MESG
MESTRADO EM ENGENHARIA DE SERVIÇOS E GESTÃO

Optimisation Analysis of an Electric Vehicle Mobile Charging Service with Demand Uncertainty

José Maria Cardoso Perez

Master Thesis

Supervisor at FEUP: Prof. João Claro

U. PORTO
FEUP FACULDADE DE ENGENHARIA UNIVERSIDADE DO PORTO

2019-09-24

To my family and friends

Abstract

Electric vehicles are facing critical problems that compromise their sales and leave potential buyers in doubt when considering purchasing this type of vehicle, especially considering the lack of infrastructure to meet the unprecedented demand. This dissertation addresses the problem of designing an appropriate infrastructure to charge electric vehicles, including the location of recharging stations, through a Mobile Charging Service (MCS). This is achieved with the development of an optimization model that considers the reduction not only of the cost per journey, but also of the costs with the construction of the recharging stations, while seeking to offer a high quality recharging service, able to satisfy strict demand time and location requirements.

Contributions from the literature were analyzed and informed the design of the core characteristics of the approach as well as the steps of the service.

A stochastic model was developed and implemented in IBM Ilog Cplex Optimization Studio. The model was formulated as a mixed integer linear program (MILP) and used to solve location routing problems (LRP) with time windows (TW) and recharging stations location. The model deals appropriately with demand uncertainty. For demonstration purposes, tests were made comparing deterministic and stochastic settings, and verifying the model's ability to improve service capacity while saving investment and operating costs.

To examine the impact of technological performance and operational capacity variations, a sensitivity analysis was applied on battery capacity, travelling consumption rate, price of the recharging stations, and number of vehicles needed to provide the service. Technological progress, in particular, may have an important impact in providing more efficient services to the customers.

Resumo

Os veículos elétricos enfrentam problemas críticos que estão a comprometer as suas vendas e a levantar dúvidas aos potenciais clientes quando consideram a aquisição deste tipo de veículos, especialmente num contexto de infraestrutura insuficiente para dar resposta a uma procura sem precedentes. Esta dissertação foca-se no problema de projetar uma infraestrutura apropriada para o carregamento de veículos elétricos, incluindo a localização de postos de carregamento, através de um Serviço de Carregamento Móvel (SCM). Tal é realizado através do desenvolvimento de um modelo de otimização que considera a redução não só do custo por viagem, mas também dos custos com a construção dos postos de carregamento, procurando em simultâneo oferecer um serviço de carregamento de elevada qualidade, capaz de satisfazer requisitos exigentes de calendarização e localização da procura.

Foram analisados contributos da literatura, que informaram a conceção dos aspetos centrais da abordagem, bem como as fases do serviço.

Foi desenvolvido um modelo estocástico, com implementação no ambiente IBM Ilog Cplex Optimization Studio. O modelo foi formulado como um modelo de programação linear inteira mista e utilizado para resolver problemas de localização-distribuição (*location routing problems – LRP*) com janelas temporais e localização dos postos de carregamento. O modelo considera apropriadamente a incerteza na procura. Com propósitos de demonstração, foram efetuados testes comparando contextos determinísticos e estocásticos, e verificando a capacidade do modelo de melhorar a capacidade do serviço e simultaneamente reduzir custos de investimento e operacionais.

Para avaliar o impacto de variações de desempenho tecnológico e capacidade operacional, aplicou-se uma análise de sensibilidade à capacidade da bateria, taxa de consumo em deslocação, preço dos postos de carregamento, e número de veículos necessários para disponibilizar o serviço. O progresso tecnológico, em particular, poderá ter um papel importante na disponibilização de serviços mais eficientes aos clientes.

Acknowledgments

I would like to express my sincere gratitude to my supervisor Prof. João Claro for the continuous support of my thesis study and research, for his patience, enthusiasm and immense knowledge. I could not have imagined having a better advisor for my study.

Secondly, I would also thanks to my family and friends for their unconditional support and help in finalizing this project within the limited time frame.

Table of Contents

List of Tables

List of Figures

List of abbreviations

BEV – Battery Electric Vehicle

CO_2 – Carbon Dioxide

EU – European Union

E-VRPTW – Electric Vehicle Routing Problem with Time Windows

E-VRPTW-PR –Electric Vehicle Routing Problem with Time Windows Partial Recharge

FCEV – Fuel Cell Electric Vehicle

GHGs – Greenhouse Gas Emissions

HEV – Hybrid Electric Vehicle

ICE – Internal Combustion Engine

ICEV – Internal Combustion Engine Vehicle

IEA – International Energy Agency

LRP – Location Routing Problem

MCS – Mobile Charging Service

MCVs – Mobile Charging Vehicles

MILP – Mixed Integer Linear Program

PHEV – Plug-in Hybrid Electric Vehicle

TW – Time Windows

VRP – Vehicle Routing Problem

VRPTW – Vehicle Routing Problem with Time Windows

1. Introduction

1.1. Background and motivation

In the early 21st century, in response to warnings about environmental and climate changes, the adoption of other types of vehicles in the automobile industry was assumed as an important measure to reduce the emissions of greenhouse gas. The sector is responsible for 14% of greenhouse gas emissions (IPCC, 2014) and produced more than 98 million cars in 2017 (European Automobile Manufacturers Association, 2018). The mission of reducing CO_2 emissions has been on the agenda of both private and public sectors. Companies have created alternatives to the Internal Combustion Engine (ICE) like Plug-in Hybrid Electric Vehicles (PHEVs) and Battery Electric Vehicles (BEVs) and governments have tried to provide incentives and tax breaks (Un-Noor, Padmanaban, Mihet-Popa, Mollah, & Hossain, 2017) to encourage the purchase of these types of vehicles.

As a consequence, society has been positively adapting and the sales of electric vehicles have been growing since 2014, reaching 1.5% of every passenger car sold in the European Union in 2017 (European Automobile Manufacturers Association, 2018).

Furthermore, a great number of countries have introduced targets for their EV fleet and have improved their infrastructures to meet the increasing demand.

1.2. Problem and goals

Addressing problems such as the reduced drive range and the extended recharging time (Tietge, Mock, Lutsey, & Campestrini, 2016) requires a highly capable infrastructure.

An emerging alternative to tackle the abovementioned issues is Mobile Charging Services for EV. These services are capable of supplying energy to customers regardless of their time and location requirements, focusing on the minimization of response times (Huang, He, Gu, Wood, & Benjaafar, 2015). The service operations' process allows the supplier to know the identification of the BEV, its state of charge, the charging time interval and the location (Cui, Zhao, & Zhang, 2018). Then, a Mobile Charging Vehicle, whose power source consists of energy storage mounted on the vehicle's back compartment (Atmaja & Amin, 2015), travels to the location and is able to charge the battery of the cars that request a power charge.

1.3. Methodology

This dissertation proposes an optimization-based approach to design an infrastructure for such a Mobile Charging Service for EV. The main operational problem that the service provider needs to tackle is a location routing problem, considering time windows and recharging station costs. To consider the significant uncertainty in the demand for the service, we develop a stochastic model that adapts the deterministic model of Cui et al.(2018) and implement it in IBM Ilog Cplex Optimization Studio.

Considering demand projections, the optimization model allows exploring the tradeoff between investment and operating costs, to assess whether it is cheaper to build just the main recharging station or to build additional recharging stations closer to the potential demand in order to respond in a more effective way to the customer requests. The model addresses two areas of decision, location and routing, and allows determining the best decision to minimize the costs while making sure that the customers are supplied within a certain period.

To put the model into practice, random instances were created based on the literature, namely including deterministic and increasingly volatile stochastic versions of a same instance, and an optimization-based sensitivity analysis was carried out for those instances, focusing on battery capacity, consumption rate, price of the recharging stations and number of vehicles available to provide the service.

1.4. Outline

The above is explored and developed in detail in the following chapters, starting with the literature review, and following with the detailed description of the mobile charging service and the Mixed Integer Linear Programing (MILP) formulation of the model. Thereafter, in chapter 4, the numerical results obtained with the optimization-based sensitivity analysis are presented, and the document closes with a discussion of the results and final conclusions.

2. Literature Review

This chapter presents some of the relevant studies in the field of Electric Vehicles (EV) that were revealed to be important references for this work. The first part will be focused on understanding the environmental changes taking place in the world and the reasons to adopt another type of vehicle. The second will focus on services in the area of EV and on the respective research that was most directly relevant for this work. The following section presents optimization approaches used in diverse studies and how to combine them to have a better solution, and the last part will present two-stage modeling structures in stochastic and deterministic settings.

2.1. Environmental changes and new types of vehicles

In a world of constant change, "the human influence on the climate system is clear and growing" (IPCC, 2014), so measures are being adopted with the aim of reducing the emission of greenhouse gas (GHG) into the atmosphere. One of the most important sectors for this goal is the transportation sector, which emits 25 percent of the GHGs produced by energy-related sectors (Yong, Ramachandaramurthy, Tan, & Mithulananthan, 2015), and especially urban mobility, which accounts for 40% of all CO_2 emissions from road transportation (Nanaki et al., 2017).

The situation required more responsible and sustainable alternatives to be presented. The market reacted and a range of Electric Vehicles emerged: Battery Electric Vehicles (BEV), Hybrid Electric Vehicles (HEV), Plug-in Hybrid Electric Vehicles (PHEV) and Fuel Cell Electric Vehicles (FCEV) (Un-Noor et al., 2017). These kinds of vehicles are different in their configurations and while being quite distinct, they promote more effective solutions to fight the negative impacts of conventional vehicles (Darabi & Ferdowsi, 2012) in terms of emissions of gases to the atmosphere and as a replacement of Internal Combustion Engine Vehicles (ICEV). The benefits surrounding these green solutions are multiple: they are four times more energy efficient compared to ICEV (Helmers & Marx, 2012), they reduce gasoline consumption and GHG from 30 to 50% with no change in the vehicle class (Romm, 2006) and, finally, they feature lower user costs per km, noise and pollution (Egbue & Long, 2012).

With all these benefits, international institutions started to deploy a variety of policies to increase the sales of these type of vehicles. With the EU trying to achieve 10% of renewable energy in transportation by 2020 (Directive 2009/28/EG, 2009), members states would need to reduce emissions from passenger cars significantly (EP, 2009). The International Energy Agency (IEA) aims to reach a combined total of 20 millions full and plug-in hybrid Electric Vehicles by 2020 (Hawkins, Singh, Majeau-Bettez, & Strømman, 2013).

