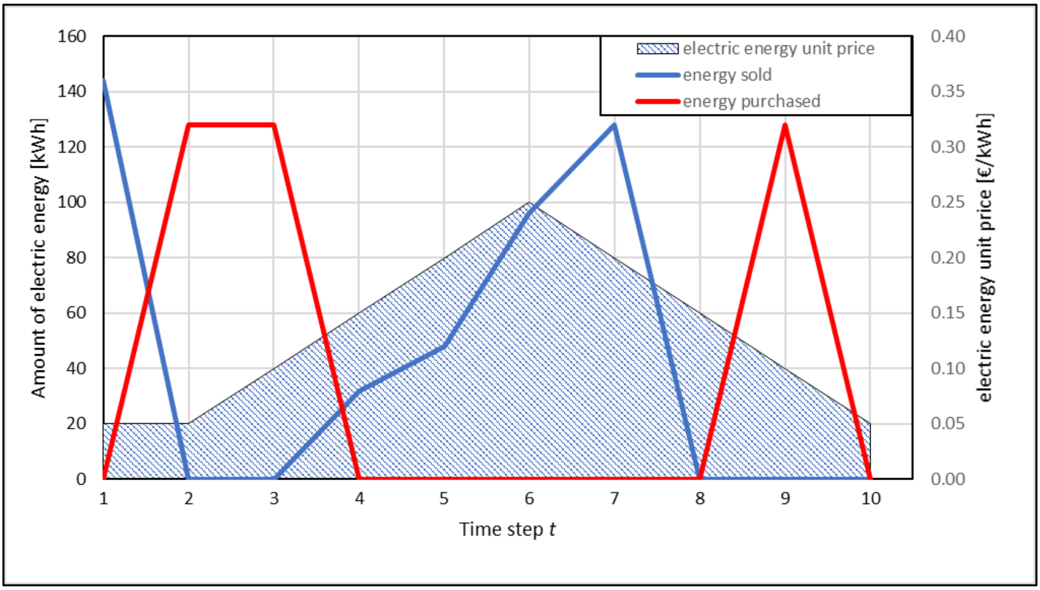

Figure 4.8 Test network results: the amount of electric energy exchange by the V2G energy management system.

Figure 4.8 shows that the proposed smart charge/discharge system allows electric energy selling when the energy unit price e_t is high and electric energy purchase when e_t is low. As a result of the optimization, it is possible to note that the smart charge/discharge schedule allows maximizing V2G profits and simultaneously satisfying the customers' demand as much as possible. Profits deriving from V2G may be valued as revenues from CSS usage. Since in this test the average revenue per user is equal to 30 €, the profits of V2G can be considered as the equivalent of about 1 more customer out of 8. The virtual increase in the number of customers is obtained without moving the EVs namely without exposing them to a part of the wear and tear (e.g., moving mechanical parts, tire, and internal wear) or car accidents and simultaneously satisfying 100% of the real demand.

EV	EV battery SoC [%]										Assigned	CSS	V2G
	Time step t										station i at	revenues	profits
v	1	2	3	4	5	6	7	8	9	10	$t = 1$	[€]	[€]
1	37.04	27.78	67.74	27.78	0	0	0	0	39.96	39.96	1	60	0
2	18.52	58.48	98.44	98.44	58.48	18.52	0	0	39.96	39.96	3	30	4
3	39.96	79.92	79.92	79.92	79.92	39.96	0	0	39.96	39.96	4	0	5.6
4	18.52	58.48	98.44	58.48	39.96	39.96	0	0	39.96	39.96	5	30	2.4
5	0	39.96	79.92	79.92	79.92	39.96	0	0	0	0	5	0	5.6
6	20.08	60.04	100	100	60.04	20.08	10.82	10.82	50.78	50.78	3	15	4
7	39.96	39.96	79.92	79.92	79.92	39.96	0	0	39.96	39.96	4	30	4
8	20.08	60.04	100	100	100	60.04	32.26	32.26	32.26	32.26	3	45	2.4
9	39.96	79.92	79.92	79.92	39.96	0	0	0	39.96	39.96	4	0	5.6
10	20.08	60.04	100	81.48	81.48	41.52	1.56	1.56	41.52	41.52	5	30	4
											Total	240	37.6

Table 4.6.Test network results: objective function terms and SoC values.

4.2.4.2 – Large-size test: the city of Delft

The proposed model has been applied to the city of Delft, the Netherlands. The numerical application is a "quasi-real" case study because only a part of the data used is real. It has been assumed a CSS with V2G-enabled EVs and charging columns that operates in the city of Delft.

The real data comes from the Dutch mobility dataset (MON 2007-2008) and the Delft road network. The mobility dataset is collected by the Dutch government for mobility research gathering daily information related to households' purposes of travel, origin and destination, transport mode, departure, and arrival times. The original dataset contains 68,640 requests made by Delft households during a day of the year 2008. These starting data are also used by Correia and van Arem, (2016) and Liang et al., (2018).

This dataset has been filtered and aggregated in order to obtain a hypothetical car-sharing demand among the Delft city zones. According to the assumed CSS operating time, set as 6:00 am - 10:00 pm, the total number of trips in the dataset using cars and taxis was reduced to 20,640. These trips have been aggregated into several groups, each consisting of households with the same characteristics i.e., gender, age, and education level. To consider only the fraction of the car-sharing demand, the total number of trips of each group has been divided by a coefficient $\mu = 20$ called expansion coefficient (Correia and van Arem, 2016). Therefore, for the 20,640 real households' trips, 1032 CSS trips have been considered. The hourly demand pattern adopted in numerical experiments is depicted in Figure 4.9. Furthermore, in this numerical application, all CSS trips are assumed as booked in advance and the origin and destination, as well as the starting departure time, are obtained from the original database.

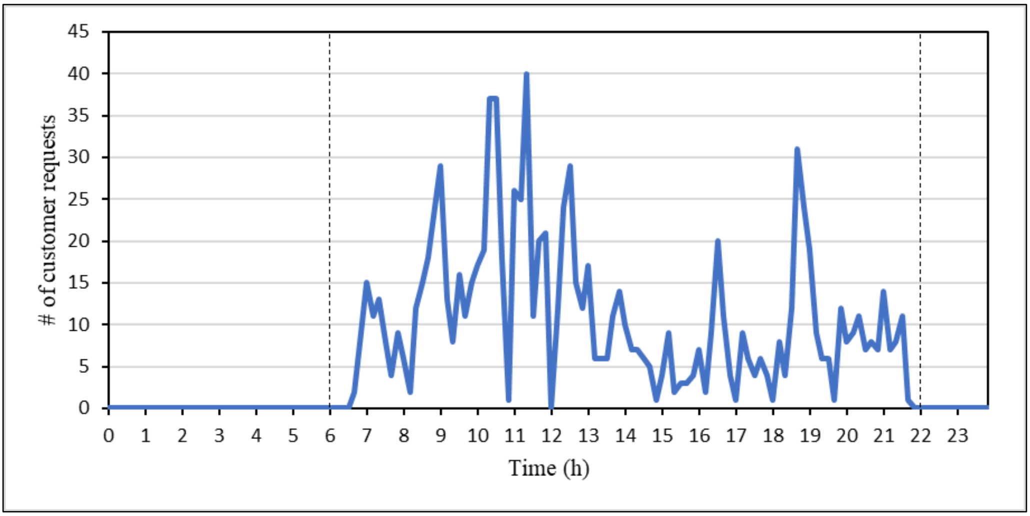

Figure 4.9. Hourly demand pattern applied to the Delft network.

The number of car-sharing stations S has been set equal to 19. These stations have been located by maximizing the CSS covered area and considering a customer catchment area of each station based on the maximum walking distance that can be covered by a car-sharing customer. This distance has been set equal to 500 m (Herrmann et al., 2014). By placing a CSS station in the center of a catchment area and considering Euclidean distances, a station can be reached from any point of a circle centered in the station and with a radius of 500 m. However, the city of Delft does not have a radial street network but a grid street layout approximately. For this reason, it has been considered Manhattan distances according to the Taxicab geometry (Krause, 1973) instead of Euclidean distances. Therefore, the customer catchment area is not a circle, but a square centered in the station with the diagonals parallel to the streets and 1000 m long (taxicab circle). In Figure 4.10 the CSS stations and the customer catchment areas are shown.

Figure 4.10. Delft network.

