ELECTRIC VEHICLES CHARGING STATIONS PLANNING IN TRANSPORTATION NETWORKS AND THEIR IMPACT ON POWER DISTRIBUTION SYSTEMS

by

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Abstract

The insertion of Electric Vehicles (EVs) represents a positive and proactive alternative in the electrifying of transportation sector. Significant benefits for the environment are notable, since carbon emissions and noise pollution are largely reduced. By the other hand, EVs can be on the order of 80 to 90% efficient at converting electrical energy into forward motion, compared with internal combustion engine (ICE) based vehicles that reach around a 20% of efficiency. In the economic context, there is an important decrease in imported oil dependence, which promotes the development of other type of energy sources (renewable energy based sources) and stimulates the dynamics of other industrial sectors, i.e., lithium ion batteries fabrication, Electric Vehicle Charging Stations (EVCSs) manufacturing, freight transportation, etc.

However, the massive EVs charging will bring a tremendous pressure and impact on power distribution system, creating power quality problems and non-desired demand peaks, which addresses in power losses and voltage drops issues. In this sense, and with the objective to improve the power grid load factor, an EVs charging demand management strategy is needed, considering aspects related with EVs' owners and utilities. Furthermore, the battery is another problem that affects the adoption of EVs, specifically for the freight transportation companies, due to the low distance autonomy in comparison to ICE based vehicles. Under these circumstances, EVCSs location could provide a virtual increase in the EV driving range, taking into account that the battery autonomy will not be improved at medium term.

Considering the issues mentioned above, this thesis is divided in several chapters that address each problem separately. In first instance, a detailed literature review in regards with EVs and their relation with PDS and transportation networks is performed in Chapter 2. In Chapter 3 a probabilistic approach for the optimal charging of EVs in distribution systems is proposed. The costs of both demand and energy losses in the system are minimized, subjected to a set of constraints that consider EVs smart charging characteristics and operative aspects of the electric network. The stochastic driving patterns for EVs' owners, battery capacity and active and reactive power demanded at load nodes are considered. The optimal charging

of EVs connected to the system benefits the system's operation, as it represents a strategy to minimize the cost of energy losses and evaluate the capability of the system to charge EVs' batteries fully under certain penetration scenarios. Priority periods of EVs' recharge and the variation of energy price contribute to an adequate demand response, assisting the network operator for complying with quality indices (decrement of power losses) set forward by regulatory entities and developing studies of risk analysis for decision making. On the other hand, there is a valuable participation of the EVs' owners in improving the operation of the distribution system. Monte Carlo simulation (MCS) is used to assess the stochastic nature of the problem in a secondary (low voltage) distribution network. Then, in chapter 4, a novel approach of EVs for merchandise transportation considering the location of EVCSs and the impact on the Power Distribution System (PDS) is addressed. This integrated planning is formulated through a mixed integer nonlinear mathematical model. Test systems of different sizes are designed to evaluate the model performance, considering the transportation network and PDS. The results show a trade-off between EVs routing, PDS energy losses and EVCSs location. Following the same streamline of Chapter 4, in Chapter 5 an optimization model for the Charging Station Location Problem of Electric Vehicles for Freight Transportation CSLP-EVFT is presented. The proposed model aims to determine an optimal location strategy of EVCSs and the routing plan of a fleet electric vehicle under battery driving range limitation, in conjunction with the impact on the PDS. Freight transportation is modeled under the mobility patterns followed by the Capacitated Vehicle Routing Problem CVRP for contracted fleet, and Shortest Path SP problem for subcontracted fleet. A liner formulation of the power flow is used in order to consider the impact on the electric grid. Several costs are examined, i.e., EVs routing, installation and energy consumption of EVCSs, and energy losses. The problem is reduced to a mixed integer non-linear mathematical model, which is linearized by using multivariable Taylor's series.

Chapter 1

Introduction

1.1 Problem Statement

One of the great obstacles for the massive adoption of Electric Vehicles (EVs) is their limited autonomy compared with the internal combustion engines. The majority of the EVs in 2017 had autonomies (considering fully charged batteries) ranging from 100 km to 400 km (Schmidt, 2017), subject to weather conditions, traffic congestion and road topology. This autonomy range in batteries may not be sufficient for all EVs to be considered as a primary mode of transportation and creates in drivers a feeling known as "range anxiety", which addresses the concern of EV's driver to reach a critical level on the battery before arriving to a charging station (Sarrafan et al., 2016).

On the other hand, the increasing in the introduction of EVs could have a large impact on the power distribution system, e.g., non-desired demand peaks and violations in the allowable voltage limits as a consequence of the simultaneous charging of batteries. Likewise, the power quality could be reduced by the introduction of harmonics on voltages and currents, due to the power-electronics-based charging infrastructure (Carradore and Turri, 2010). Other effects generated by the introduction of EVs in the power network are the congestion on feeders and transformers, overloading, and increment of power losses during charging of batteries. From the power system operator stand point, economic aspects, power quality, reliability, and power losses must be considered (Clement-Nyns et al., 2010). Nevertheless, demand management alternatives based on energy price and habits of EVs' owners associated with the recharge of batteries, contribute to mitigate the effects on the power network.

Research on Electric Vehicle Charging Stations (EVCSs) has been increased considerably in recent years. This is due to the intrinsic characteristics of the model which encourages academic research, but also due to practical reasons, since inadequate planning transportation networks and power distribution systems results in inefficient use of the infrastructure and high cost in charging stations (Zhang et al., 2017).

Considering the roll performed by an EVCS in the electric and transportation approach, the problem addressed in this work can be summarized in the following paragraph:

> *¿How can the interaction between variables associated with demand response of EVs' owners and the distribution system operation be represented, respecting the random nature in the EVs recharge habits and the variability of complex factors such as the energy price?. By the other side, considering the EV movement through a transportation network, its need to arrive a destination point and limited autonomy, ¿Is it possible to represent via a mixed integer linear mathematical model, the relationship between the power distribution system and transportation network, the impact provided by the EVs in these networks due to the recharge of batteries and, the association between electric and transportation variables; to obtain an efficient operation from the electric and mobility point of view?.*

1.2 Study justification

According to roadmap followed by *Energy Technology Perspectives* in (Tanaka et al., 2011), carbon dioxide emissions will be reduced up to 50% by 2050, compared with levels recorded in 2005. In regards with the projections, transportation sector will contribute with a 30% of this reduction, considering that EVs annual sales will reach 50 millions of units by 2050. This is mainly because EVs represent a more friendly transportation alternative with environment, in comparison with internal combustion-propelled vehicles. Some of the advantages of using EVs are the reduction of greenhouse gases, curtailment in fossil fuels dependence and few noise generation. Then, EVs represent a promising tool to improve the energetic sustainability and confront climate change effects.

Nonetheless, the emergence of EVs as a primary transportation mean is still overshadowed by the low driving autonomy (compared with internal combustion vehicles), mainly due to the lithium ion batteries that are currently leading the EVs energy storage market. The improvement of this type of batteries to increase driving range, is disrupted greatly by factors safety related, cost, operation temperature and materials availability (Scrosati and Garche, 2010), which shows that the battery autonomy will not be improved significantly in the coming years.

Under these circumstances, EVCSs play an important roll in the electric mobility, being necessary an appropriate siting and sizing of these infrastructures. In this way, both the power and transportation networks are affected. From the point of view of the transportation network, EVCSs planning contributes to enhance EVs driving range (greatly solving the poor competitiveness of the lithium-ion batteries energy storage), providing the capacity to perform longer travels whether in a huge city (Sao Paulo, Los Angeles, Mexico City, among others) or between intermediate cities. By the other side, the power distribution network is highly important in the EVCSs planning. The suitable EVCSs location has an influence on the optimal values for the energy losses and voltage regulation in the distribution system.

In this manner, the EVCS is a linkage component between power distribution system and transportation network (specifically for EVs). As shown in Section 2.1, there are several works related with EVCSs planning. Furthermore, there is no research in which charging stations location for freight EVs (considering several modalities) is solved, accompanied by the effect over the power distribution network.

By solving this problem, EVs deployment is encouraged, promoting electric mobility to the big freight transportation companies that require much less contaminating technologies to perform their activities.

Finally, with the mathematical model obtained from this research around the EVCSs planning, a solution is provided to a real life problem, considered as a high impact subject to transportation network and power distribution systems, as well the interest created in the state entities and private companies involved in the reduction of pollution levels produced by automotive sector.

1.3 Research obejctives

1.3.1 General Objective

Propose and resolve a mathematical model for electric vehicle charging stations planning, considering the impact on the power distribution systems and mobility improvement in a transportation network that involves the mixed operation of freight transportation.

1.3.2 Specific objectives

- Review the background around the planning (siting and sizing) of the electric vehicle charging stations (EVCSs) and their impact on the power distribution system.
- Study and propose a demand management based mathematical model for electric vehicles in a distribution system, considering the stochastic nature of recharge habits and the energy price variation.
- Study the mathematical models in which the freight transportation vehicles are involved.
- Study the CVRP (Capacitated Vehicle Routing Problem) and the SP (Shortest Path) Problem.
- Propose and integrate the CVRP and SP problems into a mathematical model.
- Study the LPF (Linearized Power Flow) to find the power network operation point, based on a rectangular formulation and considering the distribution system unbalance.
- Propose a mathematical model that encompasses the LPF problem, in which the EVCSs can be introduced.

- Integrate the CVRP, SP and LPF models into one mathematical model, to strategically locate the EVCSs.
- Create and develop consistent test systems.

1.4 Theoretical framework

In this work, EVCSs planning in power distribution and transportation networks mainly involves the EVs and the respective variants, i.e., driving range, and type of transportation (public, private, freight), as well as the charging mode (slow and fast). Through mathematical programming, both the electric and transportation parts of the problem (power distribution and transportation networks) can be represented, encompassing several aspects of the EVCSs planning.

1.4.1 Type of EVs

In general, EVs are classified in plug-in and not plug-in EVs. Plug-in EVs can be connected into the electrical network and recharge their batteries, in contrast with not plug-in EVs that depend on other type of charging when their batteries have reached low state of charge.

- NEVs (Non plug-in Electric Vehicles): These vehicles are 100% battery-based, which is swapped by another battery once has reached an allowable minimum state of charge.
- PEVs (Plug-in Electric Vehicles): Vehicles powered by a plug-in electric battery (Marra et al., 2012). Once the state of charge has reached a minimum level, it has to be connected into the electric network for charging proposal (See Figure 1.1).
- HEVs (Hybrid Electric Vehicles): This category encompasses not plug-in EVs, that combines an electric motor with a internal combustion engine to create propulsion (Negarestani et al., 2012). Range autonomy of these vehicles is larger in comparison with NEVs. In a series configuration (Figure 1.2), the energy coming from the

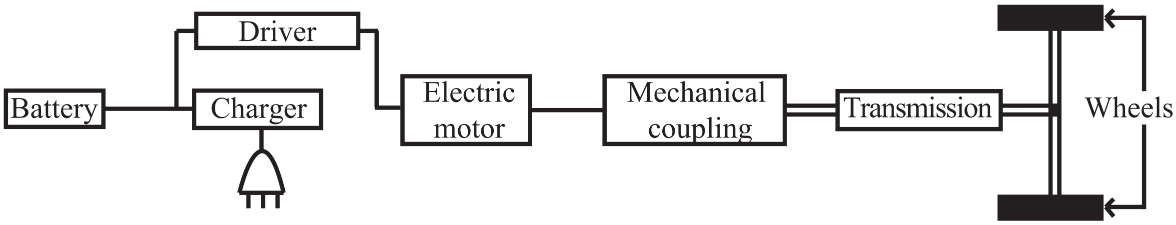

Figure 1.1: PEV system arquitecture

internal combustion is not transmitted directly to wheels. Internal combustion engine is connected to a generator, which produces energy driven to an electric motor, being this latter in charge to move the wheels. When electric generator produces surplus of energy, this is stored in the battery, otherwise, energy is drawn from both, electric generator and battery.

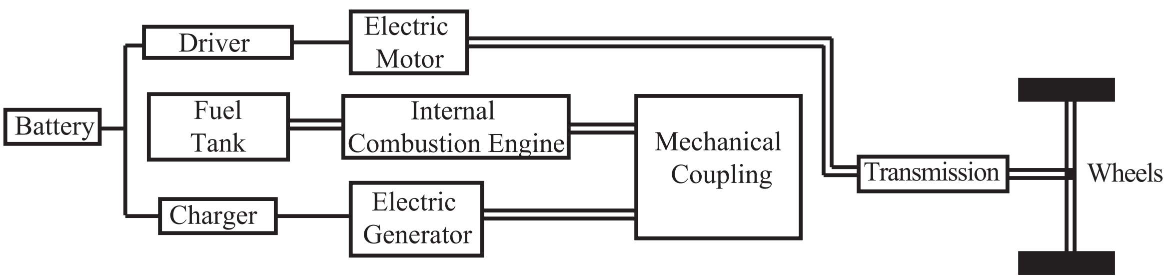

Figure 1.2: HEV series configuration system arquitecture

In a parallel configuration (Figure 1.3), both, electric and combustion motors, are connected into the mechanical coupling, which is driven to the transmission. This way, the vehicle can be powered either the electric motor, or combustion engine, or both motors, or only with the combustion engine while the electric motor is charging the battery.

- PHEVs (Plug-in Hybrid Electric Vehicles): These vehicles are classified as HEVs, able to draw and store energy from the electric network (or from a renewable energy source) for its propulsion (Williamson, 2013) (Serra, 2013). A PHEV can be in electric motor mode, combustion engine mode, or a combination of both modes depending on the efficiency.

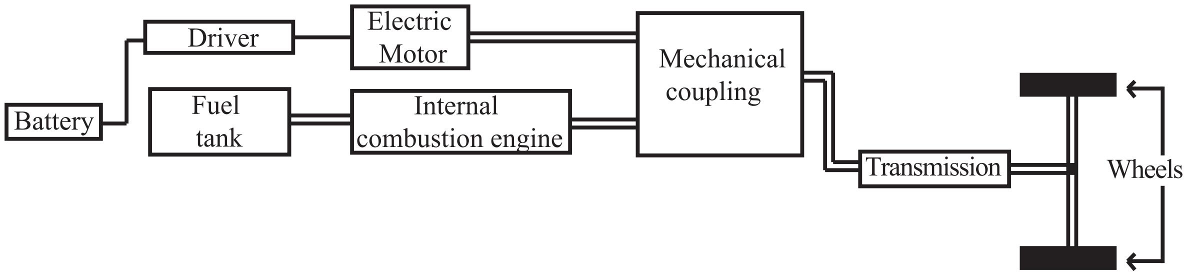

Figure 1.3: HEV parallel configuration system arquitecture

1.4.2 Electric Vehicles recharge infrastructure

Electric vehicle recharge system allows to draw energy from the electric network to the batteries, which represents an important role for the appropriate development of the EVs, and the interaction with distribution system. This transfer can be performed via inductive (wireless recharge) or conductive (wire-based recharge) means, being this latter the most used by the EVCSs.

Recharge infrastructure standards are generally well balanced, even when the industry has a large variety of manufacturers. The typical components of an EVCS icludes (Fox, 2011):

- Over current protection devices, which counteracts the effects produced by short circuits and overloading.
- Contactor for energy path control to the connector. This contactor de-energizes the connector terminals when not connected.
- Interface with EV internal on-board recharging system, providing ground fault protection.
- Indicators and alarms for proposal of state of charge information and guide the user through the operational sequence.
- Connector or physical linkage between EVCS and EV.

By the other side, battery recharge process involves two phases, deployed within the IV characteristic (Current - Voltage) in Figure 1.4. The first phase, named as main phase, consists of delivering the big majority of energy (at constant current and progressive increase of voltage) to the battery until reach up to 80% of state of charge (Pistoia, 2010). The duration of this phase depends on the available current and nominal value of the charger. In the second phase, named as the final charge, the current is reduced progressively whilst the voltage keeps constant, taking several hours to fully recharge battery.