In addition to institutions, governments also reacted, e.g., Ireland introduced a new tax system to encourage the purchase of vehicles with lower CO_2 emissions (Caulfield, Farrell, & McMahon, 2010), the United States provided a $2,000 tax deduction in the purchase of Hybrid Vehicles (Diamond, 2009), Germany exempted vehicles registered before 2016 from ownership tax for 10 years for, and vehicles registered between 2016 and 2020 for 5 years (Tietge et al., 2016), and Spain launched plan MOVELE to assist the implementation of the electric vehicle in Spanish cities (Sierzchula, Bakker, Maat, & Van Wee, 2014). In general, several countries opted for benefits such as "tax or other economic ones such as reduced/exempted parking free or congestion charges, but in some instances also allow access to bus lane or carpool lanes", according to Bjerkan et al. (2016).

Despite the global approach to incentives and policies, the outcome seems to be insufficient (Canals Casals, Martinez-Laserna, Amante García, & Nieto, 2016) as there are many limitations in this field, from social and economic to technological and operational.

From a social point of view, there are multiple challenges such as changing habits (Wolsink, 2012) and the resistance to new unproven or unfamiliar technology (Egbue & Long, 2012). On the economic side, it is important to mention the high price of EV batteries (Nykvist & Nilsson, 2015) and the high cost of these types of cars (Chan, 2002).

From the technological and operational perspectives, it is worth mentioning the limited range of the vehicles, which afflicts owners with "range anxiety", according to He et al. (2014) and Tate et al. (2008), the insufficient number of recharging stations (Masuch, Lützenberger, Ahrndt, Heßler, & Albayrak, 2011), and the lack of commercial availability of alternative fuels (Directive 2009/28/EG, 2009). This problem is present overall and in the United States of America, "individuals were willing to pay from $35 to $75 dollars for a mile of added driving range" (Hidrue, Parsons, Kempton, & Gardner, 2011). The limited range, together with the long charging period (Qin & Zhang, 2011), are the two big limitations that make customers reluctant to purchase such vehicles, and are addressed through the implementation of a Mobile Charging Vehicle (MVC) service such as the one considered in this work.

2.2. Related Applications of Mobile Charging Services

Among the different ways of recharging electric vehicles available in the market, the most common one is plug-in charging (He et al., 2014), followed by battery swapping (Adler & Mirchandani, 2014; Mak, Rong, & Shen, 2013; H. Sun, Yang, & Yang, 2019), dynamic wireless recharging (Liu & Wang, 2017), and charging lanes (Z. Chen, He, & Yin, 2016). Plug-in charging may be divided in three levels: slowest, primary, and fast charging (Shareef, Islam, & Mohamed, 2016; Yilmaz & Krein, 2012).

The services that are being applied and studied in this area can be divided in different categories:

- Mobile Charging Services, studied by Cui et al. (2018), provide the service at any time and location. Atmaja et al, (2015) present a similar service, but with two modes, the first consisting of on-grid charging, with the provider connecting to the electric grid, and the second consisting of off-grid charging, with the provider using only battery power;
- Battery Swapping Services, addressed by Mak et al., (2013), who consider a model of infrastructure where any customer can be supplied full energy at a warehouse by swapping the battery, and H. Sun et al., (2019), who consider a multi-interval battery swapping location and battery inventory-recharging planning problem;
- Infrastructures to provide energy to customers, addressed in location studies for multiple types of BEV recharging facilities (Liu & Wang, 2017), recharging stations (Bakker, 2011; Frade, Ribeiro, Gonçalves, & Antunes, 2012), and mobile charging stations through heterogeneous networks consisting of macrocells and small cells (H. Chen, Su, Hui, & Hui, 2017).

2.3. Location Routing, Time Windows and Recharging Stations Location

In this section, we introduce mathematical models relevant to the problem addressed in this work, which involves serving multiple customers who request Mobile Charging Services, while seeking to reduce distances between services and recharging stations and costs of construction.

Mobile Charging Services have been directly addressed in studies such as those by Huang et al., (2015), who use a queuing based analytical approach called “nearest job next”, Cui, Zhao, Chen, & Zhang, (2018), who seek to minimize the total distance of MCVs required to complete all charging requests for BEV drivers in distributed locations, and Cui et al,(2018), who use the Location Routing Problem (LRP) as a basis to locate recharging facilities and develop routing plans for MCVs.

The LRP is closely linked with the VRP (Wu, Low, & Bai, 2002). Although not recognized until the 1970s (Min, Jayaraman, & Srivastava, 1998), the reality is that the LRP can be defined as a VRP in which the location of the depots are calculated simultaneously with the schedules and distribution routes in order to minimize the total system cost. The LRP could be viewed more as the strategic level and the VRP as the tactical level. There are many real world applications for these kinds of problems, such as waste collection (Caballero, González, Guerrero, Molina, & Paralera, 2007), bill delivery (Lin, Chow, & Chen, 2002), drink distribution (Watson-Gandy & Dohrn, 1973) and military equipment location (Murty & Djang, 1999). In the end, the LRP joins the facility location problem with the vehicle routing problem (Barreto, Ferreira, Paixão, & Santos, 2007).

When considering delivering something by car, it is important to consider the high number of constraints that can arise in the way this service is performed. These constraints, such as distances, include also temporal windows with specific routes, which are addressed in the Vehicle Routing Problem with Time Windows (VRPTW). This problem, in which a vehicle has to reach an objective in a specified time interval (Gendreau & Tarantilis, 2010), while handling realistic complications of the basic routing model (Schrage, 1981), has been extensively studied and tested (Bräysy & Gendreau, 2005; Dalmeijer & Spliet, 2018). Time windows have multiple applications, from postal deliveries (Blanutsa, 2010; L. Sun, Zhao, & Hou, 2015), to bank deliveries (Rod, Ashill, & Gibbs, 2016) or dial-a-ride services (Sexton & Bodin, 1985).

However, using a BEV requires considering the existence of more constraints, which extend the VRPTW to the electric vehicle fleet VRPTW (E-VRPTW) (Schneider, Stenger, & Goeke, 2014): a limited range and the possibility of recharging vehicles in an available station with an appropriate scheme. The time to recharge depends on the level of battery upon arrival at the station. Moreover, with the introduction of these kinds of vehicles, the authors above sought to identify the minimum number of vehicles to be employed and total travel distance. In a similar way, Keskin et al, (2016) adopt the possibility of a partial recharge with the power required to ensure the service (E-VRPTW-PR). In this work we consider the Location Routing Problem with Time Windows and Partial Recharge Strategy, which means that the MCVs will be able to charge only what they need to provide the service and get back to the recharging station, with the intention of providing the customer an efficient and fast service.

2.4. Two-stage deterministic and stochastic models

In this work, we extend a deterministic model, whose outcome is precisely determined without any random variation and always produces the same output, to a two-stage stochastic model, which uses ranges of values for parameters in the form of probability distributions.

Many studies have been conducted comparing stochastic models with their deterministic counterparts (Blount, 1991; Cook & Russell, 1978). Those related with EV, LRP and multi-depot contexts are the most relevant for this study.

Kim et al. (2017) propose a stochastic model and charging scheduling method for an EV battery charging system. Differently, Laporte et al. (1989) combined an LRP and a VRP, considering two stages of decision: the first stage consisted of making a few decisions before having all information, and the second took place after the information became available, trying to accomplish the best outcome. Lastly, Wu et al. (2002) presented a stochastic model showing individual customer demand in order to reflect reality more accurately in future applications.

These studies have in common an effort to explicitly incorporate uncertainty to address future demand in a more accurate way, which is also the goal in considering a stochastic model in this study. The model will be able to address a few questions that cannot be considered in a deterministic model, and will allow avoiding the analysis biases that result from considering a deterministic demand (Powell, 1986).

3. Problem Description

3.1. Notation

For readability, we have listed the notations used in our work in table 1 for indices, table 2 for sets, table 3 for parameters, and table 4 for decision variables.

Table 1 Indices

Indices	Definition
s	Index of scenarios, $s \in S$
i, j	Index of nodes, $i,j \in V'_{s,0,N+1}$
(i,j)	Index of physical link between two adjacent nodes, $(i,j) \in A$
μ	The μth type of recharging station

Table 2 Sets

Sets	Definition
Φ	Set of feasible types of recharging stations; $\mu \in \Phi = \{1,2,3\}$
F	Set of recharging stations
F’	Set of dummy vertices of F
F0’	Set of dummy vertices of depot instance 0
F'_0	Set of charging visits including depot instance 0
V_s	Set of customers in scenario s
$V_{s,0}$	Set of customers including depot instance 0 in scenario s
V'_s	Set of customer vertices including visits to recharging stations in scenario s, $V'_s = V_s \cup F'$
$V'_{s,0}$	Set of customers and dummy vertices visits including depot instance 0 in scenario s, $V'_{s,0} = V'_s \cup \{0\}$
$V'_{s,N+1}$	Set of customers and dummy vertices visits including depot instance N+1 in scenario s, $V'_{s,N+1} = V'_s \cup \{N+1\}$
$V'_{s,0,N+1}$	Set of customers and dummy vertices visits including depot instance 0 and N+1 in scenario s, $V'_{s,0,N+1} = V'_s \cup \{0\} \cup \{N+1\}$
V	$= V_1 \cup V_2 \cup V_3 \cup \ldots \cup V_s$
A	$\{(i,j): i,j \in V, i \neq j\}$
S	Set of scenarios

Table 3 Parameters

Parameters	Definition
B	The budget limit for building recharging stations
Cap	Number of vehicles available
$d_{i,j}$	Distance of link (i,j) ϵ A
$c_{i,j}$	Cost of link (i,j) ϵ A
$t_{i,j}$	Travel time of link (i,j) ϵ A
ε_{μ}	Recharging rate of type μ
b^{μ}	Cost of building recharging station type μ
q_i	The power demand for one electric car in node i ϵ V
Q	Battery capacity for Service Car
h	Charge consumption rate in traveling
α	The number of corresponding dummy nodes of one candidate recharging station
$u_{i,s}$	Demand number of node i ϵ V_s, with $u_{i,s}$ = 0 if i does not belong to set V_s
a_i	Earliest start of service at node i ϵ V
l_i	Latest start of service at node i ϵ V
z_i	Service time at node i ϵ V
M	Sufficiently large constant
P_s	Probability of scenario s

Table 4 Variables

Variables	Definition
S^{μ}_i	=1 if recharging station type μ should be built in node i; otherwise = 0
$\tau_{i,s}$	The time of arrival at node i in scenario s, i ϵ $V'_{s,0,N+1}$, s ϵ S
$F_{i,s}$	The recharging amount of electricity at node i in scenario s, i ϵ $V'_{s,0,N+1}$, s ϵ S
$x_{i,j,s}$	=1 if arc (i,j) is traveled in scenario s; = 0 otherwise
$y_{i,s}$	The remaining battery on arrival at node i in scenario s

3.2. Problem characteristics

This work addresses the problem of designing an infrastructure for a mobile charging service, with the construction of one or more recharging stations.