The dataset trips are defined according to an Origin/Destination (OD) demand matrix among 46 centroids (see black nodes of Figure 4.9). However, it is assumed that all customers within the taxicab circle will use the car-sharing station located in the respective center. For this reason, a data aggregation process has been needed to define the CSS demand matrix $\boldsymbol{C}$. The OD CSS demand of the centroids falling in a taxicab circle, as well as the corresponding departure times, have been aggregated in the center of the circle. For example, the station s_1 demand is the sum of centroids 1 and 24 demand. Some centroids (see red nodes of Figure 4.9) do not present any customers' OD demand, so they have not been considered in the data aggregation process.

The time-distance matrix Δ has been calculated dividing the minimum distance between two stations along with the Delft street network by the average speed of an EV and by the duration of a time step. The shortest paths have been evaluated by applying Dijkstra's algorithm integrated with Google Maps website tool. The EV average speed has been set equal to 15 km/h and the time step equal to 10 minutes. For example, the $\delta_{1,15}$ element of the distance matrix (the time step distance between station s_1 and s_{15}) is equal to 3 since the distance between s_1 and s_{15} is equal to 7 km.

4.2.4.2.1 – Sensitivity analysis

In order to test the effectiveness of the proposed MILP model on a real-case study application, it has been applied to the real-size network of Delft city, The Netherlands. CPLEX MILP exact solver by IBM ILOG with a branch-and-cut algorithm for solving the real-size Delft network has been used. Due to the large-size problem dimension, all computational tests are performed on a computer cluster with 136 CPU Intel(R) Xeon(R) E5-2660 v3 3.3 GHz, 10 cores (20 logical processors), and 128 GB memory for each computer. Due to IBM LOG software limitations, only two computers per computational test with a maximum of 16 cores (32 logical processors) were allowed to be used. Additionally, to obtain near-optimal solutions in reasonable computation time, the relative gap tolerance in optimal solution equal to 10% and the CPU time limit equal to 72 hours have been set. The relative gap tolerance is the relative difference between the upper bound (UB), i.e., the optimal solution value, and the lower bound (LB), i.e., the objective function value, and it is calculated as $(UB - LB)/UB \times 100$ expressed in percentage.

The Delft network considered has the following characteristics: the total number of stations is set to 19 (S = 19) each one equipped with 10 parking places, respectively. (z_i= 10 for each station $i \in S$). The EV fleet consists of 50 EVs (V = 50) and the used EV model is the Nissan Leaf 2019 with three different battery energy capacity versions, i.e., $Q1$= 24 kWh, $Q2$= 40 kWh, and $Q3$ = 62 kWh enabled with bidirectional charging and CHAdeMO connector type. The whole day was discretized into 144 time steps (T = 144) considering an interval of 10 minutes for each time step t. The operating time is set to 16 hours within t_s= 36 (6:00 am) and t_e = 132 (10:00 pm) while the non-operating time is set to 8 hours within t=1 (00:10 am) and t_{s-1}=35 (05:50 am), and from t_{e+1}=133 (10:10 pm) to T =144 (12:00 pm). The electric energy unit price e_t varies between a minimum of about 0.039 €/kWh and 0.068 €/kWh according to the Dutch electricity market. Specifically, has been considered the average hourly electric energy prices of one typical working day of the whole of 2018 applying open-access data obtained from the official day-ahead Dutch electricity market (SMARD, 2019). The CS usage fee per time step is set equal to p = 15 €/h (i.e., 2.5 € per time step). Two different charging columns enabled to V2G technology for testing the proposed model have been considered, such as the charge type L2 (regular charge) with Alternative Current (AC) and the charge type L3 (fast charge) with Direct Current (DC). According to three different battery energy capacities $Q1$, $Q2$, and $Q3$ and two different types of charging/discharging speed $L2$, and $L3$, it has been solved the proposed model on the Delft network considering six different scenarios as resumed in Table 4.7. Parameters settings are calculated according to real data acquired from the official Nissan website (Nissan, 2019) and from all the above-mentioned assumptions. The results of all tests are shown in Table 4.8, Table 4.9, and Table 4.10.

According to Table 4.8, it is possible to make the following observations from an economic point of view:

- First, the results deriving from V2G profitability resulted to be lower than CS revenues, as expected, since the same hourly energy price e between the purchase and sale phases have been considered. This assumption resulted to being extremely conservative. In fact, from V2G profits KPI values, it is possible to obtain on average about 0.5 € per day per EV, i.e., about 182 € per year per EV, similar to results obtained by Kahlen et al., (2018). Indeed, it is possible to settle energy transfer agreements with a fixed sales rate much higher than the values considered on numerical applications.

- Second, despite customer demand is much higher than the number of EVs considered, the use of EVs is on average equal to about 12% in all scenarios throughout the whole day. This means that for about 88% of the daily period, EVs are parked and, consequently, do not generate any revenue for CS companies. The results of EVs usage allow the adoption of V2G technology by taking advantage of EVs' unused time to obtain slight annual profits that can amortize several costs incurred by CS companies. Additionally, all EVs usage in the CSS for all scenarios are represented in Appendix A.1.

- Third, from the sensitivity analysis, by varying both charging/discharging speed and EVs battery energy capacity in the six above-mentioned scenarios, the best result in terms of objective function is obtained from scenario L2Q2. Instead, in terms of optimal solutions, the best scenario resulted to be scenario L3Q3. Finally, it is possible to assert that the relative difference plays an important role in results evaluations. Therefore, the higher the relative difference, the higher the error in terms of objective function and, consequently, the start-of-day EVs distribution among stations, and the overall CSS performance could change.

- Fourth, according to the objective function (4.12), model (4.12)-(4.24) aims at maximizing V2G profits KPI term and CSS revenues KPI term simultaneously. The priority between the first and the second term is due to the price per time step considered. Hence, the first term priority depends on the gap value of the parameter e_t during the purchasing and selling phases (e.g., maximum gap equal to 0.028 €/kWh), while the first term priority depends on the parameter value p (e.g., 2.5€/t). Since the value of the parameter p is set higher than the gap value of the parameter e_t, the priority is to maximize the CSS use with respect to V2G profits. Therefore, V2G technology serves only as an aggregate support system to CSSs, but not vice versa.

Scenario	Charge type	Q [kWh]	β [%]	ε [%]	α [%]	k [kWh/t]	Full-charge time [h]	Max coverage distance [km]
L2Q1	AC-L2	24	3.03	95	1.25	0.855	5.50	200
L2Q2	AC-L2	40	2.22	95	0.92	0.855	7.50	270
L2Q3	AC-L2	62	1.45	95	0.65	0.855	11.50	385
L3Q1	DC-L3	24	12.50	90	1.25	2.67	1.33	200
L3Q2	DC-L3	40	7.40	90	0.92	2.67	2.25	270
L3Q3	DC-L3	62	4.76	90	0.65	2.67	3.50	385

Table 4.7. Parameters applied to different scenarios on the Delft network.

Scenario	Obj. fun. [€/day]	Optimal solution [€/day]	Rel. diff. [%]	CS revenues KPI [€/day]	V2G profits KPI [€/day]	Number of trips KPI	Demand served [%]	EVs usage Avg. [%]	CPU time [h]
L2Q1	1550.96	1582.64	2.04	1530.0	20.96	294	28.49	12.58	4.02
L2Q2	1576.30	1585.62	0.59	1550.0	26.32	295	28.59	12.83	28.27
L2Q3	1455.10	1585.15	8.94	1432.5	22.6	272	26.36	11.92	13.81
L3Q1	1466.55	1594.71	8.74	1435.0	31.55	273	26.45	11.96	56.84
L3Q2	1414.55	1617.55	14.34	1360.0	54.55	261	25.29	11.33	72.00
L3Q3	1533.03	1642.03	7.06	1532.5	1.26	293	28.39	12.85	17.63

Table 4.8. Simulation results of different scenarios applied to the Delft network

Scenario	Electric energy transferred to the grid (energy sold) [kWh]				Electric energy transferred from the grid (energy purchased) [kWh]			
	Operating time	Non-operating time	Total	Net	Operating time	Non-operating time	Total	Net
L2Q1	2232.41	148.77	2381.18	1168.79	1063.62	1569.78	2637.68	1421.01
L2Q2	2475.23	45.32	2520.50	1654.43	820.80	1916.91	2737.70	1871.59
L2Q3	2379.47	42.75	2422.22	1497.98	887.49	1779.26	2666.75	1736.51
L3Q1	3471.00	1073.34	4544.34	894.45	2576.55	2066.58	4643.13	993.24
L3Q2	4739.25	1049.31	5788.56	1639.38	3099.87	2822.19	5922.06	1772.88
L3Q3	5801.91	2667.33	5788.56	509.97	5291.94	3409.59	8701.53	742.26

Table 4.9. Results of electric energy transferred from/to the grid applied to different scenarios on the Delft Network.