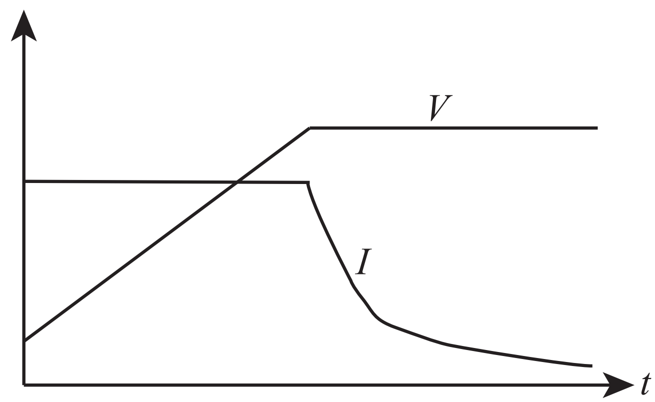

Figure 1.4: IV charging characteristic

Since 2009, the Society of Automotive Engineering has been working on the SAEJ1772 standard, where the recharge system architecture is defined in North America. According to the standards established by SAEJ1772, EVCSs can be classified in terms of the type of electrical outlet used in the infrastructure and/or the over current protection device (Falvo et al., 2014). However, nowadays the most common classification for EV chargers is in function of the nominal power and the recharge time:

- Level 1: These chargers, also named as slow recharge, have a nominal power around 3.7 kW, similar to a conventional single-phase electrical outlet rated at 120 V AC and 12 A. At this current rate, the battery recharge takes too long, between 12 and 18 hours depending on the battery energetic capacity. Its applications are intended for domestic usage.

- Level 2: These chargers account with a nominal power range within 3.7 kW and 22 kW. For this reason, a single phase electrical supply rated at 208-240 V AC with 30

A is used. In accordance with NEC (National Electrical Code) guidelines (Earley and Sargent, 2010), an improvement of the electrical wire must be done to install this type of chargers. Considering these power values, battery recharge time can be reduced up to 50% in comparison with level 1 chargers. This charger is suitable for public places.

- Level 3: In this category fast charge systems are addressed. Power levels are larger, compared with level 1 and level 2, which requires of a specialized infrastructure, beyond that required by the charging systems for domestic applications. The recharge can be performed in alternating or direct current, reaching nominal power up to 120 kW with a total recharge time no greater than 30 minutes (enough to travel 270 km). Currently, TESLA company is leading the installation of this type of chargers along the US and European territory.

The standard SAEJ1772 defines the suitable connector (Figure 1.5) that complies with conductive recharge requirements for EVs, considering both the physical and electric aspects and, the performance and communication protocols (monitoring and invoicing).

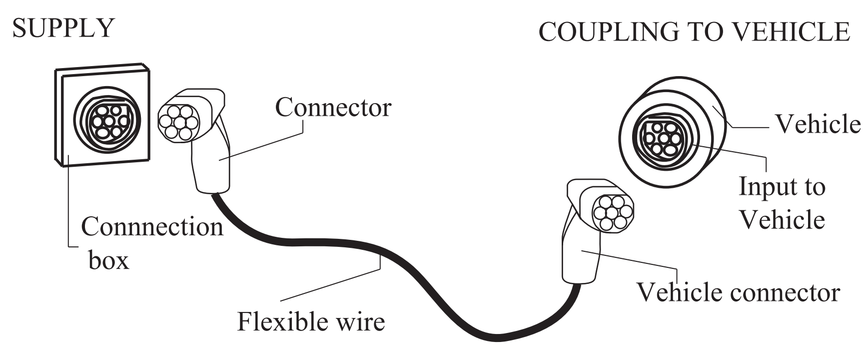

Figure 1.5: SAEJ1772 connector

1.4.3 Technical and regulatory aspects

According to (Architecture and Design, 2012), from the technical perspective, aspects related with installation, access and operation influence in the regulatory framework for the adequate EVCSs location. At installation level, some of the factors to take into account in the EVCS are:

- Recharge level: which can be of level 1, 2 or 3 (fast charge). This aspect was addressed in more detailed in 1.4.2.
- Proximity to the distribution network: Installing EVCS close to the distribution feeder, reduce the costs associated with including new wires. Additionally, EVCS installation cost is decreased if the existing wires are rated with enough ampacity to connect the EVCS.
- Mounting type: EVCSs can be configured in different forms for installation purposes, being common the wall mounted and pole mounted configurations. The correct choice depends on the available space and site environmental conditions.
- Available space: Besides the standards for EVCS location, the own components of this infrastructure should not impact neither the normal flow of adjacent traffic nor interfere with upload or download of merchandise and/or passengers.
- Technology: This encompasses the communication interface components between the EV and EVCS, including the necessary sensors to identify whether an EVCS is occupied or vacant.

From the access perspective to the EVCS, the following parameters are considered:

- Internet connection: In this way, the communication between the EVCS and the power distribution company is established, for a more efficient energy management, By the other side, EVs' drivers can locate more easily the EVCS through mobile applications.
- Handicapped people accessibility: It is necessary to consider the minimum design rules to avoid that the EVCS infrastructure represents an obstacle for people with limited mobility and hence, can enter the vehicle.
- Traffic proximity: EVCS proximity with traffic can represent an advantage (high convergence of EVs to the EVCS) or a disadvantage (installation constraint), depending on particular interests, which are reflected in studies of mobility patterns.

- Lighting: An appropriate lighting at the EVCS site, reduces the vandalism and improves the EVs' drivers safety while batteries are being recharged.
- Signalling and location: It is important the existence of an EVCS signalling strategic system along the city and roadways that allows to locate EVCS without the need of internet access. At level of detail, EVCSs have to be marked enough so that EV's driver can perform the recharge process without delays.

In regards with EVCS operation, the following components are involved:

- Agreements between EVCS owner and EVCS operator: Besides the physical infrastructure demanded (new wiring, rewiring, transformer, etc), EVCS connection to the distribution network requires a serious, solid and durable relationship between the EVCS operator (Blink/car charging point, SemaConnect, Tesla Supercharger, eVgo, aerovironment, among others) and EVCS owner.
- Metering: The majority of the EVCSs are equipped with integrated consumed energy payment technologies. When multiple EVs can be recharged in a single EVCS, it is a better strategy metering the energy of each EV by separate, in addition to use smart meters to support users and distribution companies in the energy balance at peak hours.
- Efficiency in the EVCS operation and EV stay time.

Chapter 2

Background review

This chapter presents a chronological background review of the EVs and their interaction with power systems, specifically the electric distribution networks, considering several subjects addressed in the IEEE Xplore database. Nevertheless, EVs also interact with transportation networks, in terms of mobility, requirement on travel time and make decisions about when and where to charge. In this sense, an updated state of the art of the EVCSs is also developed, considering not only the IEEE Xplore database, but also other scientific databases, such as Science Sirect, Springer and Scopus.

2.1 Electric Vehicles and power distribution systems: Literature Review

The literature review related with the interaction of the EVs and the power distribution networks, is based on an exhaustive search of the works published on the IEEE Xplore database in the range of 1973 to 2017. In first instance, the term "electric vehicle" is used as a key parameter in the database browser, obtaining around 30 thousand papers associated with this relationship (EV and power grid). Then, each work content is examined and classified according to a specific subject, as shown in Table 2.1.

Table 2.1: Ranking by number of publications

Identification	Topic	Number of publications	Total
ID1	Power quality	82	1495
ID2	Scenarios study	358	
ID3	Electricity markets	78	
ID4	Demand response	57	
ID5	Demand management	387	
ID6	Power system stability	111	
ID7	Vehicle to Grid (V2G)	260	
ID8	BSS and/or EVCS	162	

According to Table 2.1, the first column identifies the work category. The works identified as ID1, assess the reliability and the harmonics level, caused by the recharge of the EVs in the distribution network, providing results in terms of indices, such as Total Harmonic Distorsion (THD) and current and voltage signals spectrum. The importance of this category is that the EVs have internal power electronic components considered as harmonic signals sources. ID2 identifies the evaluation of the network load factor, energy losses lines and transformers overloading, among other aspects, under different insertion levels of EVs. Other aspects addressed in this category are the stochastic analysis, usage politics and EVs growth trends in the automotive park. The works belonging to ID3, consider the studies framed within the EVs participation in electricity markets, energy price and cost-benefit ratio. The publications identified as ID4, correspond to those works in which demand response provides an opportunity for EVs' owners to play a significant role in the operation of the electric grid, by reducing or shifting their EVs recharge during peak periods in response to financial incentives. In ID5, the works include mathematical programming, focused on minimizing the operation and investment costs and/or maximizing the quantity of EVs that can be plugged into the network, considering operative constraints (load factor, voltage limits and maximum current flows) and EVs' owners driving patterns. ID6 is a category of the studies in which the EVs provide signals to support the power system stability; including ancillary services and voltage, frequency and small signal stability. The V2G (Vehicle to Grid) concept and the interaction of EVs with distributed generation sources and power storage systems, is developed in publications with ID7. And last but not the least, category

ID8 presents the works that address the EV charging stations planning and battery swap stations in distribution systems, supported by one or some of the following aspects: path planning, transportation network, queuing analysis, traffic flows, routing and charging station configuration.

In accordance with Figure 2.1, the impact of EVs in distribution networks was little studied during the 70's, reporting only one publication in IEEE Xplore database in the year 1973. In the following decade, the panorama did not change notably, with only three publications. However, the research streamlines were expanded to study the quality power (ID1). Later, between 1990 and 2006, another category (ID5) came up to the list mentioned before, that determines a starting point for the mathematical modelling and optimization, focused on the timely demand management of consumers and EVs. In general, within 1973 and 2006, the efforts around this discipline involve almost twenty publications, considering power quality, scenario studies and demand management.

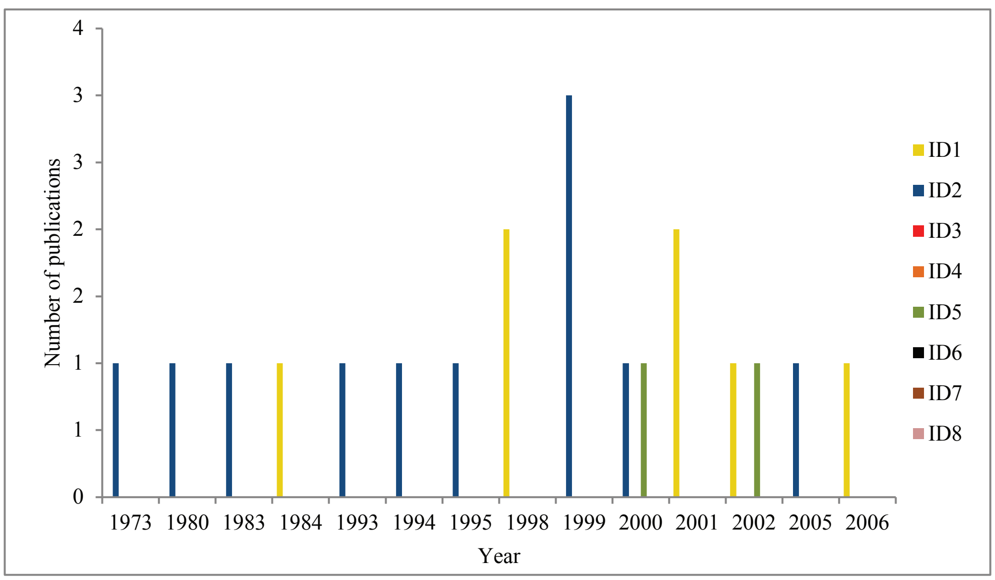

Figure 2.1: Research trends of EVs and distribution networks 1973 - 2006.

Figure 2.2 provides details of the publications from 2007 to 2017. In 2007, research trends have the same behaviour as Figure 2.1, however, in 2008 the range of study choices is expanded to EVs participation in electricity markets, power systems stability and grid support under the V2G concept. In 2009 another trend arises, featured by the works relevant the role played by EVs in the context of demand response. The year 2010 represents a point in which there is vertiginous growth of the publication of EVs and their interaction with the power networks. In the same year, the optimal location of EVs charging stations and battery swap stations are introduced in the list of study.

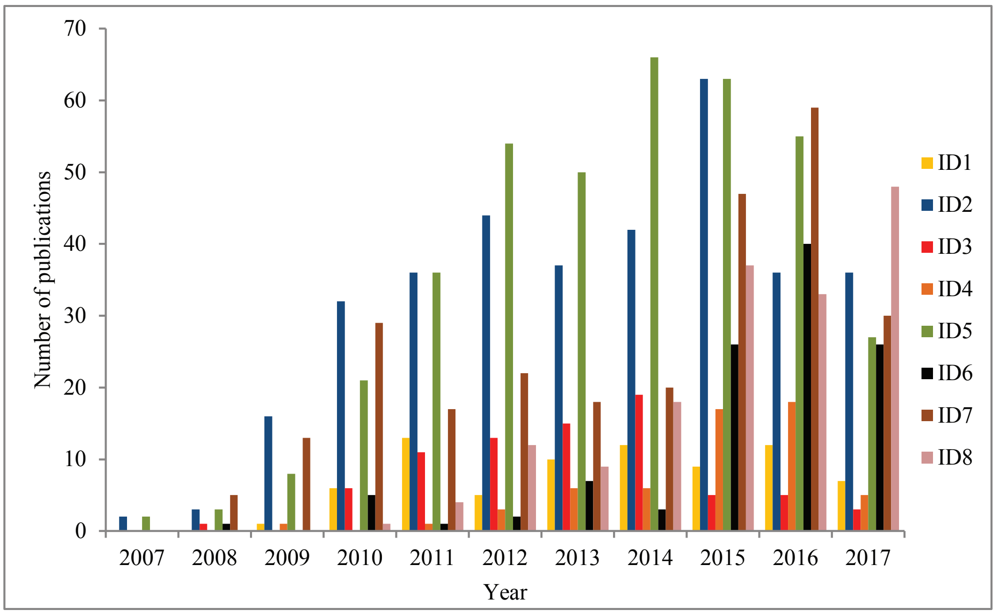

Figure 2.2: Research trends of EVs and distribution networks 2007 - 2017.

According to Figure 2.3, the period of time from 2010 to 2017 covers the largest amount of publications; due to the need of network operators and academic community to manage and confront the increase of EVs plugged into the distribution network. In the time-lapse considered for the development of this literature review (1973 - 2017), the number of works is up to 1495 publications, taking into account journals and conferences. As presented in Table 2.1, the state of the art was classified in compliance with the research stream and number of publications. This does not imply a low importance for the category with the lowest number of publications.

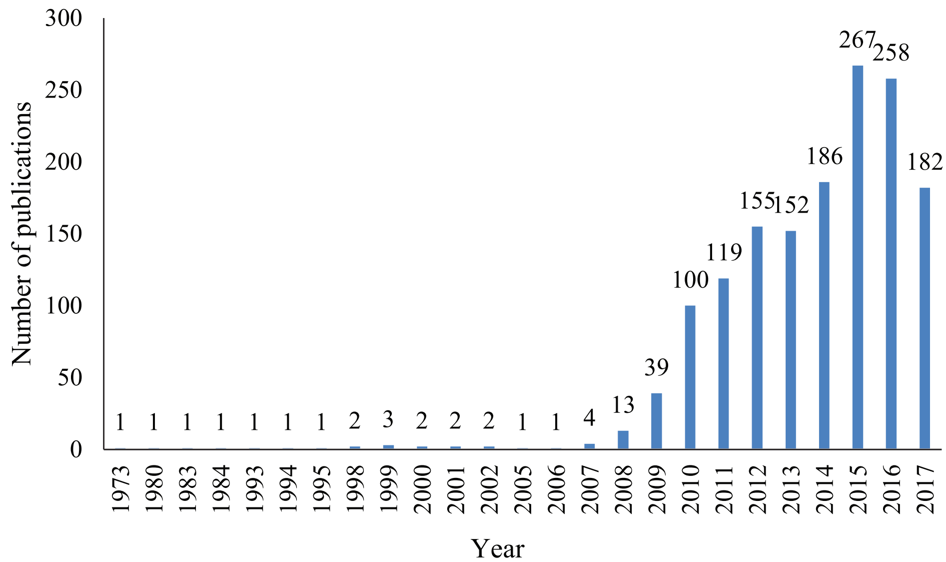

Figure 2.3: Growth of the research from 1973 to 2017.

As earlier afore mentioned, the thematic associated with the interaction of EVs and electric grids, started to be researched in the 70's, according to IEEE Xplore database. Specifically in 1973, in (Salihi, 1973) a start point of this research is presented, expressing the relevance to doing a study around the imminent deployment of EVs in the coming years and their impact on generation plants and distribution systems. However, it was not until 1980 (Patil, 1980) that electric companies become more receptive in topics related with the recharge of EVs, stimulating recharge at night time to increase the load factor of the system and decrease the cost per kWh. Hence, supported in mathematical definitions and technical arguments, (Heydt, 1983) presents a study about improving the load factor, opening the possibility for the demand management strategies focused on to cushion the collateral effects of EVs. Not only the load factor improvement is one of the study topics in the 80's, specifically in 1984 the impact over the power quality is started to be researched, due to the non-linear nature of battery chargers of EVs (Orr et al., 1984). These devices can cause distortion in voltage signal and generate harmonic currents, which create problems for power systems, e.g. increase of neutral current, hot spots in transformers and inaccuracy on measure instruments. To solve these problems, in (Orr et al., 1984) a current smoothing within EV charger circuit is proposed.