The problem, and the instances created for our experiments, feature the following main characteristics:

- There will be one fixed main recharging station, which will be a type 3 station built in a central location.
- Additional recharging stations may be built, of three different types: the first type has a recharge rate of 0.35, type 2 a recharge rate of 0.25, and type 3 a recharge rate of 0.3.
- The recharging stations just recharge MCVs, not customers. Several potentials are considered sites for the recharging stations, whose location has to be defined before knowing the customer demand.
- The multiple visits to the recharging stations are modelled with the help of a dummy node set, each node corresponding to one visit.
- Each customer, in sets whose numbers vary from 5 to 15 in the scenarios considered in our instances, is supplied once, in a specific time window given by the earliest and the latest start, to satisfy the lack of power in their batteries, which establishes the electricity demand.
- A homogenous fleet of 3 MCVs, powered by a rechargeable battery with fixed capacity, departs from the main recharging station, eventually returns to one or more of the recharging stations to recharge in order to continue serving customers, and finally returns to the main recharging station after having served all customers. The MCVs will consume energy not only with the energy they provide to customers, but also on the trips. If they do not have enough energy to supply the customer and return to a recharging station, they will recharge earlier with enough energy to provide the service faster. After all the services, the vehicle gets back to the main recharging station still with energy or empty. Seeking efficiency, the vehicles will typically recharge as few times as possible and leave the main station fully charged.
- To simplify the model, there is no congestion or relief on the road. The travel time and energy consumption therefore have a close relation with the travel distance, linking the routing of the MCV with the minimization of the total travel distance of the vehicles. The MCV’s recharging amount is thus equal to the journey that they must do from the point of departure where they recharge until they visit again a recharging station. In this journey they will serve as many customers as they can.
- Overall, the service seeks to minimize the costs of the traveled distances and of building recharging stations, exploring the trade-off between these costs, i.e., if it does not pay off for a vehicle to go back to the main recharging station and come back to the customer, a recharging station may be built.

3.3. Optimization Model

In this section, we present the mathematical model, which is based on the model proposed by Cui et al. (2018). Enhancements were made to the original model in order to improve the consideration of additional aspects of practical relevance.

Probabilistic scenarios were added to better represent randomness and make the model more robust. The objective function was expanded to include recharging stations construction costs, and accordingly the budget constraint was removed. There was also a change related to the number of cars allocated to provide the service which was kept fixed. In the flow constraints, a set of constraints were added to restrict the set of requests according to the corresponding scenario, i.e., if the scenario includes only 8 out of the of the total 15 requests, these constraints will remove the others from consideration.

When applying mathematical models to real-world problems, there are always aspects that must be assumed and others disregarded, to be able to cope with complexity. In our case, some features of the mobile service have been simplified given the many directions in which the model could evolve.

Thus, the number of services to be provided by the mobile charging vehicles as well as the number of vehicles available and the service time (arrival and departure) are set in advance. The service provider recharges the vehicle only if it does not have enough energy to provide the service or cannot return to the recharging station after the service that it has to do. Furthermore, it may recharge even if it still has some battery and may recharge more than once to be able to serve all the customers.

The average speed of the MCVs is 22 km/h, as assumed in the study by Kenworthy et al. (1999), and the cost of each recharging station was obtained from the study by Axsen et al. (2012). The cost was divided by the number of years of depreciations (5) and days of use per year (365) to fit the daily time horizon of the instances. The electricity cost was calculated based on the estimated price of the Portuguese market, for which this study was undertaken, 0.2 €/kWh (Camus, Farias, & Esteves, 2011). The energy consumption per kilometer is 0.183 kWh/km, as given by Fetene at al. (2017).

Factors such as traffic or the relief of the city are not considered (Neubauer, Brooker, & Wood, 2012). The recharging rate, ε, is assumed constant and the battery capacity, Q, varies according to different possible classes.

The mathematical model can be presented as a MILP (mixed integer linear programming) model, as follows.

The objective is the minimization of the total costs of traveling and building recharging stations:

$$Min \sum_{s \in S} \sum_{i \in V's,0} \sum_{j \in V's,N+1} P_s c_{i,j}\, x_{i,j,s} + \sum_{i \in F/\{0\}} \sum_{\mu \in \Phi} S_i^{\mu} b^{\mu} \tag{1}$$

P_s is the probability of scenario s. $c_{i,j}$ is the cost of traveling between starting node i and end node j. $x_{i,j,s}$ is a binary decision variable, which takes the value of 1 if the arc (i,j) is traveled in scenario s, and 0 otherwise. S^{μ}_i is a binary decision variable, which takes the value 1 if a recharging station of type μ is built in node i, and 0 otherwise. b^{μ} denotes the cost of building a recharging station of type μ.

The recharging stations constraints are as follows:

$$\sum_{\mu \in \Phi} S_i^{\mu} \leq 1, \forall\, i \in F/\{0\} \tag{2}$$

$$\sum_{\mu \in \Phi} S_i^{3} = 1, \forall\, i \in F\{0\} \tag{3}$$

$$S_i^{\mu} = S_{i+1}^{\mu} = S_i^{\mu} = S_{i+2}^{\mu} \dots = S_{i+\alpha-1}^{\mu}, \forall\, i \in F/\{0\}, \forall\, \mu \in \Phi \tag{4}$$

$$S_i^{\mu} \in \{0,1\}, \forall\, i \in F', i \neq j, \forall\, \mu \in \Phi \tag{5}$$

Constraints (2) ensure that only one type of charging device can be built for each dummy node, while constraints (3) limit the recharging station to be built in the depot node {0} to type 3. Constraints (4) assign the dummy nodes the same type as the corresponding recharging station. The binary constraints for the decision variables are enforced in constraints (5).

The flow constraints are as follows:

$$\sum_{j \in V'_{s,N+1}, i \neq j} x_{i,j,s} = 1, \forall\, i \in V_s, \forall\, s \in S \tag{6}$$

$$\sum_{j \in V'_{s,N+1}, i \neq j} x_{i,j,s} = 0, \forall\, i \notin V_s, \forall\, s \in S \tag{7}$$

$$\sum_{i \in V'_{s,N+1}, i \neq j} x_{j,i,s} - \sum_{i \in V'_{s,0}, i \neq j} x_{i,j,s} = 0, \forall\, j \in V'_s, \forall\, s \in S \tag{8}$$

$$\sum_{j \in V'_{s,N+1}} x_{0,j,s} \leq Cap, \forall\, s \in S \tag{9}$$

$$x_{i,j,s} \in \{0,1\}, \forall\, i,j \in V'_{s,0,N+1}, i \neq j, \forall s \in S \tag{10}$$

Constraints (6) guarantee the connectivity of the customer visits in scenario s, with each customer visited only once by any mobile charging vehicle. The customers not included in scenario s are not visited in that scenario, as implemented by constraints (7). Constraints (8) force the number of outgoing travels to be equal to the number of incoming travels at each vertex in a scenario s. Constraints (9) establish the maximum number of vehicles that will leave node {0} in scenario s to provide the service. Constraints (10) define the binary nature of flow decision variables.

The time constraints are as follows:

$$\tau_{i,s}+(t_{i,j}+z_i)x_{i,j,s}-l_0\left(1-x_{i,j,s}\right)\leq\tau_{j,s}\forall\, i\in V_{s,0},\forall\, j\in V'_{s,N+1},i\neq j,\forall\, s\in S \qquad (11)$$

$$a_i\leq\tau_{i,s}\leq l_i,\forall\, i\in V'_{s,0,N+1},\forall\, s\in\ S \qquad (12)$$

Considering the distance $d_{i,j}$ between nodes and a fixed travel speed, the travel time $t_{i,j}$ of each journey is predetermined. The service times are also predetermined. The times at which a vehicle arrives and leaves each customer have to be such that the MCV does not start charging before a_i and later than l_i. Waiting times may exist if the vehicle ends the service later than expected. Constraints (11) are the time feasibility constraints for the customer nodes and depot node with instance of 0 in scenario s. Constraints (12) enforce the time windows for the services in scenario s and constraints (13) consider the recharge time instead of the service time when the previous node, i, is a recharging station.

$$\tau_{i,s}+t_{i,j}x_{i,j,s}+\sum_{\mu\,\in\,\Phi}F_iS_i^{\varphi}\varepsilon_\mu-\left(l_0+\varepsilon_\mu Q\right)\left(1-x_{i,j,s}\right)\leq\tau_{j,s}\forall\, i\in F',\forall\, j\in V'_{s,N+1},i\neq j,s\in S \qquad (13)$$

As pointed out by Cui et al. (2018), the product $F_iS_i^{\varphi}$ is nonlinear and leads to nonconvexity. To address this problem, a nonconvex formulation is obtained through a reformulation-linearization technique (RLT).