Station i	EV v assigned to each station i at time step t=1					
	Scenario					
	L2Q1	L2Q2	L2Q3	L3Q1	L3Q2	L3Q3
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0
6	2	2	4	2	0	1
7	0	0	0	0	0	0
8	0	0	0	0	0	0
9	0	0	0	0	0	0
10	2	1	2	3	2	3
11	10	9	7	6	7	10
12	3	4	4	3	2	2
13	6	7	7	5	9	7
14	0	0	0	0	6	0
15	2	2	2	3	2	1
16	6	7	5	7	6	7
17	1	0	1	3	0	0
18	8	8	8	8	6	9
19	10	10	10	10	10	10

Table 4.10. Results of electric energy transferred from/to the grid applied to different scenarios on Delft Network.

From Table 4.9, further observations from an energy point of view can take place:

- First, the amount of net energy transferred to the grid during the operating time resulted to be significant for providing households' energy supply. Considering the charge speed type L2, the CSS could provide more than 1 MWh from 50 EVs during the operating time. Specifically, the best scenario in terms of net energy provided to the grid resulted to be scenario L2Q2 with around 1.6 MWh. Considering the charge speed type L3, the CSS could provide less than 1 MWh from 50 EVs during the operating time. Despite scenario L3Q2, from scenario L3Q1 and L3Q3, the amount of net energy provided to the grid during the operating time is around 0.8 and 0.5 MWh, respectively. According to all scenarios results, during the energy peak hour period, each EV could transfer to the grid around 20 kWh of electric energy and could satisfy around 2 households' energy supply. For more details, all energy transactions from and to the grid for all scenarios are shown in Appendix A.2.

- Second, the amount of energy transferred from the grid during the non-operating time is comparable with the amount of energy transferred to the grid during the operating time. This is useful for energy providers for frequency regulation and energy balance issues for reducing operating costs.

- Third, the regular charge L2 could provide to the grid a higher amount of electric energy than the fast charge L3. This could incentive install electric columns type L2 instead of type L3 with high savings in terms of fixed investment costs. This observation is confirmed by Zhang et al. (2020) numerical application.

Finally, from Table 4.10, it is possible to observe that in all scenarios analyzed, the start-of-day EVs distribution among stations follows almost the same configuration. This is due to the fixed customers' demand and it does not strongly depend on EVs battery energy capacity Q and on charging columns type speed. Nonetheless, EV energy management resulted to be more effective and balanced for charger type L2 instead of L3 type, as depicted in Appendix A.3.

4.2.4.2.2 – Results discussion

In this paragraph, a MILP mathematical formulation is introduced with the aim to minimize CSS revenues and V2G profits simultaneously. The goal is to provide a first-step analysis concerning V2G technology integration in CSSs in terms of profitability and shared-energy contribution. Additionally, the proposed model suggests the optimal EVs configuration obtained through an overnight relocation strategy considering the demand satisfaction and V2G profits maximization simultaneously. However, the relocation aspect was not directly treated in the proposed model.

To test the effectiveness of the proposed model, it has been tested on a small-size and a large-size test network. Customers' demand and the day-ahead hourly electric energy prices have been assumed as known, as well as the number of EVs, parking places for each station, and a linear charge/discharge pattern for EVs battery consumption rate. Furthermore, a sensitivity analysis by varying battery energy capacity and charge/discharge speed has been carried out. Results have shown V2G profitability in terms of profits and energy-share contribution to the grid during energy peak load demand. Additionally, the best CSS configuration consists of using regular charge speed type L2 and a medium-size EVs battery energy capacity Q2, as reported in scenario L2Q2 results in Table 4.8 and Table 4.9.

CHAPTER 5 – CONCLUSION AND FUTURE DEVELOPMENTS

5.1 – Conclusion

This thesis aims at providing a management system combining Car-Sharing Systems (CSSs) with V2G technology and evaluating the optimal EV distribution among stations at the beginning of the day and the EV energy management through a smart charging system. The CSS business model considered is the one-way station-based. Two type of models are developed using different programming approaches, i.e., two simulation-based models with a smart charge/discharge process and a Mixed-Integer Linear Programming (MILP) model.

The simulation-based models provide EV distribution among stations at the beginning of each day, simultaneously maximizing V2G profits and keeping revenue losses, due to lost users, as low as possible. A numerical application has been carried out on a real-size test case (i.e., the city centre of Bari, Italy) to assess the effectiveness of the proposed models achieving promising results. Furthermore, two different electricity markets have been applied with different daily energy prices for evaluating V2G profits. Moreover, two different cases of EV distribution among stations at the beginning of the day have been compared, i.e., the optimized case (the output of the proposed models) and the non-optimized case (EV random distribution). The optimized case resulted to be superior in terms of objective function value and variance. Additionally, objective function values have been compared with three different predicted demand levels (low, medium, and high) showing that V2G profits values are not affected by the correctness of prediction demand levels despite the number of lost users.

The MILP model provides, following the same goal of the simulation-based models, the optimal start-of-day EV distribution among stations maximizing CSS revenues and V2G profits through daily EVs charging/discharging schedules simultaneously. These schedules are based on daily users' EVs requests and electric energy prices. In order to test the model performance, it has been applied to a small-size test network and a

real-size test network (i.e., the Delft network, The Netherlands) obtaining promising results in terms of V2G profitability and energy supply network support.
Finally, the proposed models can act as a forerunner for further studies and insights. A first-step analysis on a real-size network (i.e., the Delft network, the Netherlands) that demonstrates the applicability and profitability of a smart charging management system combining electric CSSs with V2G technology is provided. Furthermore, according to the sensitivity analysis, the optimal CS configuration in terms of EVs battery energy capacity and charger type is provided. Nevertheless, if V2G is combined with renewable energy sources, it could generate additional economic and environmental benefits in terms of emissions reduction. Several pilots are investing in V2G integration applied to electric shared mobility systems to assess economic, energy, and environmental benefits.

5.2 – Future developments

Additional evaluations will be made to consider non-linear charge/discharge patterns and the impact of the possible reduced life cycle of batteries on the V2G profitability. They will take into account battery simulation and charge/discharge optimization models. In particular, a smart grid algorithm for optimal battery management of a CSS fleet, in the framework of the proposed relocation strategy, will be presented in an upcoming study. Nonetheless, future developments could concern more complex models that may consider EVs relocation, dynamic prices models integration, and non-linear EV battery charge/discharge patterns. Additionally, heuristic approaches for solving real-time applications and large-size problems would be necessary. Nevertheless, a model that evaluates V2G integration with the free-floating CSS would be very interesting to investigate.

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APPENDIX A: THE DELFT NETWORK SENSITIVITY ANALYSIS RESULTS

A.1 Daily electric vehicle usage for all scenarios applied to the Delft network

Scenario L2Q1

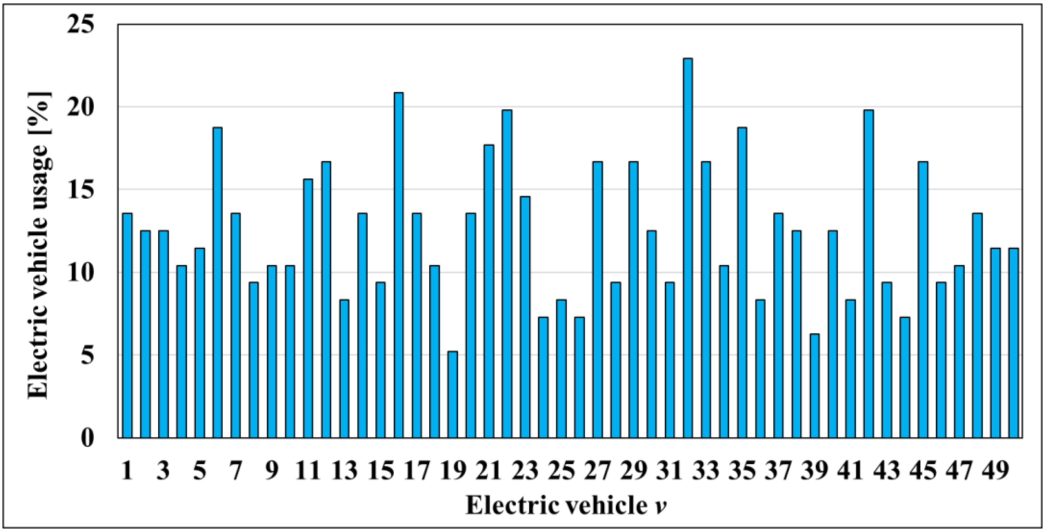

Fig.A.1. Daily electric vehicle usage for scenarios L2Q1 applied to the Delft network.