Since the 90s, the study of scenarios of EVs in electric networks had more popularity than the power quality studies. This is due to the growing interest to determine strategies allowing EVs to be recharged at hours of low conventional demand and so, to flatten the load curve. Under this context, the authors of (Rahman and Shrestha, 1993) state their position that not only the fact of having sufficient capacity of generation during valley hours has to be considered, to provide energy to EVs without adverse effects in the electric grid, but also it is necessary to study the strength of distribution systems in order to support these load additions. Due that the large quantity of EVs should be recharged at the low demand period, a considerable EVs load can generate non-desirable demand peaks at the beginning of this period, for which, the need arises of developing fast charge batteries to perform the recharge of some EVs at the end of the valley period and make more uniform the demand curve.

Thus, in (Suggs, 1994) the necessary elements are successfully established to boost EVs market, among them, the development of batteries with better characteristics and the willingness of the distribution companies to improve their electric infrastructure, to ensure the reliable and timely delivery of energy to a great quantity of EVs. By the year 1995, according to (KeKoster et al., 1995) the EV technology remained in prototype status in terms of production and development of batteries, so, the number of EVs on the streets for the next twenty years aimed to speculative data. This represented an obstacle to define the load model of the EVs. Three years later, in 1998 the efforts were concentrated again in the problems of power quality, where (Staats et al., 1998) presents a statistical method to determine a maximum threshold of penetration of EVs in a distribution system, so that the THD index was not exceeded over 5%. The same year, with the intention to model appropriately the EV load in the system, (Chan et al., 1998) shows the modeling of EV chargers from a procedure in which the Montecarlo Simulation is used, obtaining the THD in terms of an expected value and a standard deviation. Nevertheless, in contrast with the aspects mentioned in (Rahman and Shrestha, 1993), from the point of view of the distribution company, fast charge is not desired because of the resulting big demand peaks. Despite to motivate this kind of recharge in low demand periods, its usage is suggested in emergency cases. Under these supposed disadvantages, quick chargers take a lot of interest when it is known in (Koyanagi et al., 1999) the likely effect of this type of chargers in the distribution system. In that work the assessment of the size and influence of EVs charging harmonics versus the penetration level is presented. Other works such as (Peres et al., 1999) discuss about the behavior of the demand curves, considering random aspects like the initial time of recharge of EV and the State of Charge (SOC). At the end of this decade, the report presented in (Chan, 1999) explains the development of the EV in the last thirty years and the effect at environmental level and electricity generation, confirming the terms established in (Salihi, 1973) when the scale is tipped again to improve the performance of these vehicles.

At the beginning of 21st century, the field of action is extended to the role played by EVs as distributed resources, to supply partial or totally the domestic demand in periods of time where the energy price is relatively high (Brahma et al., 2000). Under this scheme some benefits are: reduction of energy cost paid by the customer, mitigation of stress perceived by the transformers and distribution lines, privileges related with taxes decrease and eases to build recharge infrastructures at their homes, among others. Taking into account the aspect above, it is important to point out the work done by the authors of (Ceraolo and Pede, 2001), where the distance travelled by EV is estimated with the remaining SOC and the ability of the battery to provide energetic capacity in function of the discharge rate. In 2002, power quality issues caused by the EVs recharge are addressed again, showing a quadratic relation between the useful life transformer and current THD index of the battery charger, establishing a limit between 25% and 30% for the THD, in function of providing a reasonable life expectancy for the transformer (Gómez and Morcos, 2003). Taking up the usage of EVs as distributed resources, it is mentioned in (Brooks, 2002) other advantages in this framework, such as: mobile AC power, backup energy for homes and offices, stability ancillary services, spinning reserve and regulation. Due to the increment of the battery activities, not only in EV mobility, but also in the area of ancillary services, it is necessary to take into account the economic viability of this framework, because the useful life of the batteries is reduced when the charge/discharge rate is increased. In 2006 and as a consequence of doing a deeper research about the potential of EVs in electric networks, the authors of (De Breucker et al.,

2006) highlight the services presented by EVs fleets:

- Elimination of harmonics, because the non-linear elements of the battery chargers act as active filters.
- Power factor improvement by injecting reactive power and peak shaving.
- Primary and secondary control for the power balance between the generation and the demand.
- Frequency regulation in low stability grids, inclusive with less quantity of EVs.
- Ancillary generation for outages and construction projects.

During the year 2007, the focus was addressed on conventional topics (scenario studies and demand management) without great contributions. The year 2008 represents a start point for the participation of EVs in power systems stability and electricity markets. A clear example is the work published in (Das and Aliprantis, 2008) where the small signal stability of a power system with EVs is analyzed, which can act as constant current or impedance load. The results show that, when the EVs are charged in constant current mode, the electric network is prone to instability. Hence, in constant impedance mode, high EVs levels of penetration can be reached before the instability point. Related with electric markets, in the same year, (Wang, 2008) works with the effect of EVs on the Locational Marginal Price (LMP). This framework of wholesale electricity prices is determined from the incremental cost of system redispatch, to supply an additional demand unit in a specific location, subject to generation and transmission constraints. The EVs are loads that can be recharged at different geographic points and can influence greatly on LMP. Apparently it was not until 2008 that the term Vehicle to Grid V2G is made official to characterize the ancillary services of EVs to grid, although in previous years this topic had already been addressed. In this context, some works like (Guille and Gross, 2008), study the requirements for V2G concept. The existing information flow between the network operator and the EV encompasses: The ID of EV, the preferences and parking status of EV, battery storage capacity, SOC and the power flow from the battery to grid. But the most important aspects consider the communication range of the system and security in the information transmission, besides the fulfillment of IEEE Standard 1547 where the minimum requirements are established to introduce energy to electric grids (Kramer et al., 2008). Other publications like (Larsen et al., 2008) consider the relevance of V2G concept for electricity generation balance in environments highly penetrated by distributed generation, as in Denmark case that around 20% of its energetic capacity comes from wind generation. However, in contrast, a study done by (Pina et al., 2008) determined that the viability of increasing EVs in the Azores islands is related with the energy usage coming from renewable sources for recharging EVs.

The efforts focused on demand management, scenario studies and V2G concept present an increment in 2009. The mathematical modeling appears as a new alternative to study the effects of EVs in distribution systems. The topics related with demand response and power quality arise again, although in low proportions. Respect to V2G concept, the study done in (Saber and Venayagamoorthy, 2009) proposes a mathematical programming model for optimal dispatch of generation units, which include the small thermal units and the energy stored in EVs, considering technical, spatial and temporary constraints. Particle Swarm Optimization (PSO) is used to solve the problem, obtaining an increase in benefits and reliability in the distribution system. It is necessary to point out through the stability stream the authors of (El Chehaly et al., 2009), which propose a Short-Term Voltage Stability Index (SVSI) for the wind generation with the ancillary services provided by EVs. This index is based on the difference between pre-fault voltage and the minimum voltage reached at fault status; in this manner with a high presence of EVs, SVSI can be reduced and voltage profile is improved. As well as in (Saber and Venayagamoorthy, 2009), in (Lopes et al., 2009) a mathematical model is designed in order to maximize the number of EVs plugged into distribution systems, subject to voltage limits and batteries energetic requirements. This same philosophy is applied in (Clement et al., 2009) where it is sought the minimization of the losses in the system through the coordinated charging of EVs. In each iteration of the optimization problem, a conventional load flow is executed to determine the actual network status. A necessary work to highlight for its connection between electric grids and the distribution network gas, is the one presented in (Acha et al., 2009), where losses of both grids are minimized through the transformers tap control and the compressors output pressure, in order to cushion the impact of the EVs load.

In 2010, one of the most studied topics was the V2G concept, whose proposal consists of providing power at peak demand hours and absorb power at minimum demand hours, taking the advantage of storing energy of EVs. This is established by (Wang and Liu, 2010), where the need of charging and discharging synchronization of EVs and the smart grid is presented in order to avoid overloading in the distribution system. A specific study of this topic is done in (Singh et al., 2010), where a known network is considered with several scenarios of EVs inclusion, from 10% to 30%. In (Acha et al., 2010), the V2G interaction is used to decrease the percentage of distribution transformers losses. There, the authors make the analysis by using a Time Coordinated Optimized Power Flow (TCOPF), where EVs are considered as distributed generation, making an optimal dispatch of energy according to their requirements in an interval of time. Efficiency improvements of the system are achieved because the EVs consume power from the grid while the demand is low, levelling the valley of the demand profile and reducing the peaks in hours of maximum demand.

Other contributions, those shown in (Mallette and Venkataramanan, 2010), explore the economic incentives that EVs users can receive by contributing to soften the load profile curve. The foregoing is made by offering refunds to EVs buyers, taking as reference the project carried out in California, where each customer with photovoltaic energy capacity installed is eligible to obtain a discount of 2.5 USD/Wp. In (Makasa and Venayagamoorthy, 2010) the inclusion of PHEVs in distribution systems is considered as a factor to repercute in the voltage stability, therefore, a method based on neural networks to determine a voltage stability index given a specific condition is shown. Additionally, in the same year some studies were developed with stochastic processes (Fluhr et al., 2010), demonstrating the importance of an intelligent strategy to charge and discharge EVs. Following this research stream, in (Soares et al., 2010) EVs are studied in different status: The first status presents a car in motion, the second status suggests a car parked in an industrial area and the third status supposes a car parked in a residential zone. The status of each vehicle at a given time is assigned according to a Montecarlo simulation. Two levels of EVs insertion are considered: 25% and 50%.

The next year, in 2011, some works like (Yamashita et al., 2011) developes a model for the market and infrastructure of EVs recharge stations. As the year before, V2G interaction gains prominence, with the study of frequency control of grids with a high degree of generation by renewable energy sources (Almeida et al., 2011). The works in (Wang et al., 2011) and (Kezunovic, 2012) present the possibility to use EVs and PHEVs as dynamic containers of electric power, which can be set up at any time; while in (Feng et al., 2011) an optimization algorithm combined with Voronoi polygons is implemented, which locates equitably recharge stations, obtaining loads balanced according to the distribution of vehicles and the network topology. In (Falahati et al., 2011), the authors evaluate reliability indices in an existing system with different EVs insertion levels; concluding in particular, that the test system used is not ready enough to supply the necessary demand for these elements in the system. Therefore, as mentioned before, the relevance of coordination of EVs and electric network is confirmed. The impact over sizing and capacity of the network is analyzed in (Rolink and Rehtanz, 2011), where a general methodology using structural data for this proposal is presented.

Several works treat the interaction between EVs and power grids from the economic and technical perspectives, posing optimal charge and discharge schedules for the EVs, however, there is an issue from the behalf of EV's owner, related with the acceptance level of this person to use the network to charge the vehicle battery when permitted, and deliver the energy stored in it when needed. This topic is studied in (Grahn and Söder, 2011), where the synchronization is not with the EV and its charge and discharge schedules, but with the owners of these vehicles and their needs, because these (EVs owners) can dispose of the energy from the network at any time, therefore, regulations have to be presented to restrict the schedules and load capacity of each vehicle.

Large variety of studies done in 2012 use advanced optimization techniques, as the case of (Turker et al., 2012), where dynamic programming is used in order to determine the minimum current needed to achieve a desired SOC in the batteries, reducing the grid losses and the chance of wires overloading. In (O'Connell et al., 2012), in order to avoid an electric system saturation, a tariff plan is proposed to decrease the quantity of EVs running daily. This is done based on day-ahead market, using a dynamic tariff that varies according to the energetic scheduling of the day. In (Zheng et al., 2012b) the concept of battery swap station is used; this is an idea that achieves to increase the dynamism around vehicular traffic. This scheme does not affect daily tasks of users when the batteries removed are charged at valley hours.

As it advances, some of the topics slightly forgotten were taken up, as the case of the power quality due to harmonic distortions, which is studied again in (Kütt et al., 2013) and (Kutt et al., 2013), demonstrating that the most important harmonics (3rd and 5th harmonics) injected into the grid, are cancelled each other when a large quantity of EVs are connected in the same grid. Later, in (Tuttle et al., 2013), the chance to use the EVs as a backup source at homes is studied, incorporating the scheme Vehicle to Home (V2H) to supply the individual demand during interruptions of power delivery during short periods.

In 2014, additional works represent the EVs smart charge, used to flatten the load curve (Andrés et al., 2014) with diverse methods and test systems. In (Su et al., 2014), the technical impact over the distribution networks is not the unique topic of interest to study, but also the environmental impact carried out by the EVs usage, through the CO_2 reduction, which is demonstrated in the results obtained. In (Zheng et al., 2014b) an optimization work is done, where the benefits of battery swap stations and the recharge stations are compared. It is demonstrated that the battery swap system is more suitable to apply in public transportation, because the times for recharging batteries can be larger than the times taken to replace a depleted battery for a fully charged one.

Some works in 2015, such as (Xu and Chung, 2016), demonstrate efforts in the improvement of the distribution system under the V2H and V2G concepts, considering non-served energy indices. Thereby, in two test cases the improvement is achieved; the first case is composed by a centralized technology of EVs recharge (V2G mode), and the second case is formed by disperse EVs charging stations (V2H mode). In the context of energy markets, prominent works were published in 2015. As mentioned in (Illing and Warweg, 2015), the revenues are the decisive factor in terms of integrating EVs into the energy market. In the United States and some European countries, EVs participate in several business cases framed in primary, secondary and tertiary reserve power, and day ahead and peak load reduction energy markets. A more detailed focus is depicted by (Vagropoulos et al., 2016), where a centralized real time EV charging management from an EV aggregator that participates in the energy and regulation markets is developed. The EV aggregator optimizes the market bidding strategy using a two-stage stochastic optimization model which produces optimal first-stage decisions for submission in the day ahead market and second-stage scenario dependent decisions for submission in the real time market. The model can account for all uncertain day ahead and real time conditions, and energy deviations between day ahead and real time energy markets. The storage technology implemented in EVs, offers an attractive alternative for EVs to support the Short Term Operating Reserve (STOR). According to (Gough et al., 2015), storage can help manage imbalances between electric power generation and consumption that could result in undesirable impacts across the entire network. Among the reasons for which this technology is a good option for STOR are:

- Storage has superior part-load efficiency.
- Efficient storage can use twice its rated capacity (i.e. it can stop discharging and start charging at the same time).
- Storage output can be varied very rapidly (e.g. output can change from 0 to 100% and from 100 to 0%)

From the EVs perspective, STOR implementation is highly dependent on several critical factors, among them: State of Charge, connection availability at times of grid requirement, fast response and capability of providing twice the rated capacity.

Ancillary services, such as active power control and voltage support are expected to be provided by EVs (González-Romera et al., 2015). The first is associated with the balance between production and demand to guarantee a secure operation of the electric grid at a constant frequency. Voltage support has to be performed locally, because voltage fluctuations in power systems are usually due to the variation of reactive power demand and its transmission along the power lines. Since reactive power cannot be transmitted over long distances, voltage control has to be carried out by using special devices dispersed throughout the system to produce the necessary reactive power to match demand and keep the voltage within appropriate limits. According to the tasks to be developed by frequency and voltage control, EVs must comply with the following four criteria: Supply duration, directional shifts, response rate and service duty. Supply duration refers to the time over which the device, in this case the EV, has to be available to provide the ancillary service. Directional shifts is associated with sudden change in charge and discharge of the batteries, which is suitable for short and volatile services. Long directional shifts are not convenient for EVs batteries due to the degradation effects on the assets. Response rate is the time within which the resource providing the ancillary service needs to initiate service, which can be from less than one minute up to one hour. Service duty refers to intermittent or continuous nature of consumption of the ancillary services. The first one enables the EV to be charged while it is not providing the service.

In the framework of frequency control, the authors of (Izadkhast et al., 2015) propose a new model to assign a participation factor to each EV, which facilitates the incorporation of several EVs fleets characteristics, i.e., minimum desired state of charge, drive train power limitations and charging modes (constant current and constant voltage). Participation factor defines the EV availability for the provision of the primary frequency control. A wider range of responsive devices, e.g., inverter-based photovoltaic systems, EVs and domestic controllable loads, are considered in (Bayat et al., 2015) for frequency and voltage control, based on power sensitivity analysis. These devices are classified according to the controllability degree. Once a voltage or frequency violation is detected in the system, the most effective buses are identified and receive the most effective control signals to perform appropriate changes in their reactive or active powers. In (Hussain and Agarwal, 2015), a control technique is proposed to mitigate the charging current ripple when the current shifts the reference. A different approach is presented in (Poornazaryan et al., 2015), where the authors propose a method for primary and secondary frequency control, based on artificial neural networks to train and validate the advanced droop control.