Let $\theta_i^{\mu}=F_iS_i^{\mu}$, for each μ ϵ Φ and i ϵ F′, to linearize the bilinear term:

$$\tau_{i,s}+t_{i,j}x_{i,j,s}+\sum\nolimits_{\mu\,\in\,\Phi}\theta_{i,s}^{\mu}\,\varepsilon_\mu-\left(l_0+\varepsilon_\mu Q\right)\left(1-x_{i,j,s}\right)\leq\tau_{j,s}\forall\, i\in F',\forall\, j\in V'_{s,N+1},i\neq j,s\in S \qquad (14)$$

Following the rules of RLT, $\theta_i^{\mu}=F_iS_i^{\mu}$ is equivalent to the following constraints:

$$\theta_{i,s}^{\mu}\geq 0,\forall\, s\in S \qquad (15)$$

$$\theta_{i,s}^{\mu}-S_i^{\mu}M\ \leq 0,\forall\, s\in S \qquad (16)$$

$$\theta_{i,s}^{\mu}-F_i\ \leq 0,\forall\, s\in S \qquad (17)$$

$$\theta_{i,s}^{\mu}-F_i+M-S_i^{\varphi}M\ \geq 0,\forall\, s\in S \qquad (18)$$

The electricity constraints are as follows:

Customer to customer

$$x_{i,j,s}q_ju_{j,s} \leq y_{j,s} \leq y_{i,s} - hd_{i,j}x_{i,j,s} - q_iu_{i,s}x_{i,j,s} + Q(1 - x_{i,j,s}), i \in V_{s,0}, \forall\, j \in V'_{s,N+1}, i \neq j, \forall\, s \in S \quad (19)$$

Dummy to customer

$$x_{i,j,s}q_ju_{j,s} \leq y_{j,s} \leq y_{i,s} + F_{i,s} - hd_{i,j}x_{i,j,s} + Q(1 - x_{i,j,s}), i \in F', \forall\, j \in V'_{s,N+1}, i \neq j, \forall\, s \in S \quad (20)$$

$$x_{0,j,s}q_ju_{j,s} \leq y_{j,s} \leq Q - hd_{0,j}x_{0,j,s}, \forall\, j \in V'_{s,N+1}, \forall\, s \in S \quad (21)$$

$$0 \leq F_{i,s} \leq \left(\sum_{\mu \in \Phi} S_i^{\mu}\right) M, \forall\, i \in F', \forall\, s \in S \quad (22)$$

$$0 \leq y_{i,s} + F_{i,s} \leq Q, \forall\, i \in F', s \in S \quad (23)$$

With the battery consumption assumed to be a constant h for each km that the MCV must travel, a trip from i to j consumes $hd_{i,j}$ of the remaining battery. The battery remaining after every trip is given by $y_{i,s}$. Each $u_{i,s}$ is assigned a positive number of requests and multiplied by the charging demand for each request, q_i, to obtain the demand. It will be zero when the node i does not belong to the set V_s. M should be a sufficiently large positive number.

Constraints (19) and (20) keep track of the state of charge of the battery for the customer and dummy nodes, respectively, and ensure that the battery state of charge never falls below the electricity demand of the next customer node. In constraints (19), the vehicle comes from serving another customer, while in constraints (20) it comes from recharging in a dummy node.

Constraints (21) address the battery remaining after traveling from node {0} to the first customer, considering the consumption made by the MCV. Constraints (22) assure that an MCV will recharge in nodes with a recharging station. Finally, constraints (23) enforce that the sum of the level of recharging and what was left in the battery does not exceed the capacity of the battery.

4. Numerical Experiments

In this chapter we present a set of numerical experiments to demonstrate the model described in the previous chapter. The computing platform used for these experiments was a personal computer with Intel ® Core ™ i7-5500U 2.40GHz CPU and 12.00 GB RAM, using the Microsoft Windows Version 10 Home (64 bit) operating system. The environment used to develop the model and carry out the numerical experiments was IBM ILOG Cplex Optimization Studio version 12.9.0.

The study is based on a subset of the instances used by Cui et al,(2018), which in turn are based on the well-known VRPTW instances of Schneider et al.,(2014).

4.1. Generation of benchmark instances

A set of 15 benchmark instances with scenarios including from 5 to 15 customers were created. The 15 instances feature three classes of customer geographic distribution – clustered (C), randomly distributed (R), and both clustered and randomly distributed (RC). The difference between the classes is the distance from the demand locations to the main station. The demand in clustered instances is closer to the main station than in the randomly distributed instances. The RC instances join both classes.

In figure 1, two of the classes are represented in terms of the geographic distribution of the demand: on the left, a clustered instance, and on the right, a randomly distributed instance. A RC instance will joins both patterns.

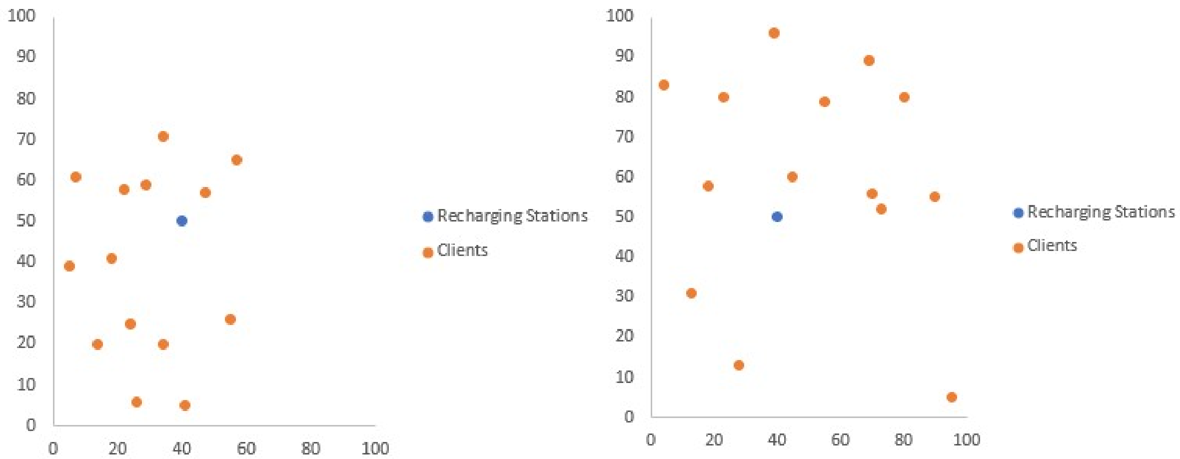

Figure 1 Geographic distribution of recharging stations and clients in two types of instances, clustered on the left and randomly distributed on the right (axes in kilometers)

In terms of scheduling horizon, short (1) and long (2) is the time frame that the MCV has to meet all the demand. In the short scheduling horizon, the MCV has less time and the times of the services are shorter than in the long scheduling horizon. In the long scheduling horizon, the earliest and latest start correspond to wider time windows and it is easier to satisfy all the demand. Geographic distribution classes and schedule horizon are combined to define each instance's demand areas and times. For each combination of geographic distribution and scheduling horizon, three types of volatility are considered: no volatility, i.e., deterministic (D), low volatility (LV) and high volatility (HV). These three types allow, for each instance, the possibility of having one deterministic and two stochastic variations. In the two stochastic variations, one has a higher volatility and the other a lower volatility.

Each type of volatility corresponds to a specific number of scenarios with specific numbers of clients. The deterministic instances have 1 scenario with 10 clients. The stochastic instances have 5 scenarios. The low volatility instances have scenarios with numbers of clients between 8 and 12. The high volatility instances have scenarios with numbers of clients between 5 and 15. In terms of notation for the scenarios, D1-C10 corresponds to the deterministic instances, LV5-C812 to the low volatility instances, and HV5-C515 to the high volatility instances.

Instances with a short scheduling horizon in general were found to require more vehicles to be available in the fleet.

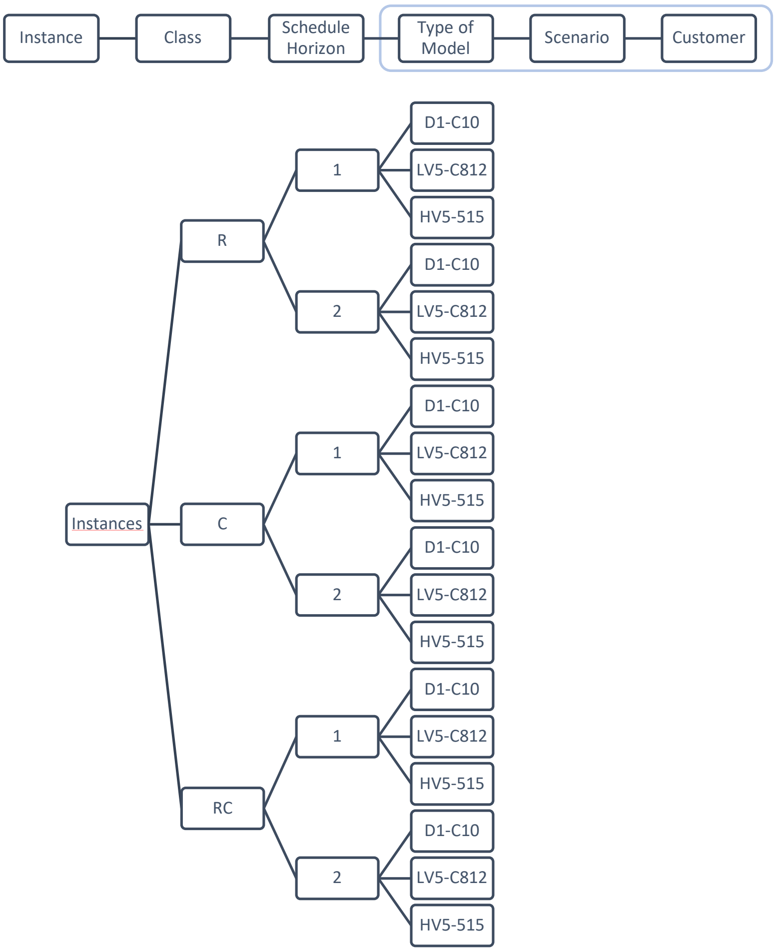

Figure 2 Types of instances and correspondences with their codes

Figure 2 presents the coding system used to identify each instance. There are multiple possible combinations, according to each instance's features: geographic distribution class (R, C or RC), scheduling horizon (1 or 2), volatility (D, LV or HV), number of scenarios (1 or 5) and customer number range (C10, C812 or C515). For example, R2LV5-C812 is an instance with randomly distributed customers (R), long scheduling horizon (2), low volatility stochastic (LV5) demand and a customer number range between 8 and 12 customers.

Given the limited time window of 16 hours per day, instances C2 were not considered in the sensitivity analyses.

In line with the demonstration purpose of these numerical experiments, and to control the size of our instances, we selected a subset of three from the 21 candidate recharging station sites in the original instances. For a clearer understanding, we illustrate that selection in figures 3 and 4. Figure 3 shows the 21 candidate recharging stations, from which we selected the one in the center to be the main station, and 3 others to cover all the set-up in the best way.