Scenario L2Q2

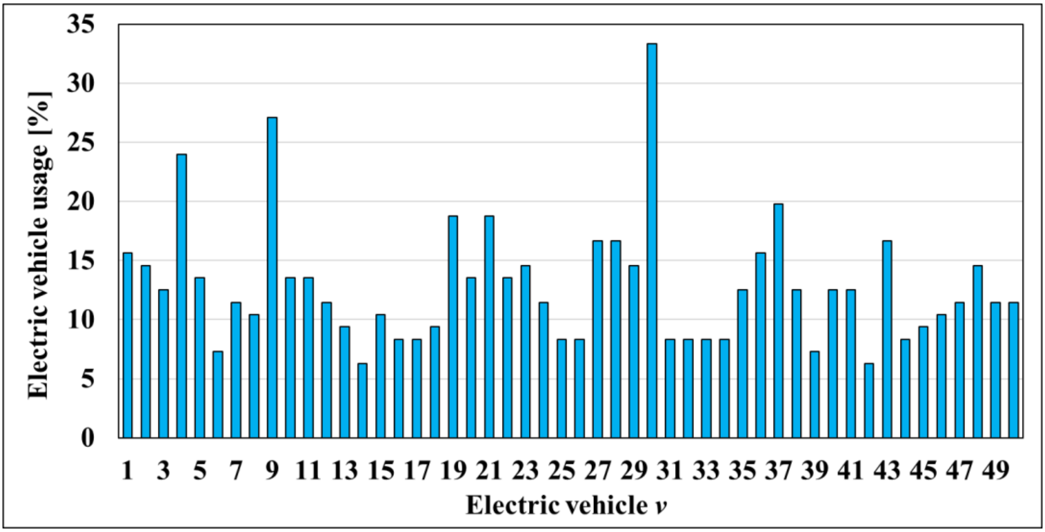

Fig.A.2. Daily electric vehicle usage for scenarios L2Q2 applied to the Delft network.

Scenario L2Q3

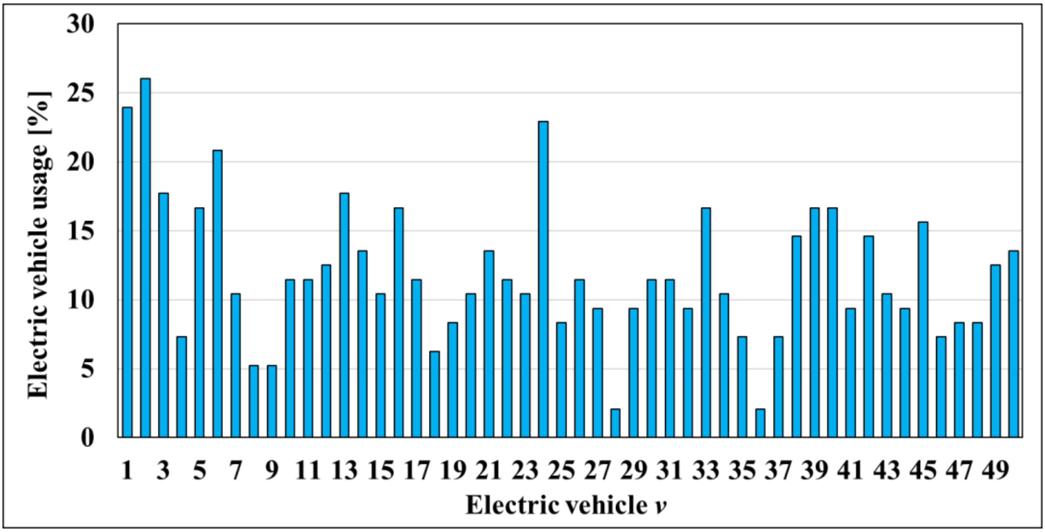

Fig.A.3. Daily electric vehicle usage for scenarios L2Q3 applied to the Delft network.

Scenario L3Q1

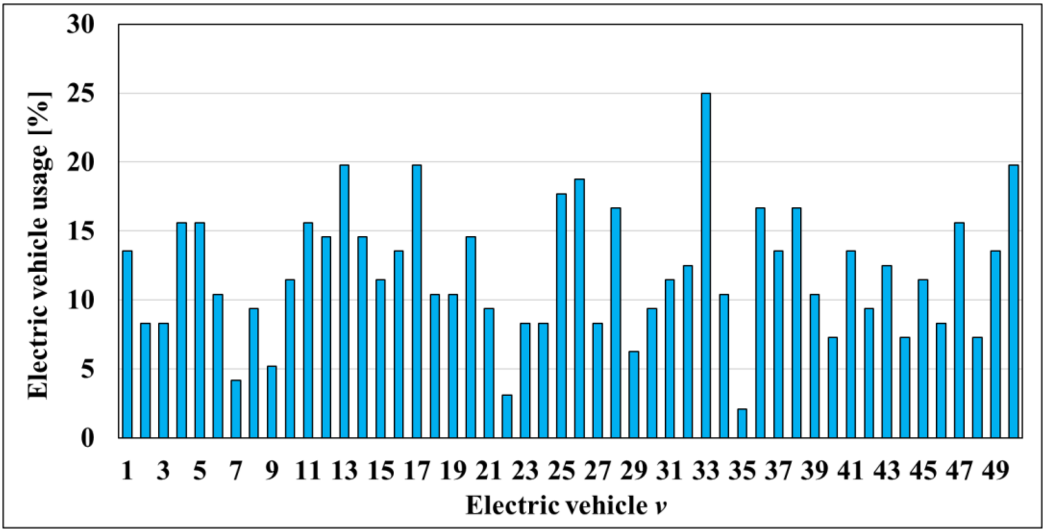

Fig.A.4. Daily electric vehicle usage for scenarios L3Q1 applied to the Delft network.

Scenario L3Q2

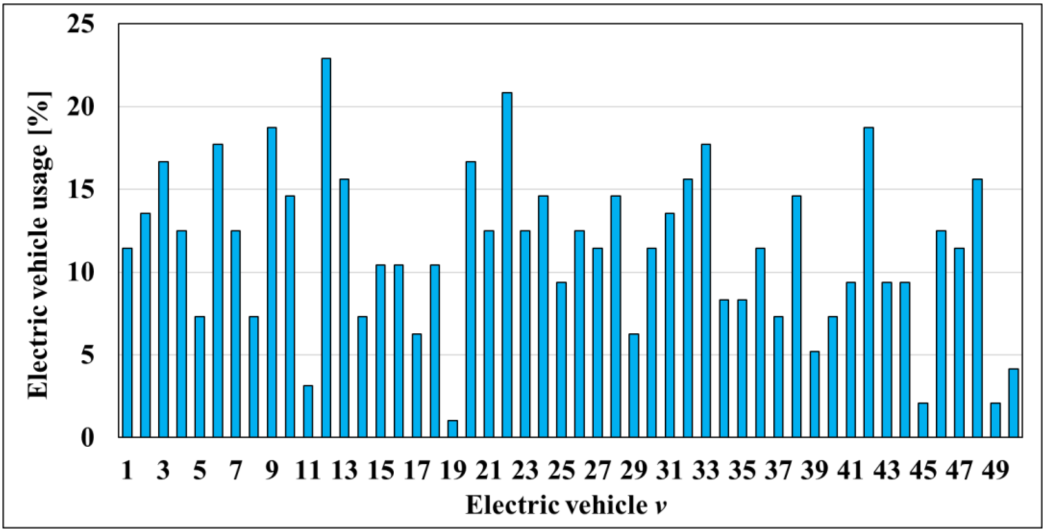

Fig.A.5. Daily electric vehicle usage for scenarios L3Q2 applied to the Delft network.