Returning to EVs and their interaction with electricity markets via aggregator concept, in 2016, the authors of (Zhang and Kezunovic, 2016) present contributions in the analytical estimate of EV aggregated charging/discharging power capacity taking into account EV stochastic mobility and driver's behaviour, to improve the ramp rate of conventional generators through cooperation, and participate in the ramp market on the system's reliability and flexibility as well as on EVs themselves. EVs fleets can be aggregated in mobile energy storages, which has the potential to compensate the uncontracted power if the contracts between the market players are breached. In this way, (Sarker et al., 2016) performs an optimal strategy for both energy and reserve markets considering trade off and effect on EV battery degradation, in order to assess the expected profit that aggregator can collect by participating in the energy and regulation market.

Continuing with the research approaches in 2016, some contributions are addressed in the context of demand response. This concept can avoid building new large-scale power generation and transmission infrastructures by improving the electric utility load factor. In (Johal et al., 2016), a demand response strategy is proposed for shaping a load profile to tackle the problem of overloading in distribution transformer when the EVs are used along with other loads. Overloading is first analysed and then, the demand response is used to mitigate it, once the total load exceeds the rated power of the distribution transformer. A more structured work is implemented in (Hafez and Bhattacharya, 2016) from the mathematical model perspective, representing the total load at a charging station, considering a queuing model followed by a neural network. The queuing model considers arrival of EVs as a non-homogeneous Poisson process, and the service time is represented by using detailed characteristics of battery. The charging station load (which is in function of number and type of EVs charging at station, total charging current, arrival rate and time) is integrated within a distribution operations framework to determine the optimal operation and smart charging schedules. Some works classified in the demand response focus, can also be enrolled in the demand management approach. This situation is presented in (Behboodi et al., 2016), where a strategy is proposed to achieve a grid-friendly charging load profile, based on the transactive control paradigm. In this way, EVs' owners can participate in real time pricing electricity markets to reduce their charging costs. Similar efforts are presented in (Catalão et al., 2016), developing a model for optimal behaviour of EV parking lots in the energy and reserve markets, within the framework of price-based and incentive-based demand response programs. Concluding with this year, a practical case study is carried out in (Cross and Hartshorn, 2016), evaluating the impact of EV uptake on Britain's power distribution networks by monitoring 200 customers during 1.5 years. At current projections for EVs insertion, upgrading low voltage infrastructure will cost consumers approximately US$3 billion by 2050. This cost can be largely avoided if demand-side response is deployed, to shift EV charging away from times of peak demand.

As depicted in Figure 2.3 at the beginning of this section, in 2017, research around EVs and their interaction with distribution systems from different perspectives, was reduced in approximately 29%, in contrast with 2016. According to Figure 2.1, the majority of the work focuses decreased in 2017, except the approach with ID8 (related with charging stations planning and battery swap stations), which presents the largest number of publications for this year. The authors of (Harb et al., 2017) take into account that when new modern technology is introduced to the power grid, it should be compatible with the grid in order to improve its operation, ensure stability and reliability. In this work, several subjects are considered in which the EVs are involved with distribution networks, this is, assessment of different insertion levels of EVs in accordance with power quality (in terms of harmonic distortion), voltage and frequency stability. In regards with power quality, the work shown in (Martinenas et al., 2017) focuses on the experimental evaluation of the EVs to reduce voltage unbalances by modulating the charging current according to local voltage measurements. This autonomous control could partially solve voltage quality issues without the need of grid upgrades or costly communication infrastructure, enabling higher number of EVs to be integrated in the existing power network. The experiment is carried out with EVs that do not have the V2G technology incorporated but are able to modulate the charging current in steps according to the predefined droop control. Some energy markets-oriented works, such as that shown in (Chen et al., 2017), proposes an eVoucher program to encourage participation of parking lots, with a high EVs penetration rate, in the retail electricity market at distribution level.

As a vital part in smart grid, demand response supports the restoration of balance between electricity demand and supply. This concept is highlighted by (Yao et al., 2017), where a real time charging scheme is proposed to coordinate the EV charging loads based on the dynamic electricity tariff. By the other hand, an optimization problem is formulated to maximize the number of EVs selected for charging at each time period. Two objective functions are in conflict: maximizing the EV owner's convenience in meeting all charging requests and minimizing the total electricity bill for the parking station. Similar contributions are presented in (Lu et al., 2017), focused on the real time interactions between energy supplier and the EVs users in a fully distributed system in which the only information available to the end users is the current price. In this sense, a real time charging pricing algorithm is introduced to maximise the aggregate utility of all the EVs users and minimise the electricity cost generated by the energy supplier. In addition, the EVs users and the energy supplier interact each other running the distributed algorithm to find the optimal power consumption level, and the optimal price values to be revealed by the energy supplier, in order to adapt the users' demands constantly and maximise their own utility. Another study in (Pal and Kumar, 2017) is presented in this context, defining demand response as "voluntary change of demand", proposing an approach to enable the EVs smart charging technology among residential customers. This propose incorporates operation and analysis of power transaction between the energy user and the electricity grid, including the concept of the power sharing among neighbours in the residential demand response framework.

In the context of V2G, power system stability and energy markets, the efforts done by (Dutta and Debbarma, 2017) are highlighted. The introduction of network characteristics (Distribution power Losses and maximum power limits of the transformers and lines) in the V2G concept, upgrades the accuracy of EV model to participate in the load frequency control. This approach shows that EVs are fast responsive during contingency and very effective in driving the error to zero. By the other side, in (Kaur et al., 2017) a multi-objective mathematical framework has been presented to cater frequency deviations at grid level using fleet of EVs. The objective functions of this model are presented below:

- Minimization of grid frequency deviations using the available frequency regulation capacity, dealing with the trade-off between fulfilling EVs' energy demands and providing maximum grid support.
- Maximization of V2G support to EVs while minimizing EV's battery degradation: The objective of this problem is to maximize the scheduling of the EVs participation while considering the trade-off with battery degradation issues.
- Optimal regulation signal dispatch among aggregators and charging stations.

This review of the literature around EVs and the impact on the power distribution systems, covers until the end of 2017, creating a promising prospect on the EVs and their capacities to counteract different issues at electric, transport and environment level. However, subject identified as ID8 (EVCSs planning) and its state of the art, deserves a separate section as comprises the essence of this thesis.

2.2 The State of the art of the Electric Vehicle Charging Stations

This section addresses a review of the studies focused on the Electric Vehicle Charging Stations (EVCSs) planning in the distribution systems, including in some of the cases the transportation networks and Battery Swap Stations (BSSs). The bibliographic review encompasses not only the IEEE Xplore database, but also references from other scientific databases, such as SCOPUS, Springer and Science Direct.

2.2.1 IEEE Xplore database

In regards with IEEE Xplore database, the study around EVCSs planning and its impact on power distribution systems, has been a subject with a start point in 2010 (See Figure

2.4). As per the bibliographic review, in this year the authors of (Ip et al., 2010) propose a two-stage model for the EVCSs location in urban areas, characterized by dense traffic, narrow streets and other complex factors, such as the power distribution constraints. The first stage associates traffic flow information in demand clusters using hierarchical grouping analysis. Then, optimization techniques are applied over the groups to meet the demands and place the EVCS according to criteria established by the optimization. These criteria include EVCSs planning in a city that is built up from the beginning or the EVCSs placement as per their capacities and demand coming from the groups.

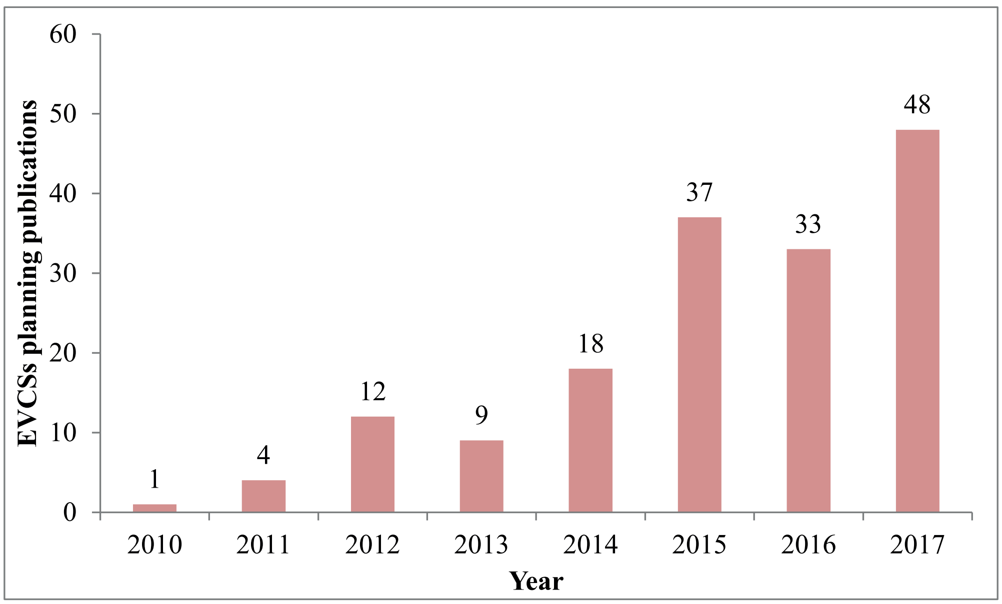

Figure 2.4: Growth of the EVCSs planning research as per IEEE Xplore database.

In 2011, neural networks and Gray prediction models were used in (Xie et al., 2011) as tools for the EVs load forecasting, due to this type of loads is more complex to be predicted than the conventional loads, which mainly depend on weather factors (temperature and humidity). Following the same forecasting guidelines, the authors of (Luo et al., 2011) are supported in the Gray prediction model and statistical data of the national automotive park, to forecast the quantity of EVs with a minimum randomness degree. Based on this information, a low cost and energy saving based EVCSs infrastructure planning is performed. Nevertheless, the work published by (Feng et al., 2012a) accounts with other component compared with (Xie et al., 2011) and (Luo et al., 2011), that besides to predict the number of EVs, analyses the travel patterns, recharge characteristics and transportation network. This information represents the input data to compute the recharge rate and the EVCSs service area with weighted Voronoi diagrams, applying a Particle Swarm Optimization algorithm to find the optimal planning of EVCSs.

The publications for the year 2012 were almost the double of the year before (only considering EVCSs planning). One of these works are found in (Feng et al., 2012b), which develops an EVCSs planning model (siting and sizing) in national highways considering the EVs mileage and the impact on the power network, minimizing a cost function composed by two objectives in conflict: charging cost and waiting fees. Supported by the queuing theory, the charger service level and its operational efficiency are evaluated. Nevertheless, the work published in (Hu and Song, 2012) is more related with the impact on the distribution network, which additional to EVCSs siting and sizing, develops in parallel the power distribution networks expansion planning. This leads to common practices carried out in power distribution planning, i.e., upgrade substations capacity, wire gauge increase, construction of new distribution branches and EVCSs, warranting safety constraints and reducing the network investment and operation cost. However, the same authors of (Hu and Song, 2012), propose in (Jia et al., 2012) an optimization mathematical model, solved with CPLEX for EVCSs planning (without including the power network explicitly), representing the road network through graph theory and minimizing the integrated cost, for both, the EVCSs and users. An added value presented by (Moradijoz and Moghaddam, 2012) is to perform the optimal location for EVs parking accompanied by the support that can provide to the distribution network with the V2G concept. In this way, the active and reactive power losses are reduced in the distribution system, meeting the allowable voltage and current limits, at the nodes and branches respectively. The optimization process is done by using a genetic algorithm and the status of the power network is obtained with an iterative backward forward sweep load flow, which is executed in each generation of the genetic algorithm. In other researches such as (Worley et al., 2012) the vehicle routing problem is developed combined with the EVCSs planning, without considering the distribution system. In contrast with (Worley et al., 2012), in (Liu et al., 2012) the power network participates in the EVCSs planning, when the distribution transformers costs, power losses and lots are taken into account. This approach is framed into a non-linear non-convex mathematical model, which is solved using particle swarm optimization. Finally, the battery swap stations operation model is studied in (Zheng et al., 2012a) to maximize the annual benefit and minimize the impact on the network caused by the battery recharge. The annual benefit is mainly composed by the subtraction of daily incomes by the concept of battery rent and costs associated to: investment, recharge and battery maintenance.

During the year 2013, as the year before, mathematical programming was widely used for EVCSs and BSSs planning. That is the case of the work published in (Sarker et al., 2013), that similar to (Zheng et al., 2012a), maximizes the profits coming from the BSSs business model, except that in this case, besides the extraction of energy from the distribution system for charge purposes, the batteries may deliver energy back to the network or interchange it with other batteries. In this manner, batteries are able to participate in electricity market and create economic advantages for both, the network operator (reduction of losses) and BSSs' owners. Other efforts framed within mathematical programming are presented in (Liu et al., 2013) to locate and scale EVCSs following a methodology composed by two stages. The first stage is to identify the points for EVCSs construction considering environmental factors and service radius (supported by Thiessen polygons); then, in the second stage, an optimization algorithm is executed to find the optimal capacities of the EVCSs, minimizing costs associated to investment, maintenance and power losses in the planning period. The mathematical model constraints are focused in the network operation and the EVCSs. The mathematical model solution is found by applying the modified interior point due to its strength and speed of convergence. Similar to the approach of (Liu et al., 2013), the authors of (Lam et al., 2013) propose a mathematical model in which EVCSs are installed considering the autonomy level of the EVs and convergence from the point of view of the users. To solve the problem, a greedy algorithm is used based on the network properties over which the EVCSs will be installed, with much lower execution times than those obtained with exact techniques. Another approach that highlights in 2013 is the Flow-capturing optimization model presented in (Cruz-Zambrano et al., 2013), which maximizes the quantity of captured flows by a charging installation, considering two perspectives: by one side the EVCS is placed to capture the large quantity of flows given a fixed number of EVCSs; by the other side, the number of EVCSs is optimized to capture a determined number of flows. The only work in which the mathematical programming is not addressed, according to this bibliographic review (at least for 2013) is developed in (Kim et al., 2013), that locates the EV fast chargers in rest areas along the highways in South Corea, with an average separation each other of 24 km. Aided by the Liquefied Petroleum Gas (LPG) based vehicles propagation model, the number of EVs can be predicted by 2034, being possible to size and determine the spots quantity in each EVCS installed throughout the highways, without ignoring some factors such as maximum traffic volume in the roadways, EVs batteries performance, utilization rate of the current EVCSs and EVs efficiency based on the brand.

Over the course of the current decade (2010 - 2017), 2017 has been the year with the largest number of publications related with EVCSs planning in distribution systems. Due to the increase of installation of clean sources of distributed generation, some works such as (Neyestani et al., 2014) research the optimal location of EV parking lots in the distribution system, affected by the introduction of high uncertainty renewable energy sources (wind and photovoltaic). In this manner, a useful tool is obtained in the future planning of the power network, without ignoring that these EVs parking lots are points of participation in the electricity reserve market, providing more economic benefits to the owners of these places and improving the system reliability. By the other side, load flow is quite important to inform about the status of power network, therefore, the research shown in (Haidar and Muttaqi, 2016) determines the EV modelling as a constant power load, which results in an unattractive alternative in comparison with ZIP (constant impedance, current and power load) model, as this latter provides more accurate results related with power losses and nodal voltages. Once more, as presented in (Cruz-Zambrano et al., 2013), the authors of (Chang et al., 2014) study through a flow refuelling location model (used in the gas stations location), the location of EVCSs and charging pads, which transfer the energy to the EV by inductive means (wireless charging) in less time. From the point of view of the voltage stability, EVCSs can be used as reactive power injectors to improve the voltage profile and reduce the active power losses, through a reactive power/voltage sensitivity analysis (Cui et al., 2014). By using graph theory, in (Pourazarm et al., 2014) vehicle routing problem is studied to minimize the travel times and charging times (homogeneous and non-homogeneous) at EVCSs. Through a mixed integer linear programming formulation and dynamic programming, computational time for the execution of the algorithm with many EVs can be reduced. From the stochastic perspective, the work perfomed in (Aghaebrahimi et al., 2014) proposes a probabilistic behaviour of the EVs presence in residential places, then, smart charge and discharge of EVs is done, supported by a novel method that combines Cuckoo Search algorithm and sequential Montecarlo simulation, executing Cuckoo search again to find the optimal location for EVCSs. For 2014, fast chargers and BSSs planning are compared in (Zheng et al., 2014a) based on the cost criteria of the battery life cycle. These two approaches (EVCSs and BSSs planning) are modeled through a non-convex non-linear mixed integer programming problem, which can be hardly solved by using exact techniques. In this way, differential evolution algorithm is used to solve the problem.