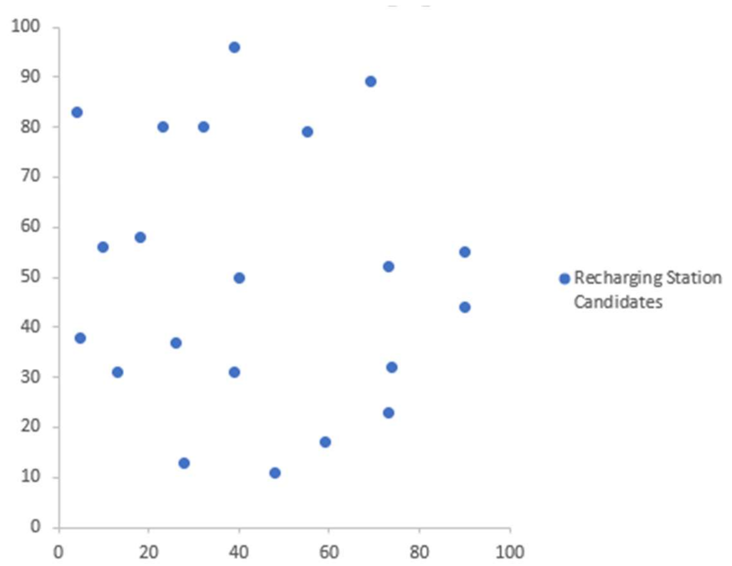

Figure 3 Geographic distribution of recharging station candidates (axes in kilometers)

Figure 3 shows the selected candidate sites, jointly with the demand in one of the 15 customer scenarios used in our instances. The availability of recharging stations becomes essential if the vehicles have little autonomy and need to be recharged often. All instances in each class share the same candidate locations for the recharging stations.

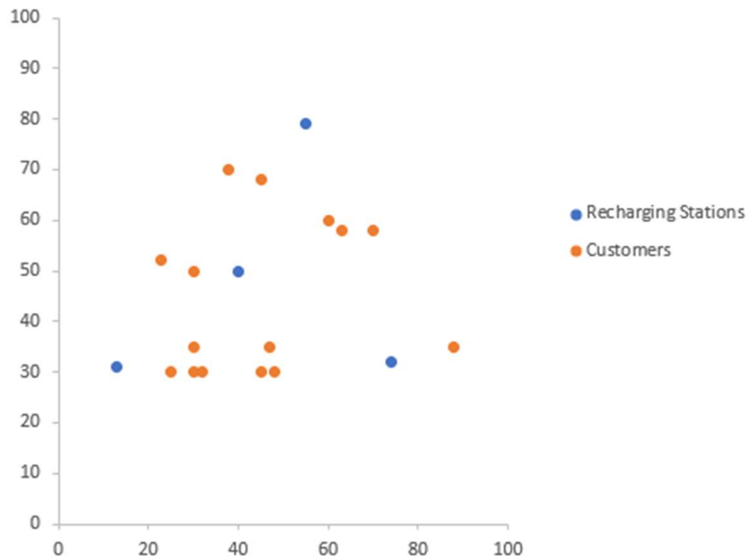

Figure 4 Example of geographic distribution of selected main and candidate recharging stations and customers for an instance (axes in kilometers)

The deterministic model has a single scenario corresponding to a probability 1, with 10 customers. The low volatility model has 5 scenarios corresponding to probabilities 0.3, 0.1, 0.1, 0.2, and 0.3, corresponding to numbers of customers of 8, 9, 10, 11, and 12 respectively. Concerning the high volatility model, the same 5 scenarios were used, with the previously mentioned probabilities, but with numbers of customers of 5, 8, 10, 12, and 15.

The sets of customers are randomly drawn from the sets of 15 customers and used the same way in all the instances.

For the power demand, q_i, we assume the values from the original instances, with one request per customer. By default, the battery of the MCVs is equal to seven times the average value of the total power demand in the customer requests. The recharge rate will be 0.3 in type 3 recharging stations, 0.25 in type 2, and 0.35 in type 1. In terms of the construction costs and the number of vehicles to provide the service the same value is assumed in all instances. When the vehicles are providing the service, it is assumed that there is no waste of energy in transferring energy from one battery to the other.

Battery capacities differ between classes of geographic distribution, but are kept equal within each class.

Regarding the time windows it should be mention the earliest and latest start as well as the geographic distribution of the clients are important factors that influence the service provider journey and can be addressed in the developed model. Power demand, service time, and latest start are all values suggested by Schneider et al. (2014).

4.2. Base results for all instances

Table 5 presents an overview of the results for the base situation. This instance will be compared in all tables, considering changes in the battery capacity, consumption rate and price of recharging stations. For the solutions obtained, the table presents the expected total costs of the journeys done by the three MCVs and the possible costs of recharging stations, if built. #RS is the number of recharging stations built in each instance, assuming that every instance necessarily builds one station. The following parameter is the average number of recharges that occurred in each instance in the different recharging stations. The table also includes the battery capacity that was considered for each instance.

Table 5 Optimal total cost, recharging amount, and number of recharging stations for the base case instances

No.	Instance	TC	#RS	# Recharges	Battery Capacity
1	C1D1-C10	9.70	2	1	200
2	C1LV5-C812	9.85	2	3	200
3	C1HV5-C515	10.51	2	5	200
4	R2D1-C10	7.87	1	2	230
5	R2LV5-C812	10.05	2	6	230
6	R2HV5-C515	11.69	3	7	230
7	RC2D1-C10	13.10	2	1	230
8	RC2LV5-C812	13.24	2	5	230
9	RC2HV5-C515	15.61	3	5	230
10	R1D1-C10	10.21	1	1	230
11	R1LV5-C812	10.98	1	3	230
12	R1HV5-C515	10.58	1	3	230
13	RC1D1-C10	10.53	1	1	250
14	RC1LV5-C812	11.99	2	4	250
15	RC1HV5-C515	11.70	2	4	250

Note: “TC” is the total expected cost in euros, “#RS” is the average number of recharging stations, “#Recharges” is the average number of recharges, and battery capacity is given in in kilometers

4.3. Sensitivity Analysis

In an era of innovation and technological progress in the electric car industry, it is possible to think of improvements in various areas leading to more efficient services. A sensitivity analysis may be useful in assessing the impact of such improvements. In the following sections, an analysis was carried out, regarding variations in battery capacity, energy consumption of the fleet that provides the service, recharging station costs and number of vehicles to provide the service. The first three are largely connected with technological aspects, while the fourth one is mostly related with operations strategy aspects.

4.3.1 Sensitivity analysis for battery capacity

Regarding battery capacity, two additional cases were created. In case I, with a decrease of 10% of the battery capacity, the service vehicles may need to recharge more times but will fill the battery faster. On the other hand, in case III, an increase of 10% of the battery capacity allows serving more clients with fewer recharges. Case II is the base situation.

Table 6 presents a comparison between base results and the case with 10% less battery capacity. The columns on the right-hand side of the table present the difference between total costs, number of recharging stations and number of recharges.

Table 6 Comparison of results for a 10% decrease in battery capacity

No.	Instance	Case I			Case II			ΔTC	ΔRS	ΔRec
		TC	#RS	#Rec	TC	#RS	#Rec			
1	C1D1-C10	9.82	2	2	9.70	2	1	1%	0	1
2	C1LV5-C812	10.01	2	4	9.85	2	3	2%	0	1
3	C1HV5-C515	10.82	2	6	10.51	2	5	3%	0	1
4	R2D1-C10	7.87	1	2	7.87	1	2	0%	0	0
5	R2LV5-C812	10.16	2	7	10.05	2	6	1%	0	1
6	R2HV5-C515	11.80	3	8	11.69	3	7	1%	0	1
7	RC2D1-C10	13.29	2	2	13.10	2	1	1%	0	1
8	RC2LV5-C812	15.45	3	7	13.24	2	5	17%	1	2
9	RC2HV5-C515	15.80	3	7	15.61	3	5	1%	0	2
10	R1D1-C10	10.25	1	1	10.21	1	1	0%	0	0
11	R1LV5-C812	11.31	1	4	10.98	1	3	3%	0	1
12	R1HV5-C515	10.73	1	3	10.58	1	3	1%	0	0
13	RC1D1-C10	10.79	1	2	10.53	1	1	2%	0	1
14	RC1LV5-C812	12.44	2	6	11.99	2	4	4%	0	2
15	RC1HV5-C515	12.01	2	6	11.70	2	4	3%	0	2

Note: "TC" is the total expected cost, "#RS" is the average number of recharging stations, "#Rec" is the average number of recharges, ΔTC is the variation of total cost in percentage, ΔRS is the variation of the average number of recharging stations, and ΔRec is the variation of the average number of recharges

With less capacity, the MCVs need to recharge more often and/or in more recharging stations. The total costs, therefore, will generally increase with the decrease in battery capacity.

As for the number of recharging stations, it is mostly stable, with some variation observed only for the RC2LV5-C812 instance that needs to build one more. For the number of recharges, the variation is significant with almost all instances presenting higher numbers of recharges to satisfy the same customer demand. Overall, the decrease in battery capacity leads to a small increase in the costs and an increase in the number of recharges.

Table 7 presents a comparison between base results and the case with 10% more battery capacity, with a structure similar to Table 6. In this case, with an improvement of 10% in the capacity, the MCVs need to recharge less often and/or in less recharging stations. The total costs generally decrease with the increase in battery capacity.

As for the number of recharging stations, it is mostly stable, with some reductions observed in some instances. A large difference in the total costs is visible if recharging stations are not required to be built. Regarding the number of recharges, the variation is significant in almost all instances. With the increase in capacity, there is a significant improvement in the total costs with savings of 15% in some cases.