Scenario L3Q3

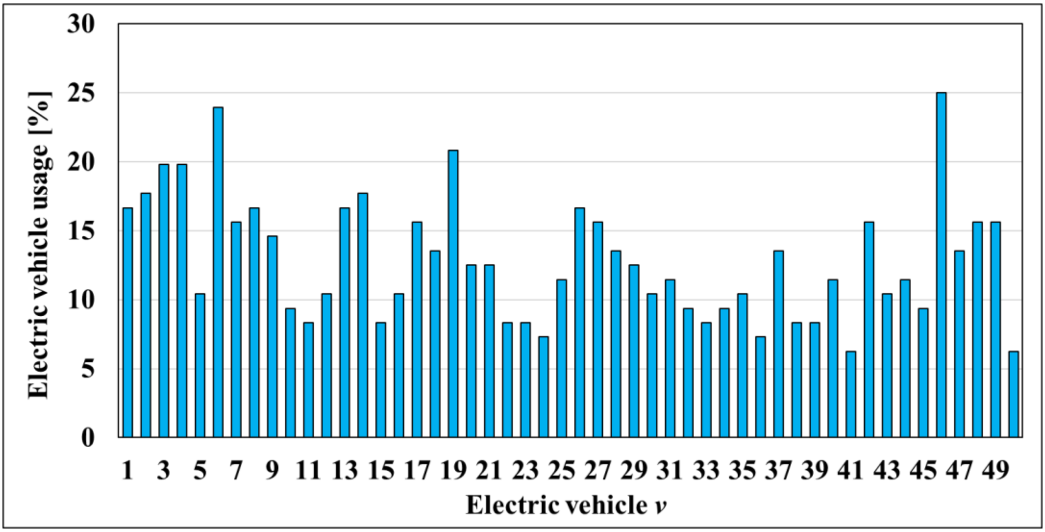

Fig.A.6. Daily electric vehicle usage for scenarios L3Q3 applied to the Delft network.

A.2 Daily electric energy transactions for all scenarios applied to the Delft network.

Scenario L2Q1

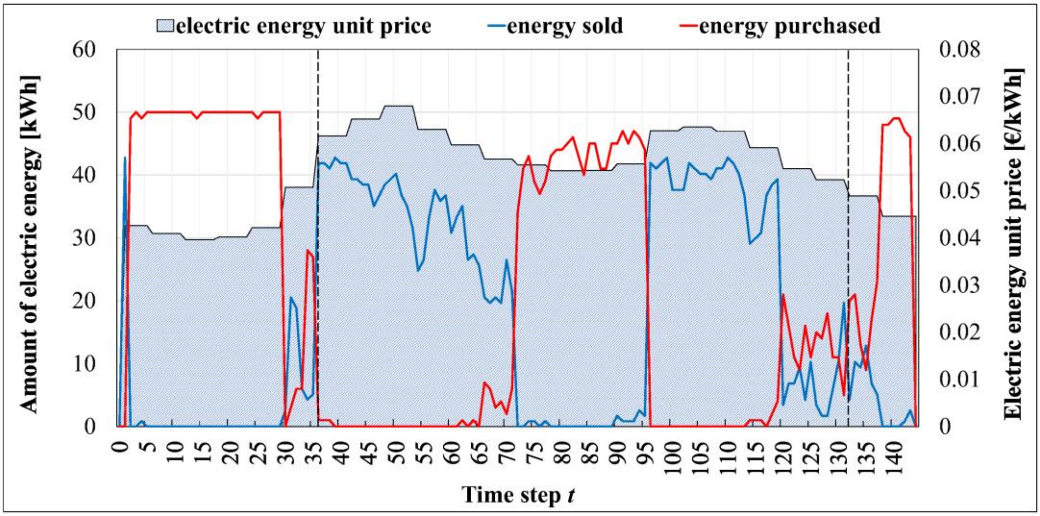

Fig.A.7. Daily electric energy transactions for scenario L2Q1 applied to the Delft network.

Scenario L2Q2

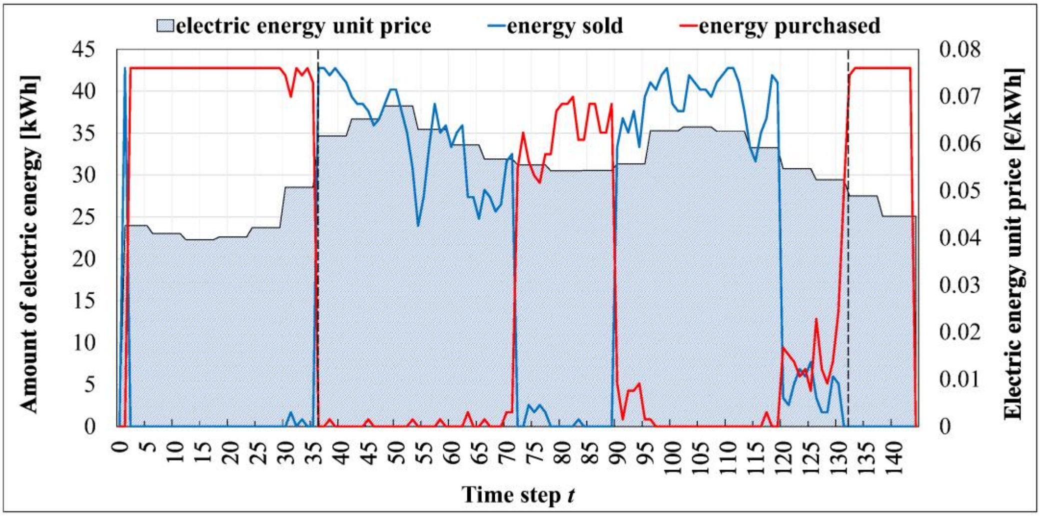

Fig.A.8. Daily electric energy transactions for scenario L2Q2 applied to the Delft network.

Scenario L2Q3

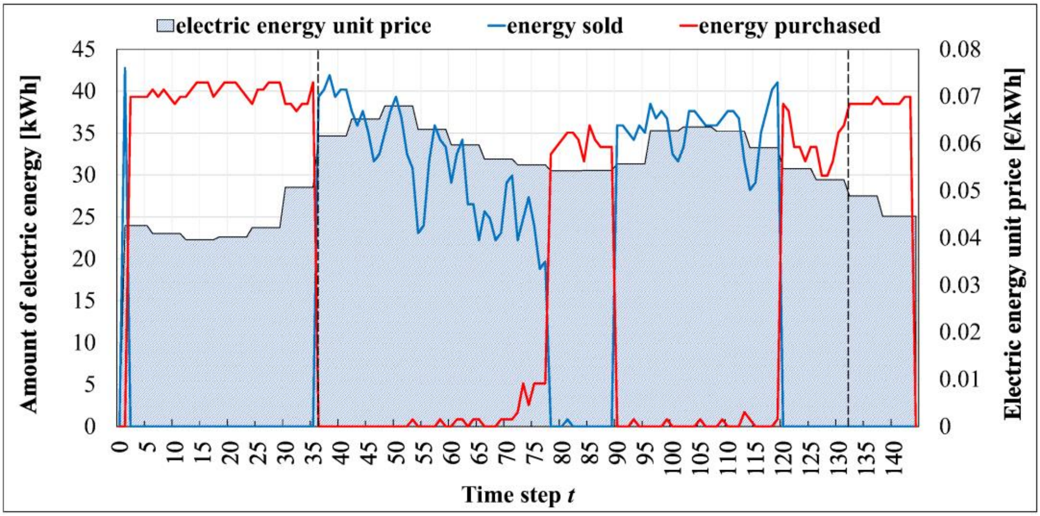

Fig.A.9. Daily electric energy transactions for scenario L2Q3 applied to the Delft network.