Research related with deployment and performance of the Battery Swap Stations (BSSs) has had a slight increment in the last years. However, in practice this technology has some disadvantages due to the low maturity in the battery standardization. Although this, research has not overlooked the BSSs, that in the year 2015 are studied by (Sarker et al., 2015), which argues that the use of these infrastructures suppresses the long waiting of the EVs. The work model of the BSS is framed into an optimization problem where the BSSs planning is done for the next day, this is, determine the energy transactions between: batteries - power network, power network - batteries, batteries - batteries, batteries - EVs and EVs - batteries. Via robust optimization, the price uncertainty and batteries demand in the BSSs are modelled. By the other hand, the battery swap strategy proposed by (Dong et al., 2016) attempts to increase chargers efficiency and reduce waiting time of the EVs' owners in the EVCS. In this manner, spots operations scheduling is optimized in the EVCS, minimizing the cost of energy consumption and maximizing the quantity of EVs to be recharged. This problem is modelled through multi-state stochastic programming, integrating distributed sources of renewable energy and energy storage. The authors of (Pazouki et al., 2015a) work with the integrated planning of EVCSs and distributed generation sources, concluding that the wrong siting and sizing of EVCSs, leads to unexpected problems in the distribution network, that can be compensated with distributed generators. The mathematical model is solved with genetic algorithm and considers in the objective function, investment costs, technical factors (system reliability, power losses and voltage profile) and environmental factors. Following a similar approach, the same authors of (Pazouki et al., 2015a), perform in (Pazouki et al., 2015b) an integrated planning of EVCSs and capacitors in power distribution systems. Some studies such as (Neyestani et al., 2015) are motivated in include jointly the EVCSs planning with uncertainty scenarios considering several factors, as follows: EVs behaviour, renewable sources of distributed generation and energy generation price. Under these scenarios, two operation stages are proposed: the first stage contains a mathematical model where the benefit in the EVCSs interaction with energetic reserve market and electricity transactions is maximized. In this sense, the EVCSs behaviour is determined, creating a key information package that works as input for the second stage, which solves the EVCSs location problem in the system. In this last stage, another mathematical model is performed, which minimizes the costs associated with EVCSs installation and power losses, reliability and voltage fluctuation, subject to operative constraints and maximum non-served energy level. Other works that follow the same focus of multi-stage studies, are shown in (Khalkhali et al., 2015), where the optimal siting and sizing of EVCSs is developed, in order to maximize the network operator benefit, obtaining technical indices related with voltage improvement, active power losses and CO_2 emissions. In the next step, and according to the network operator profit function and the technical indices computed for the possible nodes with charging station, a Data Envelopment Analysis (DEA) process is implemented to qualify the nodes at the distribution system. The nodes with the best qualification, will be the efficient places for the EVCSs. However, another EVCS approach can be found in the specialized literature, that is not to fix a location for this activity. Actually, the research developed in (Huang et al., 2015), evaluates and parametrizes through queuing theory, the feasibility of a new concept of mobile EVCSs and BSSs.

In 2016, research has been addressed towards more BSSs than EVCSs planning. That is the case of the work proposed by (Kang et al., 2016), where a novel strategy is proposed to recharge EVs batteries, which can be replaced in a short time and recharged in valley hours of energy consumption or when the energy price is low, based on real time price. The problem is solved through a population based heuristic algorithm, which combines the genetic algorithm with particle swarm optimization, taking adopted strategies of mutation and dynamic crossing. With this scheme, it is attempted to minimize the costs associated with batteries recharge and power losses, maintaining the power quality and voltage profile. By the other hand, EVs batteries can be used to confront contingencies related with blackouts or local outages. This is shown in (Sun et al., 2016), where an available capacity model is developed with EVs batteries, analysing the starting generation characteristics and restoration power supply links in the distribution system. In (Zhang et al., 2016) different types of charging facilities are planned along roadside and public areas. Then, the forecasting of the spatial and temporal distribution of EVs charging load is developed, using EVs driving parking behaviors (from real-travel survey data), charging type, arrival time and parking duration.

Compared with previous years, 2017 has had the most number of publications related with EVCSs planning, as depicted in Figure 2.4. Some important works are highlighted in this period, combining the operation of the power distribution system and some aspects framed into the transportation network, with predefined or to be defined EVCSs location. In (Bai et al., 2017), the influence of Time Of Use (TOU) price on EV charging behaviour is presented. Then, considering the EV's users' benefits and grid stable operation, a multi-objective model is proposed encompassing four objectives. The first objective maximizes the charging demands captured by EVCSs. The second objective minimizes the total cost of electricity and time consumed during charging, in regards with interests of EVs' users. As the EVs' users are encouraged to charge their vehicles at off-peak hours due the TOU policy, the pre-existing off-peak period may become a new peak demand, which can be controlled by minimizing the load variance in the third objective function. The constraints of the model are based on general aspects for EVCSs siting and sizing. Particle Swarm Optimization with constriction factor was used to solve the multi-objective model and Data Envelopment

Analysis was performed to make the final planning decision among the Pareto solution to determine the optimal EVCSs location. A similar focus is shown in (Yang et al., 2017), where the coordinated dispatch strategies of EVs is studied to smooth renewable energy and load fluctuations of a grid-connected microgrid, while ensuring the objectives of the logistic services (meeting merchandise demands of customers). Some equations from the Capacitated Vehicle Problem are used to model the logistics operation. Finally, in the collaborative context, the authors of (Alizadeh et al., 2016), study the implications of large-scale integration of EVs on power and transportation networks, concluding that the collaboration between the power and transportation system operators can lead EVs towards a socially optimal traffic pattern and energy footprint.

2.2.2 Science direct and Springer databases

The research of EVCSs planning in the context of Science direct and Springer databases, has been slightly addressed according to Figure 2.5. The search was done taking into account the following key phrases in the browser: "electric vehicle" AND "charging station".

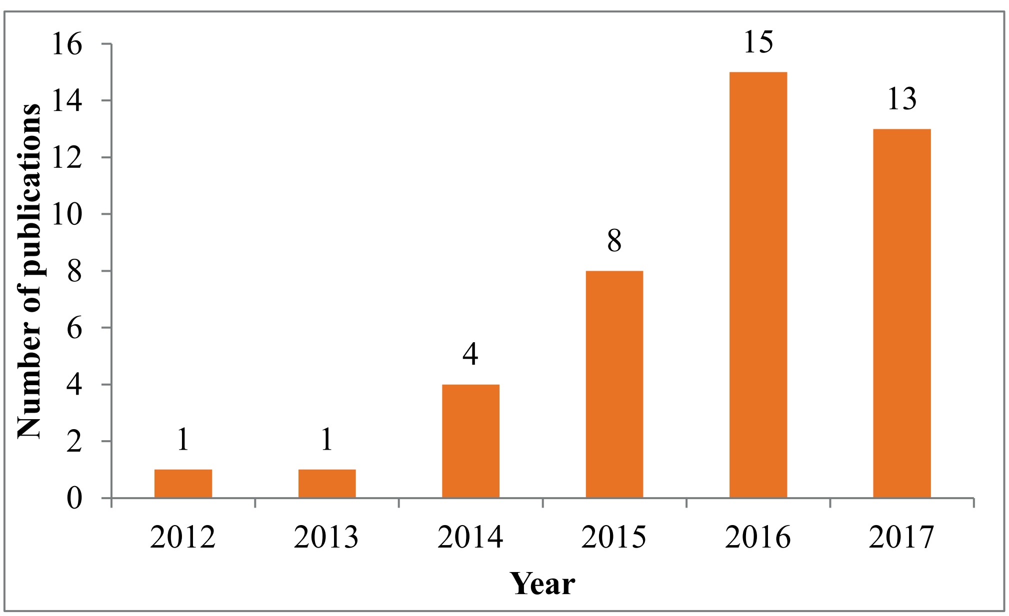

Figure 2.5: Growth of the EVCSs planning research as per Science direct and Springer databases.

As proceeded with the IEEE Xplore database search, this review is performed chronologically to provide an idea on how the EVCSs planning has progressed over the course of the time. Being the strategy to show the advance in this topic, EVCSs planning starts in Science direct and Springer databases to be research in 2012, but it was not until 2014 that relevant contributions were published, such as (Sadeghi-Barzani et al., 2014), where a mixed integer non-linear optimization model is proposed. Factors involved in the station development cost, EVs energy and electric grid losses, electric substations location and urban roads are included, supported by the geographic information. A novel assessment of grid reliability impact due to siting and sizing of EVCSs is demonstrated with a loss of charging cost index. Following this streamline of mathematical programming, in 2015, the authors of (Moradi et al., 2015) propose a multi-objective optimization problem to obtain the optimal siting and sizing of EVCSs and renewable energy sources, in order to reduce power losses, improve voltage stability, EVs charging costs and increase network load factor. The introduction of coefficients related with wind speed and solar irradiance, help in the charging process carried out by EVs aggregators. In (Chung and Kwon, 2015) a multi-period optimization model based on flow-refueling location model is proposed for EVCSs location planning, based on an extensive numerical case study with the real Korean roadway network. Other studies in which the mathematical programming is not used for EVCSs planning purposes, but prominent tools are utilized, are established in (Brooker and Qin, 2015) and (Guo and Zhao, 2015). In (Brooker and Qin, 2015) the National Travelling Household Survey (NTHS) is explored to understand the EVs travel behaviour and EVCSs usage patterns, in order to identify potential location for EVCSs. By the other side, the authors of (Guo and Zhao, 2015) employ a multi-criteria decision making method based on an evaluation index system for EVCSs selection, which consists of environmental, economic and social criteria.

Important studies were done in 2016, showing a comprehensive and extensive review presented in (Shareef et al., 2016), addressing three key areas of EVs research: EV charging technologies, EVs impacts and optimal placement and sizing of EVCSs. This latter is addressed from different perspectives, considering economic benefits, power gird impacts and solution techniques (meta-heuristic and exact techniques). The review encompasses a total of 185 references. Other objectives framed into the enhancement of the social welfare in the long term by optimally locating public fast charging stations are focused by (Gong et al., 2016). The proposed strategy maximizes the probability that EVs can be effectively charged, minimizes charging infrastructure cost and mitigates the negative impacts on both transportation and power networks. In the same context of fast charging stations, the authors in (Guo et al., 2016) state that market competition might influence in the deployment on these infrastructures. On the other side, based on a multi-agent simulation platform, the authors of (Marmaras et al., 2016) model road transport and electric power system to demonstrate how EV behavior can be adapted to changes in the underlying road transport and/or energy network. The normal operation of both networks is assured. Since the road network perspective, an adaptive routing algorithm is used to ensure EVs reach their destination at minimum time, by using battery consumption constraints and adjustments in the EV's route to include the necessary recharging stops. In addition, a charging management mechanism exists to coordinate the EV charging requests and meet the overall demand limitations of the energy network. Several contributions are provided by (Amini and Karabasoglu, 2018), among them, the development of a novel routing strategy that considers location and electricity price of charging stations, changing the EVs efficiency under different traffic situations and optimization of the power system operation with a more accurate electricity demand of EVs. Closing the review in 2016, efforts around in regards with EVCSs planning are performed by (Davidov and Pantoš, 2017b). The optimization model proposed by the authors, ensures charging reliability by placing at least one charging station within the EV's driving range using a distance criterion. A quality of service index is introduced in this proposal to assess the disposable charging time of the EV driver to complete the planned trips.

As in (Davidov and Pantoš, 2017b), and keeping the focus on fast charging stations, in 2017 the authors of (Alhazmi and Salama, 2017) propose a two-stage strategy for fast charging stations planning. The first stage consists in evaluating the system capability with the existing EVCSs by using optimal power flow, obtaining the maximum number of EVs that can be introduced without violating the technical constraints. In the second stage it is determined when the fast charging stations should be installed along with their power capacities, also taking into account the growth of public EV charging demand and considering the traffic flow patterns in the transportation network. The same authors of (Davidov and Pantoš, 2017b), present an upgraded optimization model in (Davidov and Pantoš, 2017a) considering the stochastic nature of the mobility behaviour of the EVs drivers and driving range. Real applications of EVCSs planning can be found in (Awasthi et al., 2017), where an EV transportation pilot project is being developed in the city of Allahabad. Data coming from the power distribution system infrastructure is utilized jointly with the pilot project to deal with EVCSs planning, using a hybrid algorithm based on genetic algorithm and improved version of conventional particle swarm optimization. Other contributions that are worth to mention, are shown in (Toro et al., 2017), and (Paz et al., 2018). In (Toro et al., 2017) a new mathematical model for the calculation of the greenhouse emissions is developed, considering the fuel consumption minimization. By the other hand, in (Paz et al., 2018), a multi-depot vehicle location routing problem with time windows is performed considering EVs fleet, in the context of partial recharge and battery swapping.

According to SCOPUS, one of the most promising multi-disciplinary databases in the academic community, research around EVs is widely addressed, from different perspectives and diverse solution tools. However, for the sake of this review, the search is carried out by using the advanced filter considering the following key phrases, highly related with the essence of this research:

- electric vehicle AND
- charging AND
- station AND
- vehicle routing problem AND
- distribution system OR
- grid

In this manner, a total of forty nine papers are found until 2017, as shown in Figure 2.6. Among them, the authors of (Li-ying and Yuan-bin, 2015), provide an optimal solution with a minimal cost for a logistic company that plans to adopt EVs for freight transportation and to construct its own EVCSs. In the proposed model, customer time window and battery capacities of the EVs are considered, incorporating the location and ECVS type decision with the vehicle routing plan. Notice that the transportation network is only considered, neglecting the power grid. Under a similar framework, in (Sassi et al., 2015), the study performed finds optimal routes for heterogeneous freight EVs considering the existing EVCSs. EVs account with different operational costs and diverse batteries capacities. By the other side, the efforts done by (Yang and Sun, 2015) aim to optimal locate battery swap stations considering the conventional CVRP focus, using the driving range as a swapping station placement criteria. The mathematical model is solved by using exact techniques for small scale instances and meta-heuristic techniques for medium and large scale instances from the specialized literature.

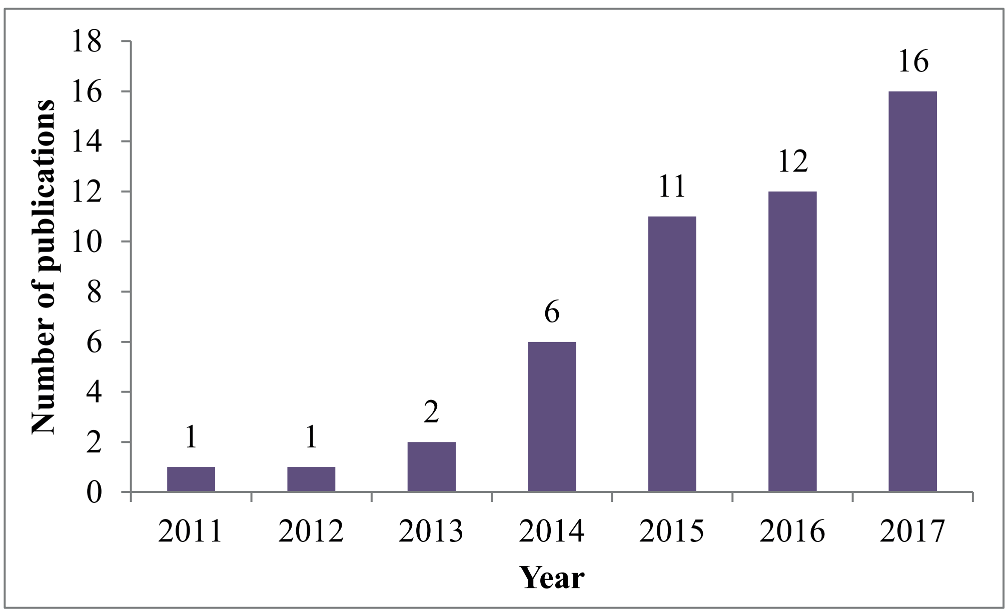

Figure 2.6: Growth of the EVCSs planning research as per SCOPUS database.