Table 7 Comparison of results for 10% more battery capacity

No.	Instance	Case II			Case III			ΔTC	ΔRS	ΔRec
		TC	#RS	#Rec	TC	#RS	#Rec			
1	C1D1-C10	9.70	2	1	7.87	1	0	-23%	-1	-1
2	C1LV5-C812	9.85	2	3	9.85	2	3	0%	0	0
3	C1HV5-C515	10.51	2	5	10.31	2	4	-2%	0	-1
4	R2D1-C10	7.87	1	2	7.72	1	1	-2%	0	-1
5	R2LV5-C812	10.05	2	6	9.70	2	4	-4%	0	-2
6	R2HV5-C515	11.69	3	7	9.60	2	5	-22%	-1	-2
7	RC2D1-C10	13.10	2	1	11.27	1	1	-16%	-1	0
8	RC2LV5-C812	13.24	2	5	13.24	2	5	0%	0	0
9	RC2HV5-C515	15.61	3	5	13.81	2	4	-13%	-1	-1
10	R1D1-C10	10.21	1	1	10.14	1	1	-1%	0	0
11	R1LV5-C812	10.98	1	3	10.71	1	2	-3%	0	-1
12	R1HV5-C515	10.58	1	3	10.37	1	2	-2%	0	-1
13	RC1D1-C10	10.53	1	1	10.41	1	0	-1%	0	-1
14	RC1LV5-C812	11.99	2	4	10.59	1	2	-13%	-1	-2
15	RC1HV5-C515	11.70	2	4	9.98	1	2	-17%	-1	-2

Note: "TC" is the total expected cost, "#RS" is the average number of recharging stations, "#Rec" is the average number of recharges, ΔTC is the variation of total cost in percentage, ΔRS is the variation of the average number of recharging stations, and ΔRec is the variation of the average number of recharges

4.3.2 Sensitivity analysis for traveling consumption rate

With a decrease in consumption, the vehicles will achieve better results with a reduced need for recharging. The first case that we consider is a 50% reduction in consumption, and the second a reduction of 20% in consumption. Case III will be the base results. The comparison is presented in tables 8 and 9 between cases I and III, and between cases II and III, respectively.

With an improvement of 50% in the consumption rate of the MCVs, the costs of traveling are reduced and the need for constructing recharging stations is less intensive. When a car has lower consumption with equal battery capacity, it will travel longer distances and be able to offer more service. As is visible in Table 8, this happened in almost all instances, with decreases of close to 20% in costs when the operations no longer required the same number of recharging stations. The number of recharges also decreases in all instances, with a more efficient service.

With an improvement of only 20%, the cost reduction is not as significant as in the previous case, but the incentive to reduce the number of recharging stations is still visible in some instances, as can be seen in Table 9. The number of recharges follows the same trend.

Table 8 Results for a 50% decrease in travelling consumption rate

No.	Instance	Case I			Case III			ΔTC	ΔRS	ΔRec
		TC	#RS	#Rec	TC	#RS	#Rec			
1	C1D1-C10	7.65	1	0	9.70	2	1	-21%	-1	-1
2	C1LV5-C812	7.83	1	1	9.85	2	3	-21%	-1	-2
3	C1HV5-C515	8.01	1	1	10.51	2	5	-24%	-1	-4
4	R2D1-C10	7.56	1	0	7.87	1	2	-4%	0	-2
5	R2LV5-C812	7.98	1	1	10.05	2	6	-21%	-1	-5
6	R2HV5-C515	9.51	2	3	11.69	3	7	-19%	-1	-4
7	RC2D1-C10	10.67	1	0	13.10	2	1	-19%	-1	-1
8	RC2LV5-C812	11.34	1	1	13.24	2	5	-14%	-1	-4
9	RC2HV5-C515	11.69	1	2	15.61	3	5	-25%	-2	-3
10	R1D1-C10	9.96	1	0	10.21	1	1	-2%	0	-1
11	R1LV5-C812	10.53	1	1	10.98	1	3	-4%	0	-2
12	R1HV5-C515	10.12	1	1	10.58	1	3	-4%	0	-2
13	RC1D1-C10	10.36	1	0	10.53	1	1	-2%	0	-1
14	RC1LV5-C812	9.87	1	1	11.99	2	4	-18%	-1	-3
15	RC1HV5-C515	9.53	1	2	11.70	2	4	-19%	-1	-2

Note: "TC" is the total expected cost, "#RS" is the average number of recharging stations, "#Rec" is the average number of recharges, ΔTC is the variation of total cost in percentage, ΔRS is the variation of the average number of recharging stations, and ΔRec is the variation of the average number of recharges

Table 9 Results for a 20% decrease in travelling consumption rate

No.	Instance	Case II			Case III			ΔTC	ΔRS	ΔRec
		TC	#RS	#Rec	TC	#RS	#Rec			
1	C1D1-C10	7.85	1	0	9.70	2	1	-19%	-1	-1
2	C1LV5-C812	8.05	1	2	9.85	2	3	-18%	-1	-1
3	C1HV5-C515	10.18	2	3	10.51	2	5	-3%	0	-2
4	R2D1-C10	7.63	1	1	7.87	1	2	-3%	0	-1
5	R2LV5-C812	9.72	2	3	10.05	2	6	-3%	0	-3
6	R2HV5-C515	9.66	2	5	11.69	3	7	-17%	-1	-2
7	RC2D1-C10	10.98	1	1	13.10	2	1	-16%	-1	0
8	RC2LV5-C812	12.60	2	3	13.24	2	5	-5%	0	-2
9	RC2HV5-C515	13.80	2	4	15.61	3	5	-12%	-1	-1
10	R1D1-C10	9.96	1	0	10.21	1	1	-2%	0	-1
11	R1LV5-C812	10.83	1	2	10.98	1	3	-1%	0	-1
12	R1HV5-C515	10.31	1	2	10.58	1	3	-3%	0	-1
13	RC1D1-C10	10.28	1	0	10.53	1	1	-2%	0	-1
14	RC1LV5-C812	11.68	2	2	11.99	2	4	-3%	0	-2
15	RC1HV5-C515	11.19	2	2	11.70	2	4	-4%	0	-2

Note: "TC" is the total expected cost, "#RS" is the average number of recharging stations, "#Rec" is the average number of recharges, ΔTC is the variation of total cost in percentage, ΔRS is the variation of the average number of recharging stations, and ΔRec is the variation of the average number of recharges

4.3.3 Sensitivity analysis for the recharging station cost

The cost of recharging stations assumed in the base situation (case II in this section) is given by Axsen et al. (2012), assuming 5 years of depreciation and 365 days of activity per year. The cost is 2 € per day, considering that each instance corresponds to one day of activity. In case I the costs are reduced from 2 to 1 and in case III increased from 2 to 3. For the analysis of the results, it is important to keep in mind that the cost of the base recharging station is always incurred and therefore not considered in our analysis. Only additional recharging stations are considered.

Table 10 presents the comparison between the base situation (case II) and the case with a cost decrease. There are some differences in the costs due to the reduction in the recharging station costs. Only in two instances there are fewer stations than in the base case, and there are no differences in the number of recharges.

Table 10 Results for a 50% decrease in recharging station costs

No.	Instance	Case I			Case II			ΔTC	ΔRS	ΔRec
		TC	#RS	#Rec	TC	#RS	#Rec			
1	C1D1-C10	8.70	2	1	9.70	2	1	-10%	0	0
2	C1LV5-C812	8.85	2	3	9.85	2	3	-10%	0	0
3	C1HV5-C515	9.51	2	5	10.51	2	5	-10%	0	0
4	R2D1-C10	7.87	1	2	7.87	1	2	0%	0	0
5	R2LV5-C812	9.05	2	6	10.05	2	6	-10%	0	0
6	R2HV5-C515	9.69	3	7	11.69	3	7	-17%	0	0
7	RC2D1-C10	12.10	2	1	13.10	2	1	-8%	0	0
8	RC2LV5-C812	13.02	3	5	13.24	2	5	-2%	-1	0
9	RC2HV5-C515	13.61	3	5	15.61	3	5	-13%	0	0
10	R1D1-C10	10.21	1	1	10.21	1	1	0%	0	0
11	R1LV5-C812	10.85	2	3	10.98	1	3	-1%	-1	0
12	R1HV5-C515	10.58	1	3	10.58	1	3	0%	0	0
13	RC1D1-C10	10.53	1	1	10.53	1	1	0%	0	0
14	RC1LV5-C812	10.99	2	4	11.99	2	4	-8%	0	0
15	RC1HV5-C515	10.70	2	4	11.70	2	4	-9%	0	0

Note: "TC" is the total expected cost, "#RS" is the average number of recharging stations, "#Rec" is the average number of recharges, ΔTC is the variation of total cost in percentage, ΔRS is the variation of the average number of recharging stations, and ΔRec is the variation of the average number of recharges

Table 11 Results for a 50% increase in recharging station costs

No.	Instance	Case II			Case III			ΔTC	ΔRS	ΔRec
		TC	#RS	#Rec	TC	#RS	#Rec			
1	C1D1-C10	9.70	2	1	10.71	2	1	9%	0	0
2	C1LV5-C812	9.85	2	3	10.21	1	4	4%	-1	-1
3	C1HV5-C515	10.51	2	5	11.51	2	5	9%	0	0
4	R2D1-C10	7.87	1	2	7.87	1	2	0%	0	0
5	R2LV5-C812	10.05	2	6	9.74	1	8	-3%	-1	-2
6	R2HV5-C515	11.69	3	7	10.28	2	8	-14%	-1	-1
7	RC2D1-C10	13.10	2	1	11.50	1	2	-14%	-1	-1
8	RC2LV5-C812	13.24	2	5	14.24	2	5	7%	0	0
9	RC2HV5-C515	15.61	3	5	14.76	2	7	-6%	-1	-2
10	R1D1-C10	10.21	1	1	10.21	1	1	0%	0	0
11	R1LV5-C812	10.98	1	3	10.98	1	3	0%	0	0
12	R1HV5-C515	10.58	1	3	10.58	1	3	0%	0	0
13	RC1D1-C10	10.53	1	1	10.53	1	1	0%	0	0
14	RC1LV5-C812	11.99	2	4	10.39	1	6	-15%	-1	-2
15	RC1HV5-C515	11.70	2	4	9.86	1	5	-19%	-1	-1

Note: "TC" is the total expected cost, "#RS" is the average number of recharging stations, "#Rec" is the average number of recharges, ΔTC is the variation of total cost in percentage, ΔRS is the variation of the average number of recharging stations, and ΔRec is the variation of the average number of recharges

With the increase in the cost, there are some differences, as can be seen in Table 11, with some instances featuring a reduction in the number of stations and recharges, and others showing just an increase in costs due to the higher station costs.