Scenario L3Q1

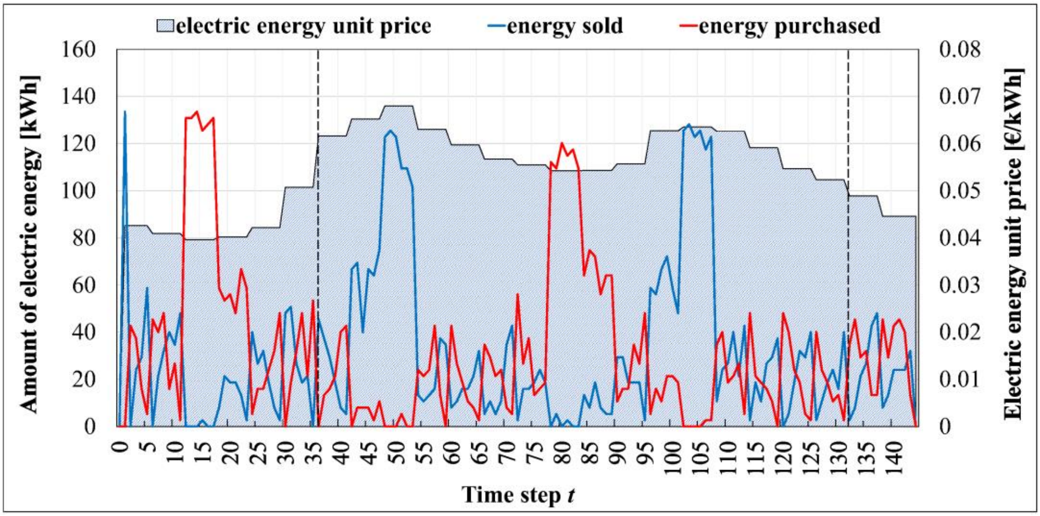

Fig.A.10. Daily electric energy transactions for scenario L3Q1 applied to the Delft network.

Scenario L3Q2

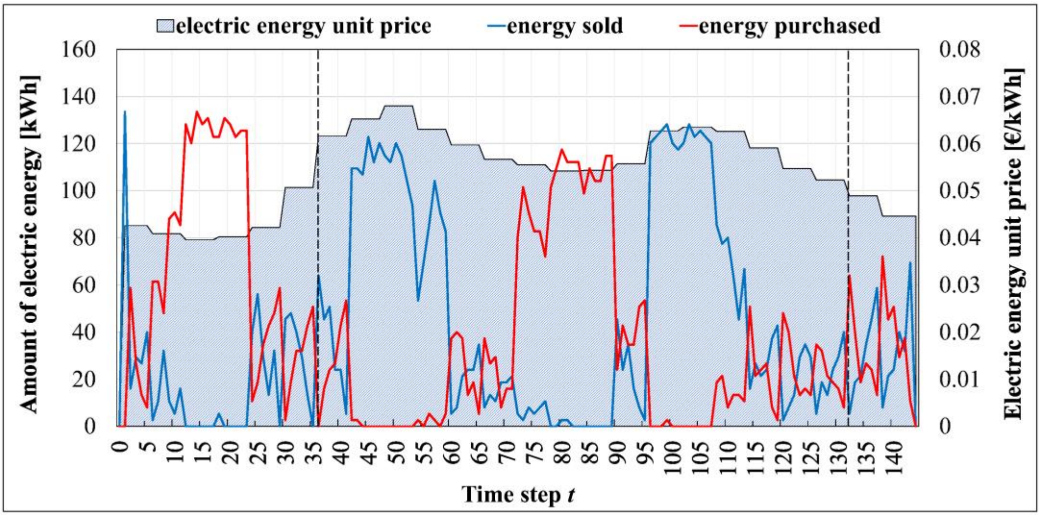

Fig.A.11. Daily electric energy transactions for scenario L2Q1 applied to the Delft network.

Scenario L3Q3

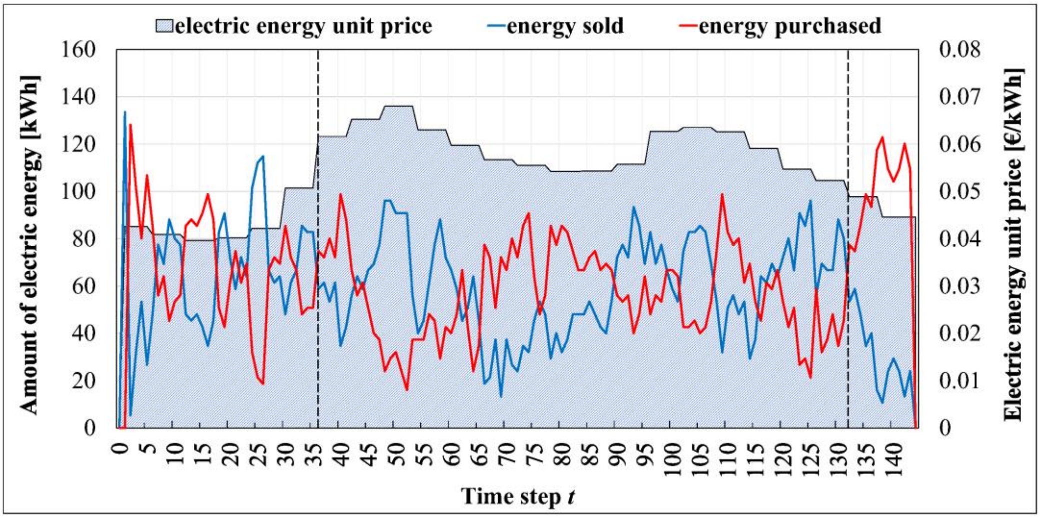

Fig.A.12. Daily electric energy transactions for scenario L3Q3 applied to the Delft network.

A.3 Daily EVs battery SoC per time step for all scenarios applied to the Delft network.

Scenario L2Q1

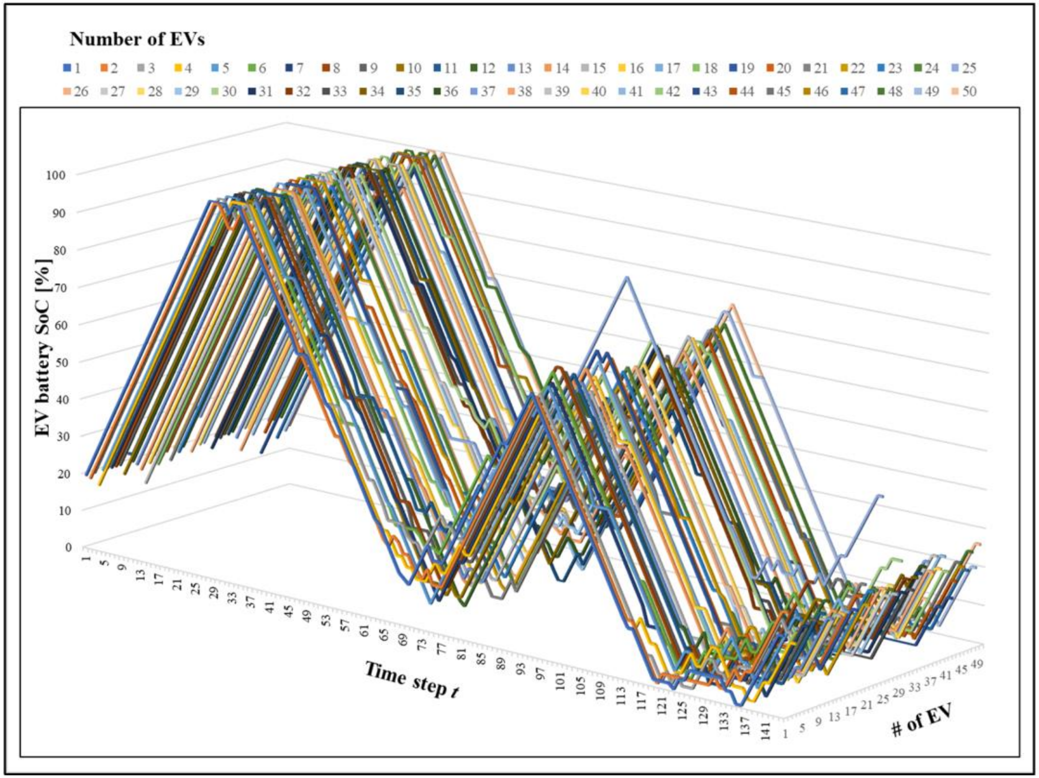

Fig.A.13. Daily EVs battery SoC per time step for scenario L2Q1 applied to the Delft network.