In addition to the key phrases depicted above, the term "city logistics" is also used, as this concept is considered as critical to ensure quality of life in cities, by focusing on the efficient and effective transportation of goods in urban areas while taking into account the negative effects on congestion safety and environment (Savelsbergh and Van Woensel, 2016). Under these key phrases, only five papers were found encompassing the topics under study. Electric mobility has a strong participation in the city logistics objective, however, logistics companies are often skeptical in using freight EVs as they are too costly compared to vehicles powered by combustion engines. The logic solution is to increase the battery driving range, which can enhance its competitiveness in comparison with the conventional vehicles. In this sense, a battery swaping approach in (Taefi et al., 2017) is developed, by performing a numeric simulation approach to analyse the optimal balance cost between a high utilization of medium-duty EVs (with low operational cost) and the common requirement that their batteries will need for expensive replacements.

Chapter 3

Optimal EVs demand management: A probabilistic perspective

3.1 Overview

In this chapter, the optimal charging of EVs in distribution systems is addressed from the probabilistic approach. The costs of both demand and energy losses in the system are minimized, subject to a set of constraints that consider EVs smart charging characteristics as well as operative aspects of the electric network. By using a probabilistic framework, a scenario that is closer to reality is shown, as it considers the variation to the prediction of the daily load profiles. This approach constitutes a support to quadratic and dynamic programming techniques, where it is possible to obtain optimal charging of EVs, aimed to improve demand management strategies. Being that the case, the stochastic behavior of the input variables are considered, i.e., active and reactive conventional power demanded at the nodes, initial state of charge iSOC of the batteries and arrival and departure time of EVs. The purpose is to analyse statistically the total optimal rate of EVs recharge in a distribution system, in terms of the expected value and probability density function.

Considering the nature of this problem, a procedure is performed by using Monte Carlo Simulation (MCS) in a secondary (low voltage) distribution network. The conclusive study contributes to risk analysis, defining the uncertainty level of the results and supporting the process of appropriate decision making, such as electricity generation dispatch, contingency criteria, location and installation of EVCSs, distribution planning, among others. The optimal charging of EVs connected to the system benefits the system's operation, representing a strategy to minimize the cost of energy losses and to evaluate the capability of the system to perform the complete recharge of EVs' batteries under certain penetration scenarios.

The development of a probabilistic load model is not within the scope of this work, neither to express the random nature of the power load data nor the driving patterns (arrival and departure times) and initial state of charge. For that reason, the probabilistic behavior of the demand through a load model with normal distribution is assumed, and log-normal distribution is considered for random variables as arrival time, departure time and initial state of charge. However, this proposal allows the use of other types of probabilistic distributions for the input variables.

3.2 Problem description and mathematical formulation

Several aspects can be considered to manage the EVs charging in a distribution system, depending on the charging habits of vehicle owners and the automation level of the network. The following EVs charging conditions are established:

- It is assumed that EVs' owners arrive at their homes at 18:00 and departure the next day at 07:00. During this frame of time the EVs are plugged to the network. Nevertheless, arrival time and departure time of EVs are described by probability distributions, hence, EVs do not arrive exactly at 18:00 or departure at 07:00. Therefore, the study period of this problem, known as T, will be from 17:00 to 08:00, in order to encompass the EVs that eventually arrive before 18:00 and/or departure after 07:00, depending on their arrival and departure times.
- The time period T, is divided into several charging subperiods with different priorities (Deilami et al., 2011a), as depicted in Figure 3.1. The priority scheme for the subperiods

is previously defined by the network operator as a charging policy to be complied by the EVs' users. Before the beginning of period T, the vehicle's owner is encouraged to choose the priority subperiod under which his/her EV will be recharged, taking into account that the EV battery will be totally recharged during the chosen subperiod. Additionally, the selection of the EV charging subperiod depends on the level of urgency of the vehicle's owner for its availability. Therefore, if it is required that the EV be recharged as soon as possible, high priority degree should be chosen, otherwise, another recharge subperiod may be chosen with a more favourable energy price. Another aspect consists in the variation of the starting time of high priority subperiod, which can be a little before 18:00, depending on the EV arrival time. For the low priority subperiod, the ending time can be a little after 07:00, depending on the departure time of the EV.

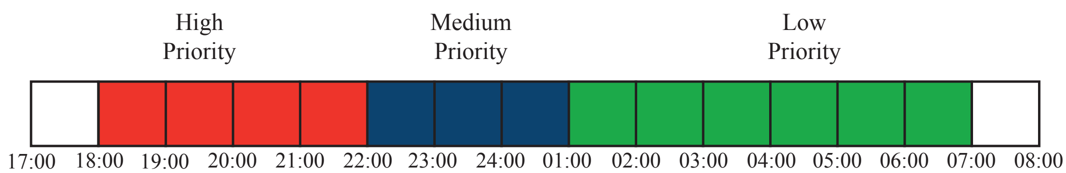

Figure 3.1: Priority subperiods for the EV charging

- The power delivered to EVs is controlled for each time period t (set to 5 min in this work), which implies the existence of a remote communication between the distribution utility and the EV charging infrastructure.

- Each node of the system is able to recharge just one EV, taking into account that its priority is to supply the demand connected to the node (as a residential load), regardless the energy required by the EV.

- EVs' batteries have a State of Charge SOC determined by a probability distribution. For all EVs the minimum State of Charge SOC_{min} is 20%.

The nomenclature for indices, sets, parameters and variables involved in the proposed mathematical model are presented as follows:

Indices

l	Network branch
n	Network node
t	Time interval of period T

Sets

nl	Number of network branches
nn	Number of network nodes
nt	Number of time intervals within period T

Parameters

$C(t)$	Energy price during time interval t $[US\$/kWh]$
$\delta(t)$	Duration of time interval t
$E_d(n)$	Distance travelled by the EV $[km]$
$E_v(n)$	Energy to be transferred to the EV
$E_{vr}(n)$	Range of the battery $[km]$
$I(l)_{max}$	Maximum current of branch l
iSOC(n)	Initial state of charge of EV's battery at the node n
K(n,t)	Priority charging factor at node n during time interval t, in case an EV is connected to node n
η	Penalty factor in case an EV was not fully recharged
P_{gmax}	Maximum power generated at the nodes
P_{vmax}	Maximum power of EVs
$R(l)$	Resistance of branch l
SOC_{min}	Minimum state of charge
V_{max}	Maximum voltage magnitude at the nodes
V_{min}	Minimum voltage magnitude at the nodes
$\Omega(l)$	Reactance of branch l
$Z(l)$	Impedance of branch l

Variables

$f_p(l,t)$	Active power flow through line l during time interval t

$f_q(l,t)$	Reactive power flow through line l during time interval t
$i(l,t)^{sqr}$	Square of the current flowing through branch l in time interval t
$p_d(n,t)$	Active power demanded by conventional loads at node n during time interval t
$p_g(n,t)$	Active power generated at node n during time interval t
$q_g(n,t)$	Reactive power generated at node n during time interval t
$\phi(n))$	Missing energy for the full recharge of the EV at node n at the end of the study period T
$p_v(n,t)$	Active power demanded by the EV at node n in time interval t
$q_d(n,t)$	Reactive power demanded by conventional loads at node n during time interval t
$SOC(n,t)$	State of charge of the EV connected at node n during time interval t
$t_{arr}(n)$	Arrival time of the EV at node n
$t_{dep}(n)$	Departure time of the EV at node n
$v(n,t)^{sqr}$	Square of the voltage at node n during time interval t

The mathematical model presented as follows, is based on (Franco et al.), and involves several aspects of a coordinated smart EVs charging in a distribution system:

$$f = \left[\begin{array}{l} \sum\limits_{t=1}^{nt} \sum\limits_{l=1}^{nl} \left[C\left(t\right) \delta\left(t\right) \right] \left[R\left(l\right) i\left(l,t\right)^{sqr} \right] + \sum\limits_{t=1}^{nt} \sum\limits_{n=1}^{nn} \left[C\left(t\right) \delta\left(t\right) \right] \left[p_d\left(n,t\right) + p_v\left(n,t\right) \right] - \\ \sum\limits_{t=1}^{nt} \sum\limits_{n=1}^{nn} \left[\delta\left(t\right) p_v\left(n,t\right) K\left(n,t\right) \right] + \eta \sum\limits_{n=1}^{nn} \left[\varphi\left(n,t\right)^2 \right] \end{array} \right] \tag{3.1}$$

s.t.

$$\begin{array}{l} \sum\limits_{l=1}^{nl} \left[f_p\left(l,t\right)_{in} \right] + p_g(n,t) = p_d(n,t) + p_v(n,t) + \\ \sum\limits_{l=1}^{nl} \left[f_p\left(l,t\right)_{out} + R\left(l\right)_{out} i\left(l,t\right)^{sqr}_{out} \right] \quad \forall n = 1,2,...,nn \quad \forall t = 1,2,...,nt \end{array} \tag{3.2}$$

$$\begin{array}{l} \sum\limits_{l=1}^{nl} \left[f_q\left(l,t\right)_{in} \right] + q_g(n,t) = q_d(n,t) + \\ \sum\limits_{l=1}^{nl} \left[f_q\left(l,t\right)_{out} + \Omega\left(l\right)_{out} i\left(l,t\right)^{sqr}_{out} \right] \quad \forall n = 1,2,...,nn \quad \forall t = 1,2,...,nt \end{array} \tag{3.3}$$

$$
\begin{aligned}
&v\left(n_s,t\right)^{sqr}-v\left(n_r,t\right)^{sqr}=Z\left(l\right)^2 i\left(l,t\right)^{sqr}+\\
&+2\left[R\left(l\right)f_p\left(l,t\right)+\Omega\left(l\right)f_q\left(l,t\right)\right]\quad\forall l=1,2,...,nl\quad\forall t=1,2,...,nt
\end{aligned}
\tag{3.4}
$$

$$
v\left(n_s,t\right)^{sqr} i\left(l,t\right)^{sqr}=f_p\left(l,t\right)^2+f_q\left(l,t\right)^2\quad\forall l=1,2,...,nl\quad\forall t=1,2,...,nt \tag{3.5}
$$

$$
\sum_{t=1}^{nt}\left[\delta\left(t\right)p_v\left(n,t\right)\right]+\varphi\left(n\right)+iSOC(n)=E_v\left(n\right)\quad\forall n=1,2,...,nn \tag{3.6}
$$

$$
SOC(n,t)=SOC(n,t-1)+\delta\left(t\right)p_v\left(n,t\right)\quad\forall n=1,2,...,nn\quad\forall t=1,2,...,nt \tag{3.7}
$$

$$
V_{\min}^2\leq v\left(n,t\right)^{sqr}\leq V_{\max}^2 \tag{3.8}
$$

$$
0\leq i\left(l,t\right)^{sqr}\leq I\left(l\right)_{\max}^2 \tag{3.9}
$$

$$
0\leq p_v\left(n,t\right)\leq P_{v\max} \tag{3.10}
$$

$$
0\leq p_g\left(n,t\right)\leq P_{g\max} \tag{3.11}
$$

Equation 3.1 represents a cost function which involves four terms. The first term is the energy losses cost of the system; the second term represents the energy cost drawn by the EVs and conventional loads (residential loads). An incentive cost by the EVs recharge is established in the third term considering the priority degree of recharge, and the last term corresponds to a penalty cost when one or several EVs are not fully recharged at the end of the study period T (composed by the nt subperiods). Model constraints are described by 3.2 to 3.7. Equations 3.2 and 3.3 represent the active and reactive power balances at each node. Voltage drops at the nodes and currents through the lines are implied in 3.4 and 3.5

respectively. Notice that nodes n_s and n_r are the send and receive nodes of the line l under study. Equation 3.6 relates the total battery energy, the energy drawn by the EV in each time interval t of the study period T, and the missing battery energy in case this is not fully recharged. In 3.7 the SOC for the EV is computed for each time period t, taking into account the SOC of the preceding interval. The limits of nodal voltages, currents through the lines and maximum recharge power of EVs are set in 3.8 to 3.10 respectively. Equation 3.11 limits the generated power at node n in a time interval t, which means that the distribution system under study may contain distributed generation. The subscripts *in* and *out* denote the flow entering and leaving a node respectively. Although the mathematical model has as output variable the recharge power of each EV for each time period, this is, $pv(n, t)$, the optimal recharge rate is the summation of all the contributions of power delivered to the EVs, describing quantitatively the impact on the entire system.

3.3 Probabilistic analysis: Frame of reference

The assessment from the probabilistic perspective, provides well-defined information about the capability of the network to afford the insertion of EVs, in regards with the range of EVs recharge powers. This indicates the risk levels and conditions under which the components of the distribution systems (e.g. transformers, feeders, protective devices etc.) are submitted, providing important information to the network operator to evaluate the system performance.

3.3.1 Random behavior of input data

In order to obtain a model of this problem, closer to reality, the random behavior of the input data is considered by using probability distributions. One of the input parameters of the problem is the arrival time $t_{arr}(n)$; this is, the moment in which the EV's owner gets home and connects EV to the electric network. The other parameter is the departure time $t_{dep}(n)$, this is, the moment in which the EV is disconnected from the electric network depending on the departure of the EV's owner. To model these uncertainties, arrival and departure times are modelled as lognormally distributed random distributions, as suggested in (Shaaban et al., 2013). The mean values of the arrival and departure times are 18:00 and 07:00, respectively, and their probability distributions are shown in Figures 3.2 and 3.3, respectively.

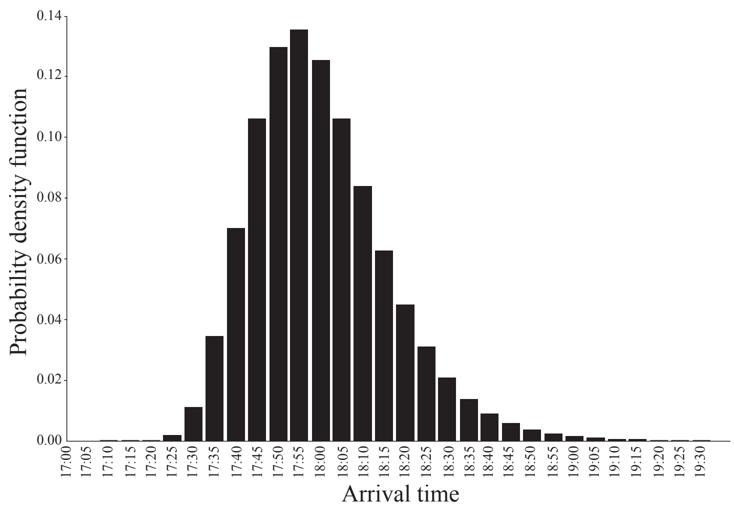

Figure 3.2: Probabilistic behavior of the arrival time

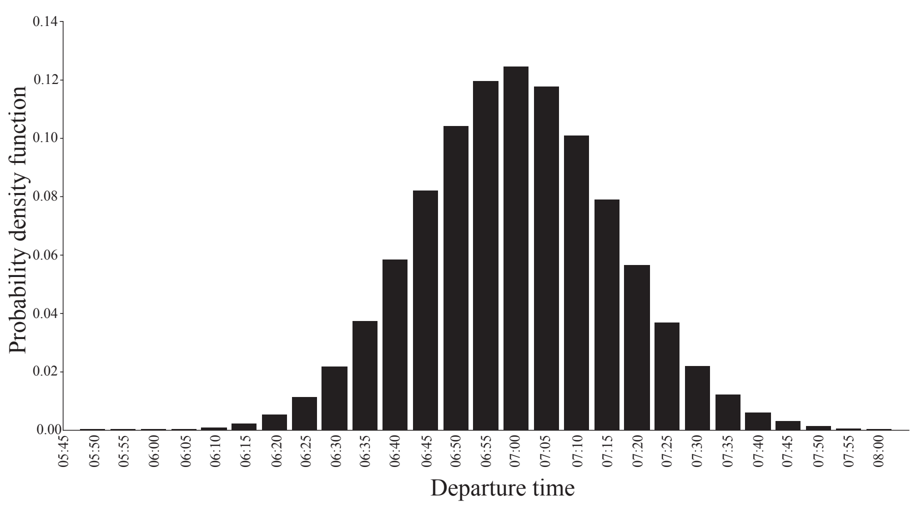

Figure 3.3: Probabilistic behavior of the departure time

The initial state of charge $iSOC(n)$ of the EV is calculated by 3.12, based on the daily distance $E_d(n)$ travelled by the EV, which is a random variable, following a lognormal probability distribution function. In this case, the mean and variance of $E_d(n)$ are 26.1 and 20.37 km, respectively, considering $E_{vr}(n) = 30$ km as the range of an EV mid-size sedan with a battery capacity $E_v(n)$ of 8 kWh. It is assumed that the charging is performed at level 2, i.e. up to a maximum of $P_{vmax} = 4\ kW$ (Mehboob et al., 2015).

$$iSOC(n) = 1 - \frac{E_d(n)}{E_{vr}(n)} \tag{3.12}$$

The loads connected to the nodes (conventional demand), other than the EVs demand, behave randomly, assuming a normal distribution function. The mean value for the active power at each node is $\mu = 2\ kW$ with a power factor of 0.9. The standard deviation σ is 15% of the mean value (Deilami et al., 2011b).