4.3.4 Sensitivity analysis for the number of vehicles

The last sensitivity analysis concerns the number of vehicles needed to provide the service. Although adding a vehicle could be expensive, in the long term and with an increase in the number of customers it could be beneficial. Given the short range of vehicles nowadays, we do not consider the situation where the fleet is reduced.

In Table 13, the reduction of the costs and the impact on the number of recharging stations are clearly visible. When there is a reduction of the number of recharging stations, the cost decreases more than 10%. For the instances that kept the same number of recharging stations, the total cost decreased no more than 4%. In terms of number of recharges, there is not a very significant reduction.

Table 12 Results for an increase of one in the number of vehicles

No.	Instance	3 Vehicles			4 Vehicles			ΔTC	ΔRS	ΔRec
		TC	#RS	#Rec	TC	#RS	#Rec			
1	C1D1-C10	9.70	2	1	9.70	2	1	0%	0	0
2	C1LV5-C812	9.85	2	3	9.85	2	3	0%	0	0
3	C1HV5-C515	10.51	2	5	10.30	2	3	-2%	0	-2
4	R2D1-C10	7.87	1	2	7.71	1	2	-2%	0	0
5	R2LV5-C812	10.05	2	6	9.90	2	5	-2%	0	-1
6	R2HV5-C515	11.69	3	7	9.97	2	6	-17%	-1	-1
7	RC2D1-C10	13.10	2	1	11.43	1	1	-15%	-1	0
8	RC2LV5-C812	13.24	2	5	12.72	2	4	-4%	0	-1
9	RC2HV5-C515	15.61	3	5	15.38	3	4	-1%	0	-1
10	R1D1-C10	10.21	1	1	10.16	1	1	0%	0	0
11	R1LV5-C812	10.98	1	3	10.59	1	3	-4%	0	0
12	R1HV5-C515	10.58	1	3	10.16	1	2	-4%	0	-1
13	RC1D1-C10	10.53	1	1	10.44	1	1	-1%	0	0
14	RC1LV5-C812	11.99	2	4	10.27	1	4	-17%	-1	0
15	RC1HV5-C515	11.70	2	4	11.47	2	4	-2%	0	0

Note: "TC" is the total expected cost, "#RS" is the average number of recharging stations, "#Rec" is the average number of recharges, ΔTC is the variation of total cost in percentage, ΔRS is the variation of the average number of recharging stations, and ΔRec is the variation of the average number of recharges

5. Conclusions

5.1. Conclusion

This study addresses a Mobile Charging Service approach that focuses on the concept of recharging Electric Vehicles that require energy at some point in the day to increase the range of their journey. Every day, many EV users are restricted in the distances that they would like to cover with their cars because of battery capacity constraints. With the kind of service studied in this dissertation, these users are able to be provided a recharge without moving and wasting the corresponding time.

The optimization model presented in this dissertation is able to propose a design for the infrastructure of the operations of such a service, considering appropriately the close relationship between recharging station locations, vehicle routing, and construction cost, which are the higher expenses of many companies that work in this field, and, most importantly, the stochastic nature of the demand. The two-stage nature of the model makes it more robust and able to handle unpredictable demand, optimizing for a variety of possible scenarios the combination of strategic and tactical decisions.

The results obtained make it possible to understand the changes that can be made in order to make the entire service more efficient and cheaper. With a daily scope and a maximum of 15 customers, some changes that may not seem important, may in fact in the long term be significantly beneficial, allowing the service provider to offer the same service with significantly fewer resources.

With the sensitivity analysis, it was possible to understand how different directions of technological progress, from battery capacity to MCV consumption, may improve the service, making it more efficient and effective.

5.2. Future Research

For future research, the continuous improvement and work with small instances like the ones presented is relevant. Although these small instances may seem obvious to address, the variety of combinations of parameters introduces many changes in the design of the solutions. It would be of the highest importance to apply this model to a real-world situation to understand the performance that it would require a solver like the one used.

If allowed by the IBM Ilog Cplex’s limitations, environmental factors such as relief, weather and temperature should be reflected in the model to allow achieving more detailed and implementable solutions. With the corresponding introduction of more variables, parameters, and constraints, the model will become more robust and effective.

Concerning the technological context and specifically the electric vehicles industry, the constant change in multiple areas of high improvement potential requires a constant update of data such as the price of electricity or the costs of the infrastructure.

It would also be important to interview service stakeholders to better understand practical details that often have a critical role in daily operations, such as how recharging stations work and what types of problems appear, and how frequently.

References

Adler, J. D., & Mirchandani, P. B. (2014). Online routing and battery reservations for electric vehicles with swappable batteries. *Transportation Research Part B: Methodological, 70, 285-302*. https://doi.org/10.1016/j.trb.2014.09.005

Atmaja, T. D., & Amin. (2015). Energy storage system using battery and ultracapacitor on mobile charging station for electric vehicle. *Energy Procedia, 68(2015), 429-437*. https://doi.org/10.1016/j.egypro.2015.03.274

Axsen, J., & Kurani, K. S. (2012). Who can recharge a plug-in electric vehicle at home? *Transportation Research Part D: Transport and Environment, 17(5), 349-353*. https://doi.org/10.1016/j.trd.2012.03.001

Bakker, J. (2011). Contesting range anxiety: The role of electric vehicle charging infrastructure in the transportation transition. In *Eindhoven University of Technology*.

Barreto, S., Ferreira, C., Paixão, J., & Santos, B. S. (2007). Using clustering analysis in a capacitated location-routing problem. *European Journal of Operational Research, 179(3), 968-977*. https://doi.org/10.1016/j.ejor.2005.06.074

Bjerkan, K. Y., Nørbech, T. E., & Nordtømme, M. E. (2016). Incentives for promoting Battery Electric Vehicle (BEV) adoption in Norway. *Transportation Research Part D: Transport and Environment, 43, 169-180*. https://doi.org/10.1016/j.trd.2015.12.002

Blanutsa, V. I. (2010). The postal-geographical location: The notion and measurement algorithm (exemplified by the postal network of Siberia in the early 20th century). *Geography and Natural Resources*, 31(4), 308-316. https://doi.org/10.1016/j.gnr.2010.11.003

Blount, D. (1991). Comparison of Stochastic and Deterministic Models of a Linear Chemical Reaction with Diffusion. *The Annals of Probability, 1440-1462*. https://doi.org/10.1214/aop/1176990219

Bräysy, O., & Gendreau, M. (2005). Vehicle routing problem with time windows, Part I: Route construction and local search algorithms. *Transportation Science, 39(1), 104-118*. https://doi.org/10.1287/trsc.1030.0056

Caballero, R., González, M., Guerrero, F. M., Molina, J., & Paralera, C. (2007). Solving a multiobjective location routing problem with a metaheuristic based on tabu search. Application to a real case in Andalusia. *European Journal of Operational Research, 177(3), 1751-1763*. https://doi.org/10.1016/j.ejor.2005.10.017

Camus, C., Farias, T., & Esteves, J. (2011). Potential impacts assessment of plug-in electric vehicles on the Portuguese energy market. *Energy Policy, 39(10), 5883-5897*. https://doi.org/10.1016/j.enpol.2011.06.042

Canals Casals, L., Martinez-Laserna, E., Amante García, B., & Nieto, N. (2016). Sustainability analysis of the electric vehicle use in Europe for CO2 emissions reduction. *Journal of Cleaner Production, 127, 425-437*. https://doi.org/10.1016/j.jclepro.2016.03.120

Caulfield, B., Farrell, S., & McMahon, B. (2010). Examining individuals preferences for hybrid electric and alternatively fuelled vehicles. *Transport Policy, 17(6) 381-387*. https://doi.org/10.1016/j.tranpol.2010.04.005

Chan, C. C. (2002). The state of the art of electric and hybrid vehicles. *Proceedings of the IEEE, 90(2), 247-275*. https://doi.org/10.1109/5.989873

Chen, H., Su, Z., Hui, Y., & Hui, H. (2017). Optimal approach to provide electric vehicles with charging service by using mobile charging stations in heterogeneous networks. *IEEE Vehicular Technology Conference, (pp.1-5)*. https://doi.org/10.1109/VTCFall.2016.7881135

Chen, Z., He, F., & Yin, Y. (2016). Optimal deployment of charging lanes for electric vehicles in transportation networks. *Transportation Research Part B: Methodological*. *91*, 344-365. https://doi.org/10.1016/j.trb.2016.05.018

Cook, T. M., & Russell, R. A. (1978). A SIMULATION AND STATISTICAL ANALYSIS OF STOCHASTIC VEHICLE ROUTING WITH TIMING CONSTRAINTS. *Decision Sciences, 9(4), 673-687*. https://doi.org/10.1111/j.1540-5915.1978.tb00753.x

Cui, S., Zhao, H., Chen, H., & Zhang, C. (2018). The mobile charging vehicle routing problem with time windows and recharging services. *Computational Intelligence and Neuroscience*. https://doi.org/10.1155/2018/5075916

Cui, S., Zhao, H., & Zhang, C. (2018). Multiple types of plug-in charging facilities' location-routing problem with time windows for mobile charging vehicles. *Sustainability (Switzerland, 10(8), 2855*. https://doi.org/10.3390/su10082855

Dalmeijer, K., & Spliet, R. (2018). A branch-and-cut algorithm for the Time Window Assignment Vehicle Routing Problem. *Computers and Operations Research, 89, 140-152*. https://doi.org/10.1016/j.cor.2017.08.015

Darabi, Z., & Ferdowsi, M. (2012). Impact of Plug-In Hybrid Electric Vehicles on Electricity Demand Profile. *Power Systems(pp. 319-349)*. https://doi.org/10.1007/978-3-642-21578-0_11

Diamond, D. (2009). The impact of government incentives for hybrid-electric vehicles: Evidence from US states. *Energy Policy, 37(3), 972-983*. https://doi.org/10.1016/j.enpol.2008.09.094

Directive 2009/28/EG. (2009). Directive 2009/28/EC of the European Parliament and of the council on the promotion of the use of energy from renewable sources. In *Publicatieblad van de Europese Unie*.