Scenario L2Q2

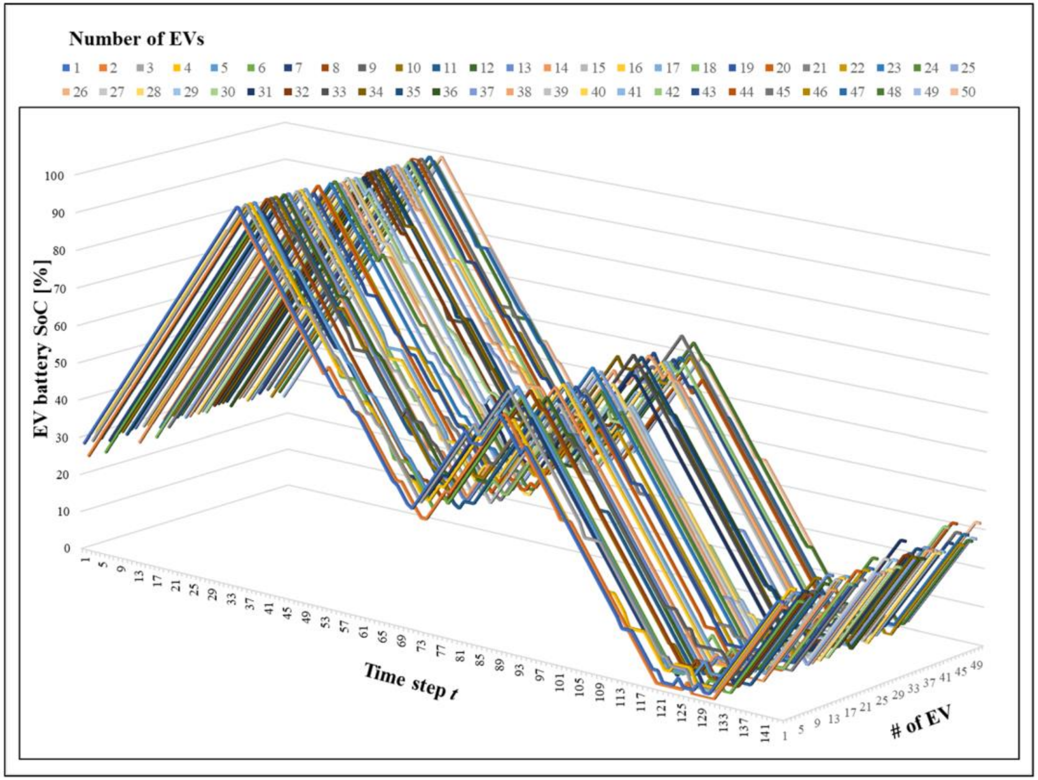

Fig.A.14. Daily EVs battery SoC per time step for scenario L2Q2 applied to the Delft network.

Scenario L2Q3

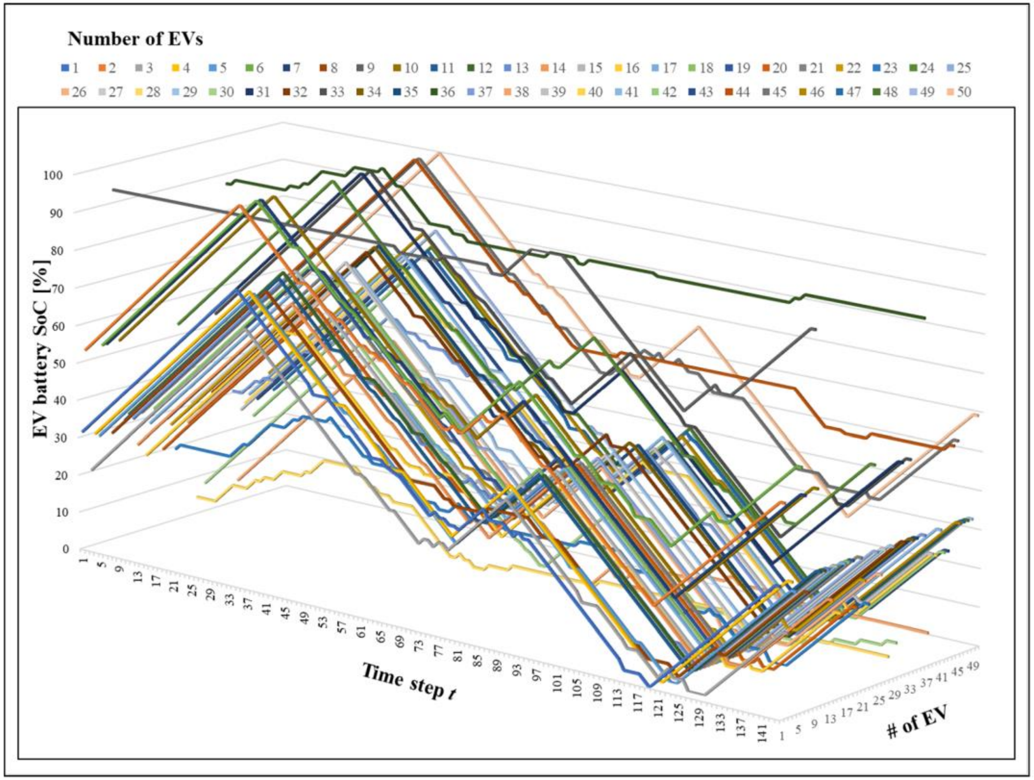

Fig.A.15. Daily EVs battery SoC per time step for scenario L2Q3 applied to the Delft network.

Scenario L3Q1

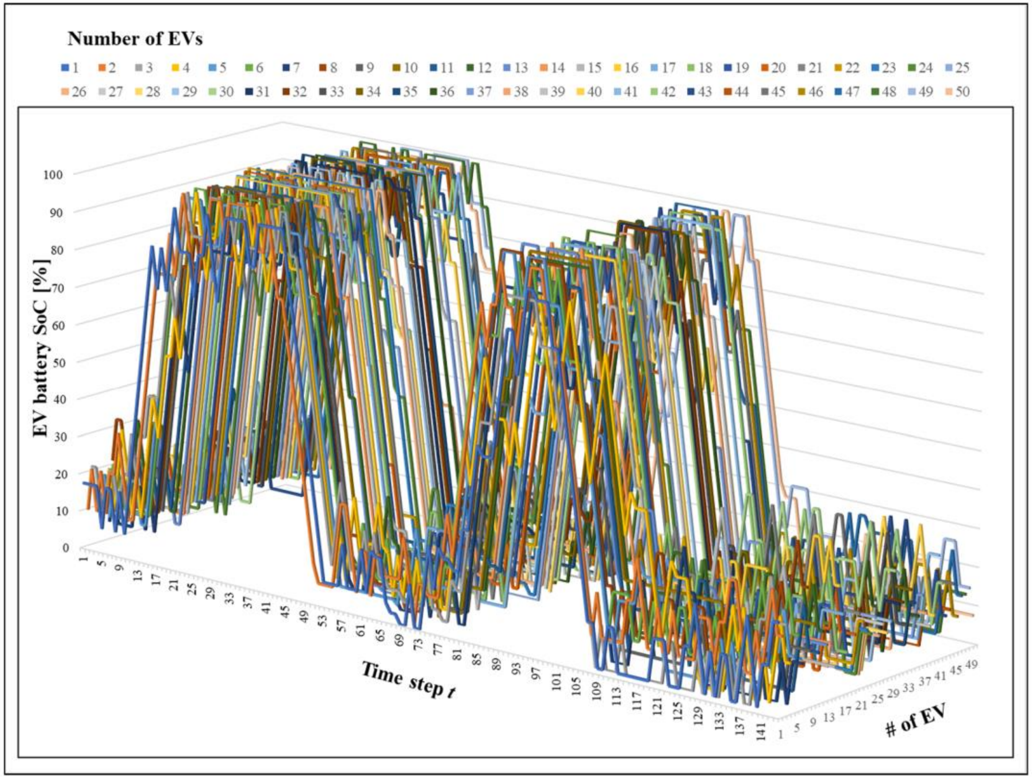

Fig.A.16. Daily EVs battery SoC per time step for scenario L3Q1 applied to the Delft network.