3.3.2 Montecarlo Simulation

In each iteration, Montecarlo Simulation (MCS) (Gill et al., 2000) generates random values of input variables (conventional active and reactive demand for all nodes, initial state of charge of the EVs' batteries and arrival and departure times) with a probability distribution for each one. Next, an optimization algorithm is performed, to build, iteratively the probabilistic behavior of the output variables (optimal charging rate of EVs).

MCS procedure can be summarised as depicted in Figure 3.4. Once the system parameters (electric parameters, energy cost, demand curve, priority factors, mean value, standard deviation and probability distribution function) are read, random variations are generated for the input variables, following the respective probability distribution. Subsequently, the optimization algorithm is executed to obtain the EVs charging value for each time interval t of the study period T (and other output variables of interest). This procedure is repeated until convergence is reached. Finally, the expected value and standard deviation of the output variable of interest are obtained by using the equations 3.13 and 3.14 respectively.

$$E\left(Y\right) = \frac{1}{n}\sum_{i=1}^{n} Y_i \tag{3.13}$$

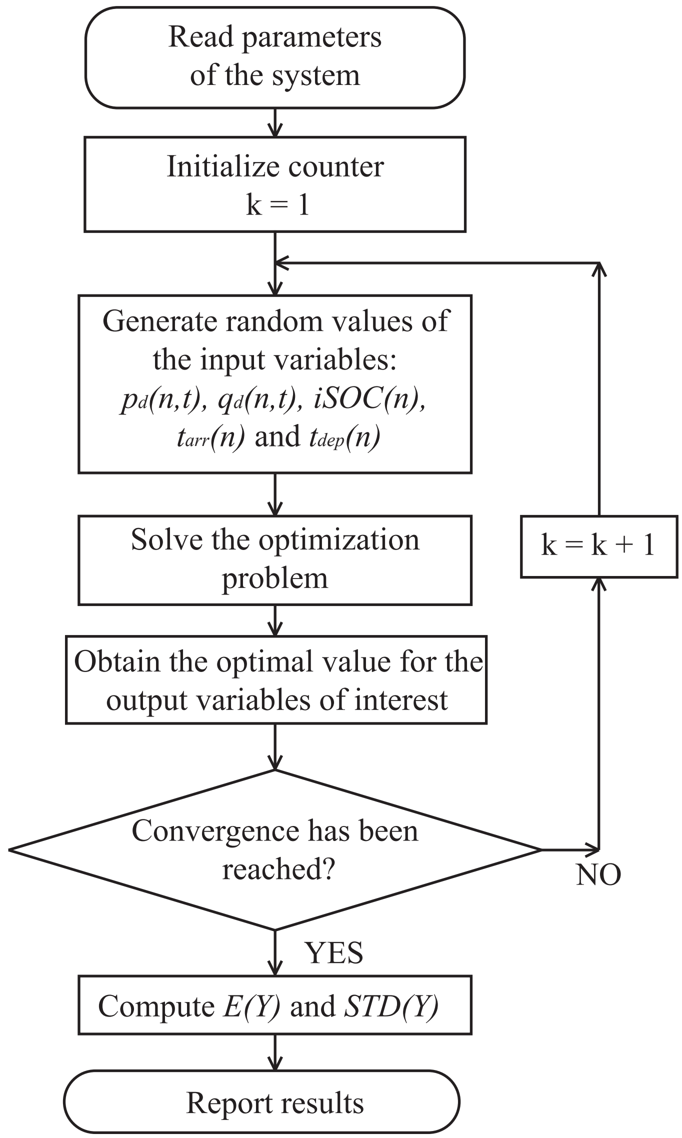

Figure 3.4: Procedure of MCS

$$STD(Y) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2} \tag{3.14}$$

3.4 Simulation results

3.4.1 19 nodes test system

To perform the probabilistic analysis using MCS, the 19 nodes test system presented in Table A.1 is used. This system corresponds to a 415 V-low-voltage distribution network, with a 130 kVA transformer and 19 residential load nodes. The information related with the existence of EVs at the end node of the branches is also shown, where "1" indicates that the node has an EV and "0" otherwise. Likewise, the degree of priority for the EV recharge (High, Medium and Low) is presented for each node.

During the study period T, the conventional load connected at each node, is affected by the load curve measured at the distribution transformer, as illustrated in Figure 3.5.

Once the MCS is executed for the test system of Table A.1 (16% penetration level of EVs), the expected value of the power delivered to all EVs and the conventional demands are shown in Figure 3.6. During the charging subperiod of low priority, no EVs are recharged (from 01:00 to 02:40 and from 04:30 to 07:00), since during those hours the electricity price is higher than that at intermediate hours, as shown in Figure 3.7. This aspect makes the mathematical model of 3.1 to 3.11 be more sensitive to the energy price, thus the recharge of EVs is attractive in periods where the energy price is relatively low. In this context, it is assumed that the energy price varies all the time (in this work every 5 min). It is worth noting that this does not occur in schedule rates adopted by many utilities (flat, time of use TOU, seasonal and tiered, among others).

The next scenario corresponds to a 63% of EVs penetration level. According to Figure 3.8, the recharging behavior of the EVs is similar to the case shown before (with 16% of EVs penetration level). Note that some EVs with high priority (red color) arrive at the houses

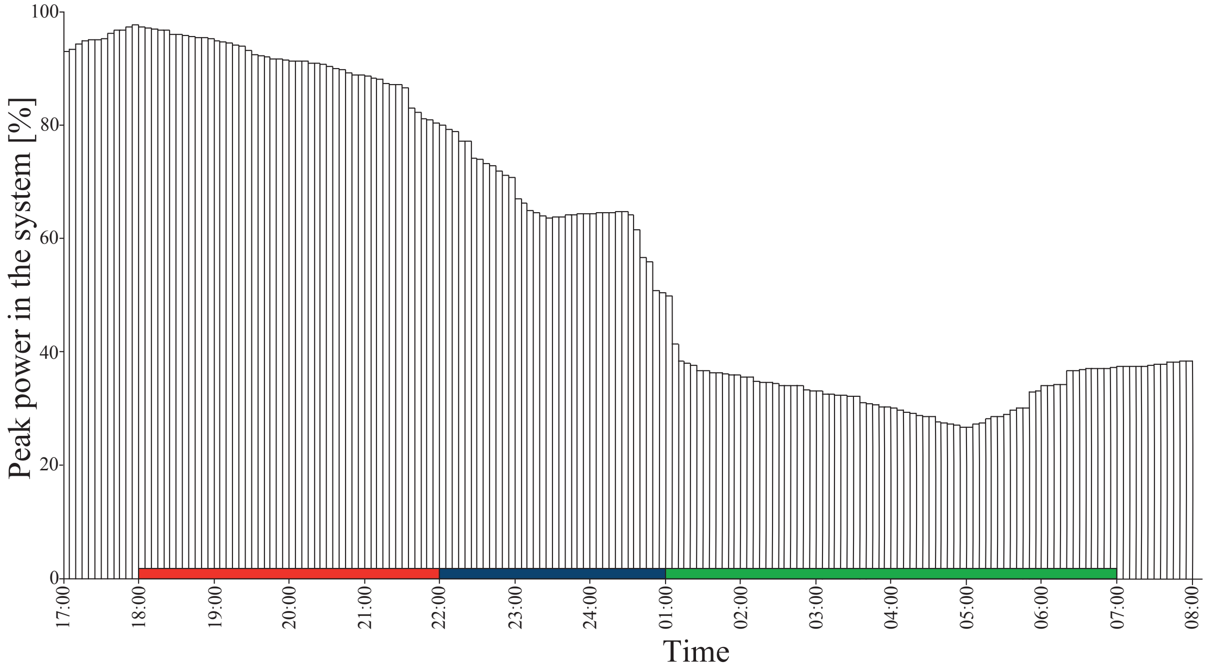

Figure 3.5: Percentage of the peak power in the system during each along the studyperiod T

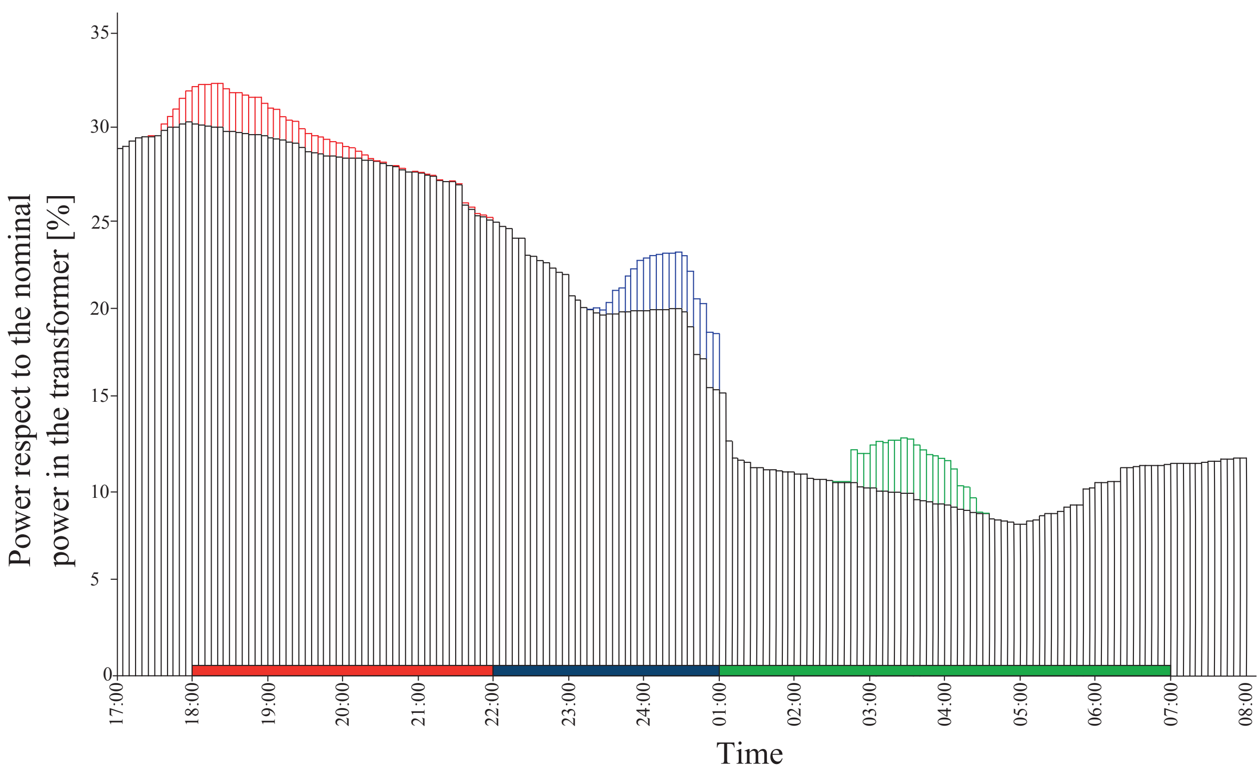

Figure 3.6: EVs recharge under 16% penetration level (19 nodes test system)

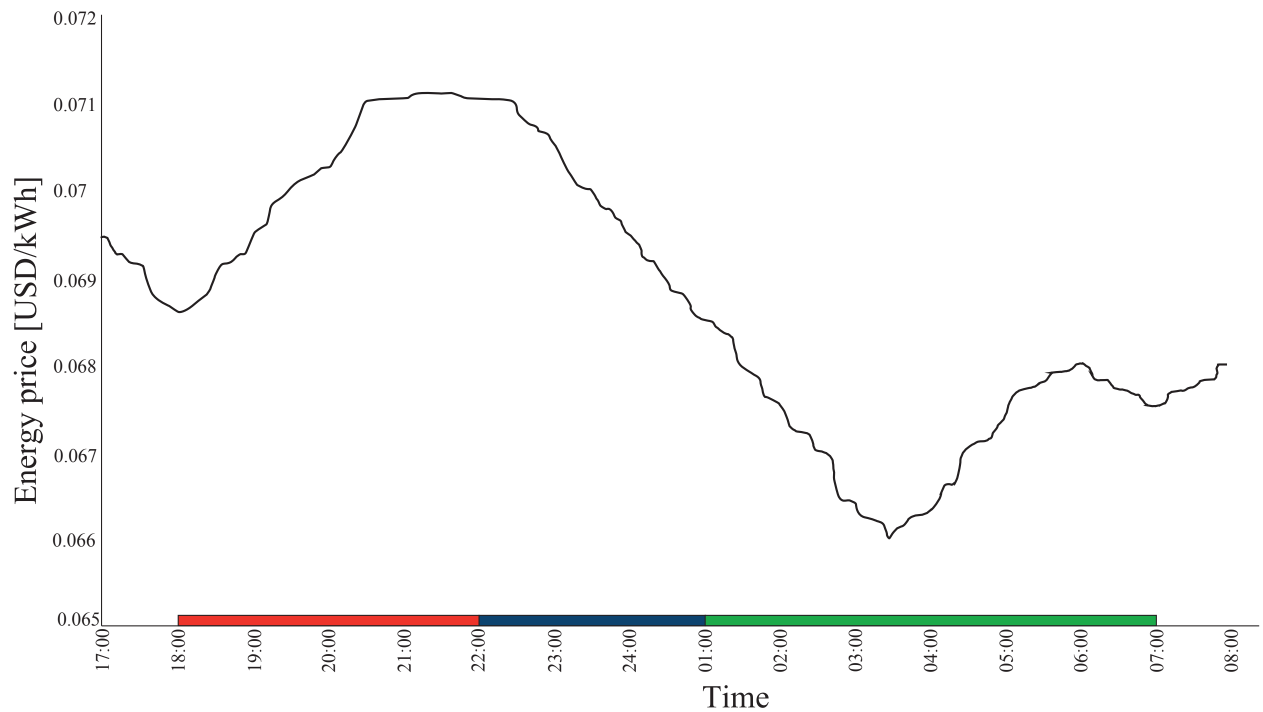

Figure 3.7: Variation of energy price

before 18:00. They start to draw energy from the network with an increasing rate of recharge until 18:00, where the energy price starts to rise. At this point, the recharging decreases due to the increase of the energy price until 22:00, where the EVs charging with high priority is completed. The presence of power peaks is due to the variable nature of energy price. In this context, the load curve (conventional loads and EVs) may be flatter in case of flat rate of energy price.

In Figure 3.9, MCS evolution is presented for the 16% and 63% EVs penetration levels. The cost of both, energy losses and energy demanded (EVs and conventional loads) reach convergence in MCS after 500 iterations approximately. It is obvious that the cost for 63% penetration level is higher than that for 16% penetration level cost, since the insertion of EVs increases almost four times, leading to an increase of the overall cost. For both insertion levels, all EVs were fully recharged, therefore, there was no penalization for the cost presented.