Egbue, O., & Long, S. (2012). Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy Policy, 48, 717-729*. https://doi.org/10.1016/j.enpol.2012.06.009

EP. (2009). Regulation (EC) no 443/2009 setting emission performance standards for new passenger cars as part of the Community's integrated approach to reduce CO2 emissions from light-duty vehicles. *Official Journal of the European Communities*. https://doi.org/10.1524/zkri.2009.1105

European Automobile Manufacturers Association. (2018). Automobile Industry Pocket Guide.

Fetene, G. M., Kaplan, S., Mabit, S. L., Jensen, A. F., & Prato, C. G. (2017). Harnessing big data for estimating the energy consumption and driving range of electric vehicles. *Transportation Research Part D: Transport and Environment, 54, 1-11*. https://doi.org/10.1016/j.trd.2017.04.013

Frade, I., Ribeiro, A., Gonçalves, G., & Antunes, A. P. (2012). Optimal Location of Charging Stations for Electric Vehicles in a Neighborhood in Lisbon, Portugal. *Transportation Research Record: Journal of the Transportation Research Board, 2252(1), 91-98.*. https://doi.org/10.3141/2252-12

Gendreau, M., & Tarantilis, C. (2010). Solving large-scale vehicle routing problems with time windows: The state-of-the-art. *Cirrelt*.

Hawkins, T. R., Singh, B., Majeau-Bettez, G., & Strømman, A. H. (2013). Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles. *Journal of Industrial Ecology, 17(1), 53-64*. https://doi.org/10.1111/j.1530-9290.2012.00532.x

He, F., Yin, Y., & Lawphongpanich, S. (2014). Network equilibrium models with battery electric vehicles. 67, 306-319 *Transportation Research Part B: Methodological*. https://doi.org/10.1016/j.trb.2014.05.010

Helmers, E., & Marx, P. (2012). Electric cars: Technical characteristics and environmental impacts. *Environmental Sciences Europe, 24(1), 14*. https://doi.org/10.1186/2190-4715-24-14

Hidrue, M. K., Parsons, G. R., Kempton, W., & Gardner, M. P. (2011). Willingness to pay for electric vehicles and their attributes. *Resource and Energy Economics, 33(3), 686-705*. https://doi.org/10.1016/j.reseneeco.2011.02.002

Huang, S., He, L., Gu, Y., Wood, K., & Benjaafar, S. (2015). Design of a Mobile Charging Service for Electric Vehicles in an Urban Environment. *IEEE Transactions on Intelligent Transportation Systems*., 16(2), 787-798. https://doi.org/10.1109/TITS.2014.2341695

IPCC. (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. In *Ipcc*.

Kenworthy, J. R., & Laube, F. B. (1999). Patterns of automobile dependence in cities: An international overview of key physical and economic dimensions with some implications for urban policy. *Transportation Research Part A: Policy and Practice, 33(7-8), 691-723*. https://doi.org/10.1016/S0965-8564(99)00006-3

Keskin, M., & Çatay, B. (2016). Partial recharge strategies for the electric vehicle routing problem with time windows. *Transportation Research Part C: Emerging Technologies, 65(2016): 111-127*. https://doi.org/10.1016/j.trc.2016.01.013

Kim, J., Son, S. Y., Lee, J. M., & Ha, H. T. (2017). Scheduling and performance analysis under a stochastic model for electric vehicle charging stations. *Omega (United Kingdom),66, 278-289*. https://doi.org/10.1016/j.omega.2015.11.010

Laporte, G., Louveaux, F., & Mercure, H. (1989). Models and exact solutions for a class of stochastic location-routing problems. *European Journal of Operational Research, vol. 39, pp. 71-78*. https://doi.org/10.1016/0377-2217(89)90354-8

Lin, C. K. Y., Chow, C. K., & Chen, A. (2002). A location-routing-loading problem for bill delivery services. *Computers and Industrial Engineering, 43. 1-2(2002):5-25*. https://doi.org/10.1016/S0360-8352(02)00060-8

Liu, H., & Wang, D. Z. W. (2017). Locating multiple types of charging facilities for battery electric vehicles. *Transportation Research Part B: Methodological, 103,30-55*. https://doi.org/10.1016/j.trb.2017.01.005

Mak, H. Y., Rong, Y., & Shen, Z. J. M. (2013). Infrastructure planning for electric vehicles with battery swapping. *Management Science, 59(7), 1557-1575*. https://doi.org/10.1287/mnsc.1120.1672

Masuch, N., Lützenberger, M., Ahrndt, S., Heßler, A., & Albayrak, S. (2011). A context-aware mobile accessible electric vehicle management system. *2011 Federated Conference on Computer Science and Information Systems, FedCSIS 2011, (pp.305-312)*.

Min, H., Jayaraman, V., & Srivastava, R. (1998). Combined location-routing problems: A synthesis and future research directions. *European Journal of Operational Research, 108(1), 1-15*. https://doi.org/10.1016/S0377-2217(97)00172-0

Murty, K. G., & Djang, P. A. (1999). U.S. Army National Guard's mobile training simulators location and routing problem. *Operations Research, 47(2), 175-182*. https://doi.org/10.1287/opre.47.2.175

Nanaki, E. A., Koroneos, C. J., Roset, J., Susca, T., Christensen, T. H., De Gregorio Hurtado, S., … López-Jiménez, P. A. (2017). Environmental assessment of 9 European public bus transportation systems. *Sustainable Cities and Society,*. https://doi.org/10.1016/j.scs.2016.08.025

Neubauer, J., Brooker, A., & Wood, E. (2012). Sensitivity of battery electric vehicle economics to drive patterns, vehicle range, and charge strategies. *Journal of Power Sources*. https://doi.org/10.1016/j.jpowsour.2012.02.107

Nykvist, B., & Nilsson, M. (2015). Rapidly falling costs of battery packs for electric vehicles. *Nature Climate Change*. https://doi.org/10.1038/nclimate2564

Powell, W. B. (1986). STOCHASTIC MODEL OF THE DYNAMIC VEHICLE ALLOCATION PROBLEM. *Transportation Science*. https://doi.org/10.1287/trsc.20.2.117

Qin, H., & Zhang, W. (2011). Charging scheduling with minimal waiting in a network of electric vehicles and charging stations. *Proceedings of the Annual International Conference on Mobile Computing and Networking, MOBICOM*. https://doi.org/10.1145/2030698.2030706

Rod, M., Ashill, N. J., & Gibbs, T. (2016). Customer perceptions of frontline employee service delivery: A study of Russian bank customer satisfaction and behavioural intentions. *Journal of Retailing and Consumer Services*. https://doi.org/10.1016/j.jretconser.2016.02.005

Romm, J. (2006). The car and fuel of the future. *Energy Policy*. https://doi.org/10.1016/j.enpol.2005.06.025

Schneider, M., Stenger, A., & Goeke, D. (2014). The electric vehicle-routing problem with time windows and recharging stations. *Transportation Science, 48(4), 500-520*. https://doi.org/10.1287/trsc.2013.0490

Schrage, L. (1981). Formulation and structure of more complex/realistic routing and scheduling problems, 11(2), 229-232. *Networks*. https://doi.org/10.1002/net.3230110212

Sexton, T. R., & Bodin, L. D. (1985). OPTIMIZING SINGLE VEHICLE MANY-TO-MANY OPERATINS WITH DESIRED DELIVERY TIMES: II. ROUTING. *Transportation Science, 19(4), 378-410*. https://doi.org/10.1287/trsc.19.4.411

Shareef, H., Islam, M. M., & Mohamed, A. (2016). A review of the stage-of-the-art charging technologies, placement methodologies, and impacts of electric vehicles. *Renewable and Sustainable Energy Reviews, 64, 403-420*. https://doi.org/10.1016/j.rser.2016.06.033

Sierzchula, W., Bakker, S., Maat, K., & Van Wee, B. (2014). The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy, 68, 183-194*. https://doi.org/10.1016/j.enpol.2014.01.043

Sun, H., Yang, J., & Yang, C. (2019). A robust optimization approach to multi-interval location-inventory and recharging planning for electric vehicles. *Omega, 86,59-75 (United Kingdom)*. https://doi.org/10.1016/j.omega.2018.06.013

Sun, L., Zhao, L., & Hou, J. (2015). Optimization of postal express line network under mixed driving pattern of trucks. *Transportation Research Part E: Logistics and Transportation Review, 77, 147-169*. https://doi.org/10.1016/j.tre.2015.01.003

Tate, E. D., Harpster, M. O., & Savagian, P. J. (2008). The electrification of the automobile: From conventional hybrid, to plug-in hybrids, to extended-range electric vehicles. *SAE Technical Papers, 1(2008-01-048), 156-166*. https://doi.org/10.4271/2008-01-0458

Tietge, U., Mock, P., Lutsey, N., & Campestrini, A. (2016). Comparison of Leading Electric Vehicle Policy and Deployment in Europe, 49, 847129-102. *Icct*.

Un-Noor, F., Padmanaban, S., Mihet-Popa, L., Mollah, M. N., & Hossain, E. (2017). A comprehensive study of key electric vehicle (EV) components, technologies, challenges, impacts, and future direction of development. *Energies, 10(8), 1217.* https://doi.org/10.3390/en10081217

Watson-Gandy, C., & Dohrn, P. (1973). Depot location with van salesmen - A practical approach. *Omega, 1(3), 321-329*. https://doi.org/10.1016/0305-0483(73)90108-4

Wolsink, M. (2012). The research agenda on social acceptance of distributed generation in smart grids: Renewable as common pool resources. *Renewable and Sustainable Energy Reviews, 16(1), 822-835*. https://doi.org/10.1016/j.rser.2011.09.006

Wu, T. H., Low, C., & Bai, J. W. (2002). Heuristic solutions to multi-depot location-routing problems. *Computers and Operations Research, 29(10), 1393-1415*. https://doi.org/10.1016/S0305-0548(01)00038-7

Yilmaz, M., & Krein, P. T. (2012). Review of charging power levels and infrastructure for plug-in electric and hybrid vehicles. *2012 IEEE International Electric Vehicle Conference, IEVC 2012*. https://doi.org/10.1109/IEVC.2012.6183208

Yong, J. Y., Ramachandaramurthy, V. K., Tan, K. M., & Mithulananthan, N. (2015). A review on the state-of-the-art technologies of electric vehicle, its impacts and prospects. *Renewable and Sustainable Energy Reviews, 49, 365-385*. https://doi.org/10.1016/j.rser.2015.04.130