Scenario L3Q2

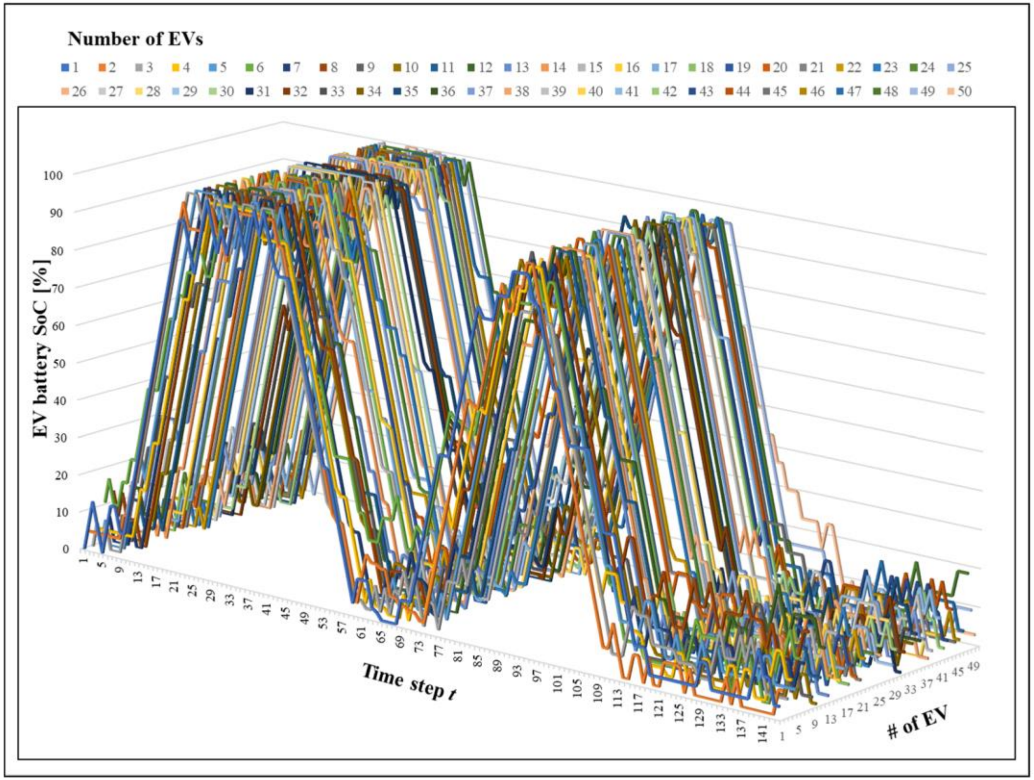

Fig.A.17. Daily EVs battery SoC per time step for scenario L2Q2 applied to the Delft network.

Scenario L3Q3

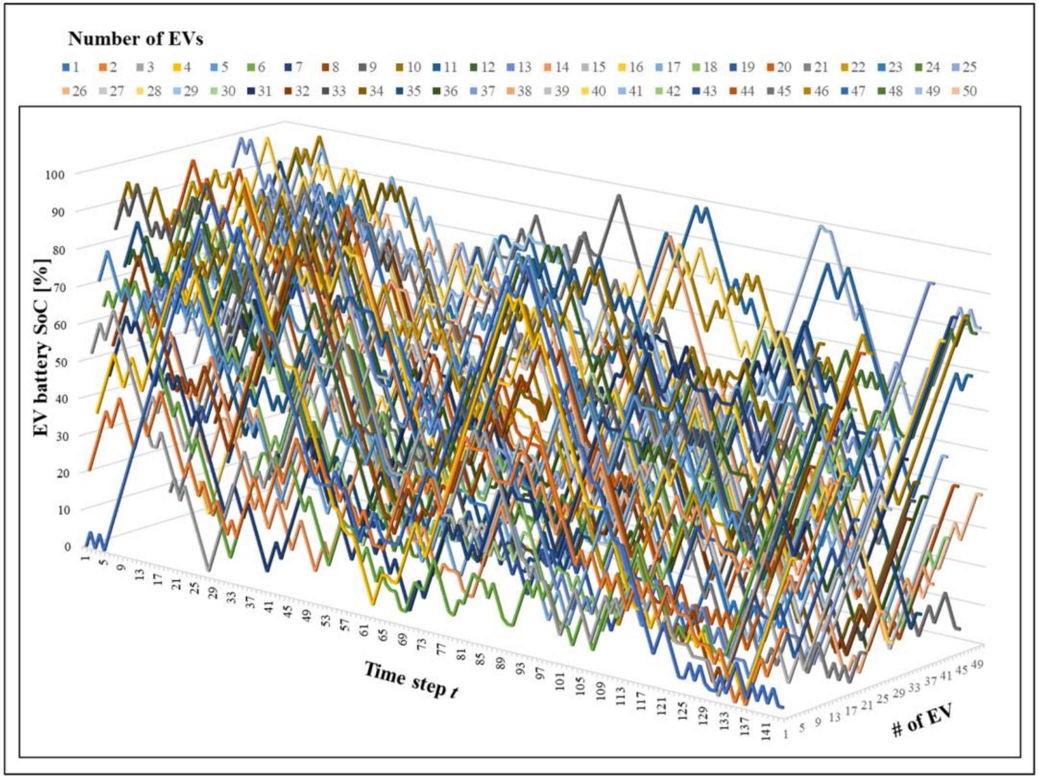

Fig.A.18. Daily EVs battery SoC per time step for scenario L3Q3 applied to the Delft network.

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Education

- October 2013, 9: BSc degree in Civil Engineering with 105/110 marks at Polytechnic University of Bari, discussing a thesis on ‘STUDIO DEGLI ALLAGAMENTI NEL BACINO IDROGRAFICO DELLA “LAMA SCALORIA’. Supervisor: prof. A. F. Piccinni, co-supervisor: prof. C. Apollonio.
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Other activities

- 01/05/2019 – 31/07/2019 (3 months): visiting Ph.D. student at Department of Mathematics and Computer Science – Technical University of Delft (TU Delft), Delft, The Netherlands, under the supervision of prof. Theresia van Essen and prof. Gonçalo Homem de Almeida Correia.
- Participation in data collection and analysis activities related to the Potenza-Sicignano highway traffic flow data collection. Project agreement with ENI and Polytechnic University of Bari. Project manager prof. Mario Binetti.
- Member of the Technical Program Committee (TPC) of the 23rd European Working Group on Transportation 2020 (EWGT 2020).
- Peer reviewer of Discrete Dynamics in Nature and Society, Hindawi (IP: 0.870).

Scientific interests

My research activities focus on Transportation, with specific interest on sustainable mobility, linear programming, path choice models, network design, optimization models, heuristics and meta-heuristics algorithms to solve transportation and logistic problems.

Scientific production

Articles

- Prencipe L.P., Marinelli M. (2020). "*A novel mathematical formulation for solving the dynamic and discrete berth allocation problem by using the Bee Colony Optimisation algorithm*". Applied Intelligence (in press). DOI: 10.1007/s10489-020-02062-y

- Caggiani L., Prencipe L.P., Ottomanelli M., (2020). "*A Static Relocation Strategy for Electric Car-Sharing Systems in a Vehicle-to-Grid Framework*". Transportation Letters: The International Journal of Transportation Research. (in press). DOI: 10.1080/19427867.2020.1861501

- Caggiani L., Colovic A., Prencipe L.P., Ottomanelli M., (2020). "*A green logistics solution for last-mile deliveries considering e-vans and e-cargo bikes*". 23rd EURO Working Group on Transportation Meeting, EWGT 2020. Transportation Research Procedia, vol. 52, pp. 75-82. DOI:10.1016/j.trpro.2021.01.010

Conference papers

- Caggiani, L., Prencipe, L. P., Colovic, A., and Dell'Orco, M., (2020). "*An eco-friendly Decision Support System for last-mile delivery using e-cargo bikes*," 2020 IEEE International Conference on Environment and Electrical Engineering and 2020 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), Madrid, Spain, 2020, pp. 1-6, DOI: 10.1109/EEEIC/ICPSEurope49358.2020.9160817

Conferences and workshops:

- 21st EURO Working Group on Transportation Meeting, EWGT 2018, 17-19 September 2018, Braunschweig, Germany. *Presented paper*: Bee Colony Optimization-based model for solving the Dynamic and Discrete Berth Allocation Problem.

- 22nd EURO Working Group on Transportation Meeting, EWGT 2019, 18-20 September 2019, Barcelona, Spain. *Presented paper*: A Static Relocation Strategy for Electric Car-Sharing Systems in a Vehicle-to-Grid Framework.
- 23rd EURO Working Group on Transportation Meeting, EWGT 2020, 16-18 September 2020, Paphos, Cyprus. *Presented paper*: A green logistics solution for last-mile deliveries considering e-vans and e-cargo bikes.

Poster session:

- Poliba PhD. Days, Workshop of Poliba Phd students research, Bari, Italy, 11-12 December 2017. *Presented poster*: Bee Colony Optimization-based model for solving the Dynamic and Discrete Berth Allocation Problem.

Bari, 18/02/2021