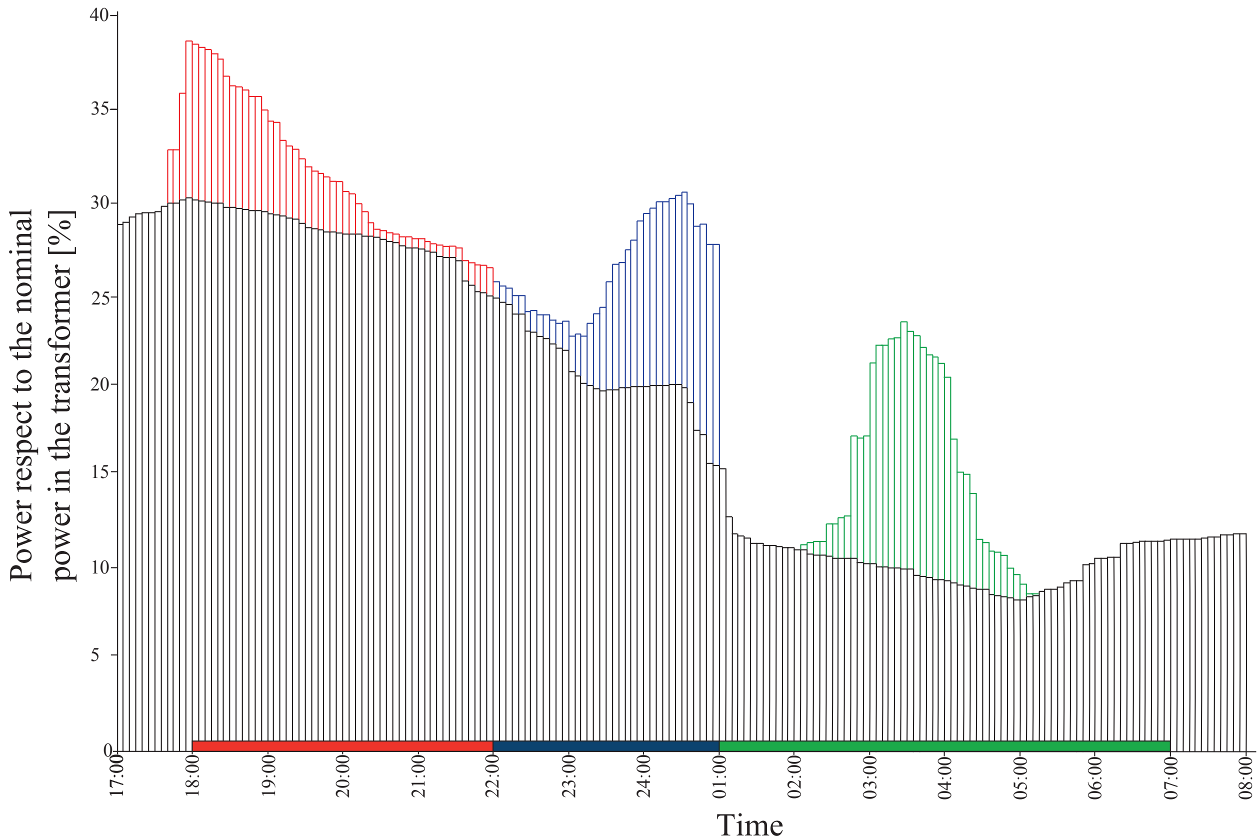

Figure 3.8: EVs recharge under 63% penetration level (19 nodes test system)

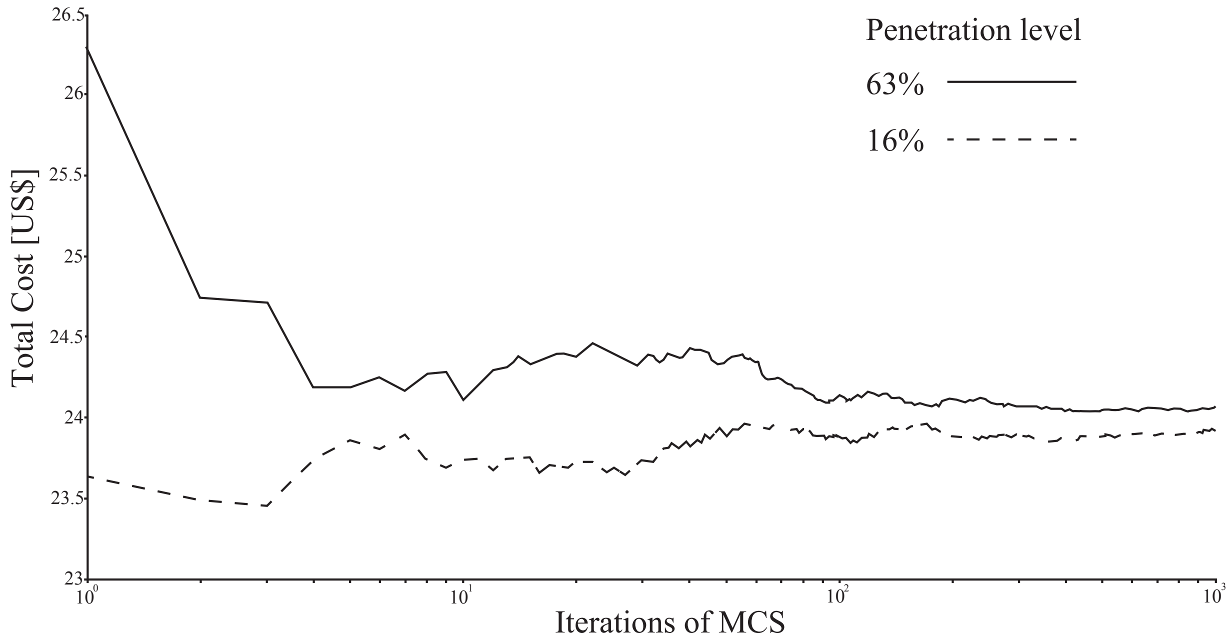

Figure 3.9: Convergence of MCS for 16% and 63% EVs penetration levels

3.4.2 35 nodes test system

The proposed approach is also assessed in a larger network, which is composed by a 35 nodes low voltage distribution network. The test system is presented in Table A.2. This feeder is submitted to 63% of EVs insertion, resulting in a huge stress level. Figure 3.10 shows that the power at the substation transformer reaches roughly 85% of its rated power.

In regards with Figure 3.10, EVs recharge is performed throughout the time window with a 63% EVs penetration level. At the beginning of the medium priority subperiod (blue), the EVs recharge rate is low. As time goes by, recharge rate increases due to the decrease of energy price. Just after the medium priority period (01:00), there is a steep decrease of the EVs recharge power since at this time the recharge occurs only for EVs with low priority (green). Likewise, from that point on, energy price becomes less expensive, encouraging the recharge of EVs until 03:30 approximately where the energy price starts to increase. Then, EVs recharge starts to decrease once again. Some of the EVs with low priority recharge have to draw energy from the network until their respective departure times, later than the end of study period (07:00), to be fully recharged, even when the energy price becomes higher.

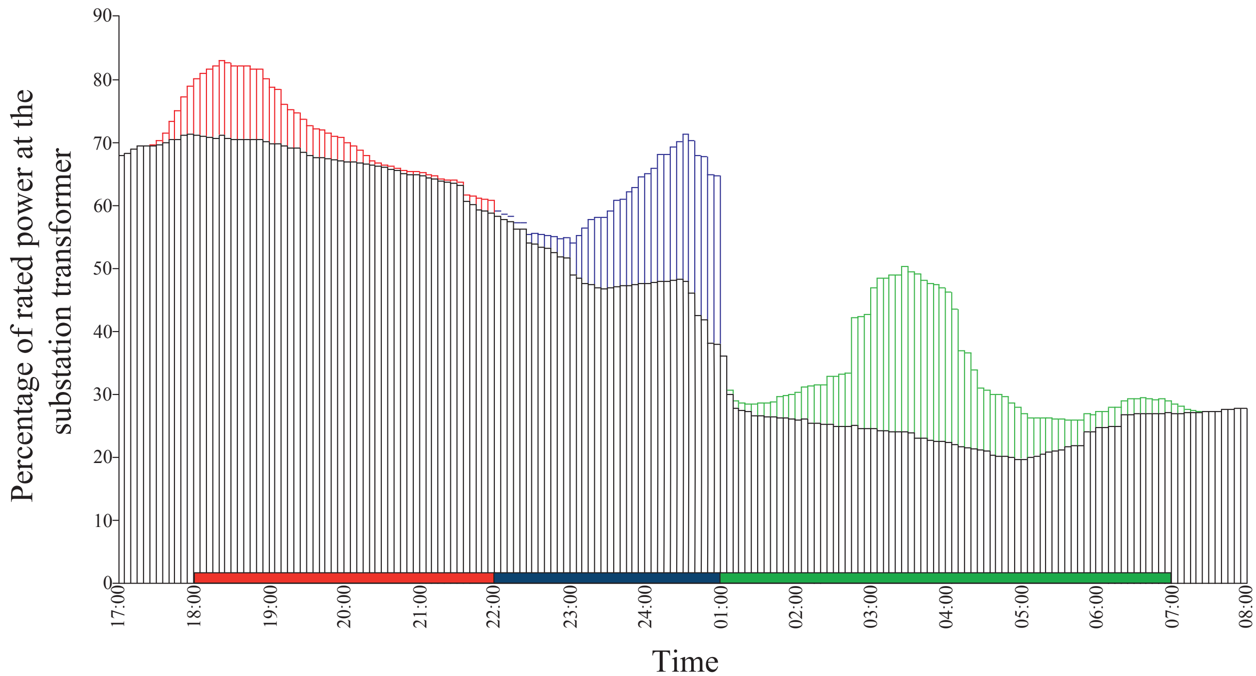

Figure 3.10: EVs recharge under 63% penetration level (35 nodes test system)

This aspect shows that EV recharge is more important than the cost of the energy that will affect the objective function, without ignoring the fact that the energy price represents an important factor in the mathematical model.

In Table 3.2 the expected values and standard deviations are presented for various decision variables obtained using MCS, namely, energy drawn by the feeder, feeder losses, EVs charging energy and cost of energy drawn by the feeder. According to the distribution of the values given by the frequency histogram, normal distribution was the best distribution that represented these output variables, being a very common continuous probability distribution.

Table 3.2: Probabilistic studies for 35-node test system

Output Variable	Expected value	Standard deviation
Energy drawn by the feeder	769.2611	4.7546
Feeder losses [kWh]	26.1826	0.315
Evs charging energy [kWh]	113.3339	3.6116
Cost of energy drawn by the feeder [US$]	45.8176	0.2239

3.4.3 Computational details

The mathematical model of this work has been implemented and run using the GAMS environment (Gill et al., 2000), in a desktop with an Intel Core 3.3 GHz processor and 4 GB of RAM. This model is a NLP problem, which is solved using the MINOS solver. The convergence criteria used for Montecarlo Simulation is based on the number of iterations, set in 1000.

3.5 Conclusions

In this chapter, demand management for EVs in power distribution systems was tackled from the stochastic point of view. Operative aspects of the distribution network and smart procedures for EVs recharge were modelled mathematically, considering the probabilistic behavior of driving patterns (arrival and departure times) and state of charge of EVs' batteries. This latter is expressed in terms of the distance travelled by the EV.

Probabilistic studies, to account for different penetration levels of EVs, were performed by using MCS. Statistical values, such as the expected value and probability density function of the optimal rate of EVs recharge in the system and other output variables were found, taking into consideration priority subperiods along the period of time under study. This aspect establishes the fact that an EV has to be recharged as soon as possible, or has to wait for a more appropriate time, depending on other factors, i.e., energy price.

If each priority subperiod is analyzed separately, the mathematical model presents sensitivity from the point of view of the energy price, reflecting a tendency to provide charging power at hours when the energy price is lower. Nevertheless, the feasibility in this problem is more related with priority than optimality, because the technical constraints of voltage at the nodes and currents through the lines have to be met before searching for minimising objective function cost.

Chapter 4

Electric vehicles routing and charging stations location: First approach

4.1 Overview

The use of EVs has become a promising tool for the logistics sector electrification and the inherent curtailment in the air pollution. Transportation companies are highly responsible to reduce the green house gases emissions, emerging several pilot projects for merchandise transportation with EVs in multinational companies such as DHL, FedEx and UPS, where EVs have been included for routing planning. However, the EVs driving range still represents a disadvantage to adopt them as main transportation means in logistics, compared with ranges provided by internal combustion based vehicles. Batteries driving range depend largely on their improvement, based on safety, cost, operation temperature and availability of materials, which are difficult issues to handle (Hannan et al., 2017). This implies that the EVs driving range will not be widely improved for the coming years.

Under these circumstances, charging stations play an important role on the electric mobility, allowing to travel longer distances by indirectly increasing EV driving range. In this manner, it is necessary to perform an appropriate siting of Electric Vehicle Charging Stations (EVCSs), as this type of installations are strategic for the massive incorporation of EVs, reaching driving ranges comparable with conventional vehicles. Furthermore, optimal EVCSs siting does not depend exclusively on the transportation network requirements, because those installations imply large consumption of electricity. Therefore, the effect of the charging stations on the power distribution networks has to be taken into account, in order to avoid congestion or additional costs associated with energy losses.

In this chapter the Electric Vehicles Integrated Planning Problem (EVs-IPP) for cargo transportation is presented. The optimal location of EVCSs is performed considering the mobility of cargo EVs along the transportation network and the impact on the Power Distribution System (PDS). This results as a consequence of the poor capacity that may be presented on the EVs' battery to provide enough autonomy to complete the routes adequately, since the EVs are part of merchandise transport where considerable distances are traveled too often. By the other side, EVCSs represent huge additional loads for the electric network, being the proper location of this type of loads a critical aspect when the energy losses of the PDS are assessed.

The proposed formulation is based on a mixed integer non-linear mathematical model to portray the EVs mobility with the well known Capacitated Vehicle Routing Problem (CVRP) and the distribution system operation with the power flow equations. Costs associated with cargo EVs routing, EVCSs installation and energy losses are minimized, obtaining an optimal operation in the transportation and electric networks. Additionally, the introduction of a consistent penalty in the objective function helps to determine until what level the current EVs' battery autonomy is suitable to perform the routes. In regards with the battery autonomy, the mathematical model tends to be feasible, as long as this term is not greatly weighted in the objective function. This way, under a non-sufficient battery autonomy scenario, the decision maker can realize that EVCSs installation is not enough to meet the needs of EVs routing, being necessary to replace current batteries for others that can provide larger driving range.

4.2 EVs-IPP formulation

In the context of discrete mathematics, the integrated planning problem proposed can be formulated as a graph theory problem. Let $G = (V, A)$ a complete graph, where $V = C \cup N$ is the vertices set of the integrated problem and A is the arc set that interconnects all the vertices. Set $C = 1, ..., c$ represents the customers vertices and conform the transportation network. Set $N = c + 1, ..., +n$ represents the power demand vertices and conform the PDS. Set $J \subset N$ contains all the candidate vertices to install EVCS that in this case is the set of all the nodes except the PDS substations. Sets N and C and their respective arcs can be seen as two disjunctive graphs, and the interaction between these graphs is given by the EVs charging. The EVs are required to meet the customers merchandise demand. PDS vertices of set N are connected each other through lines, which represent the electrical wires, conforming set $L = 1, ..., l$.

In this sense, EVs-IPP considers the interaction of three different subproblems. The first subproblem is known in the literature as the Capacitated Vehicle Routing Problem (CVRP), where a vehicles fleet with limited cargo capacity leave from a unique depot and deliver merchandise to several customers. The vehicles have to fully meet the merchandise demands, seeking a travelling minimal cost (Toth and Vigo, 2002). The second subproblem is related with the location of EVCSs, which indirectly provides an increase of the EVs battery range in order to complete the travel successfully. The third subproblem addresses the power flow formulation, involving the operation point of the PDS under the additional loads in accordance with the EVCSs installation.

4.2.1 Nomenclature

For better understanding of the mathematical formulation, the notations used in this chapter are listed as follows:

Sets

C	Set of customers
J	Set of candidate nodes to install EVCSs
0	Depot
0'	Copy of Depot
V	$C \cup J \cup 0 \cup 0'$
K	Set of Electric Vehicles
N	Set of nodes belonging the PDS
L	Set of lines belonging the PDS

Parameters

W_1	Weight factor for EVCSs installation cost term
W_2	Weight factor for routing cost
W_3	Weight factor for penalization term
W_4	Weight factor for energy losses cost
f_h	EVCSs installation cost $[USD]$
fm_h	EVCSs maintenance cost $[USD]$
CPI	Consumer Price Index
nt	Number of years to shift to future value
a_k	Cost per kilometer traveled by vehicle k $[USD/km]$
d_{gh}	Distance from node g to node h $[km]$
am_k	Maintenance cost of vehicle k to travel one kilometer $[USD/km]$
ap_k	Cost of the additional capacity of the EV's battery $[USD/km]$
b	Cost of 1 kWh of energy losses $[USD/kWh]$
$Loss_{w/oEVCSs}$	Power losses of the PDS without EVCSs installed $[kW]$
M	Big number
$\|K\|$	Cardinality of set K
q_g	Merchandise demand at customer node g

U_k	Merchandise cargo capacity of vehicle k
Q	Battery autonomy $[km]$
P_n^d	Active power demanded at node n $[kW]$
R_{mn}	Resistance of line mn belonging the PDS $[\Omega]$
X_{mn}	Reactance of line mn belonging the PDS $[\Omega]$
Z_{mn}	Impedance of line mn belonging the PDS $[\Omega]$
V_{min}	Lower voltage bound at PDS nodes $[V]$
V_{max}	Upper voltage bound at PDS nodes $[V]$
I_{max}	Upper current bound at PDS lines $[A]$
P_{max}^G	Upper level of active power generated at PDS nodes $[W]$
$PEVCS$	Nominal active power drawn by EVCS installed $[W]$

Variables

α	Cost of EVCSs installed $[USD]$
β	Cost of EVs routing on transportation network $[USD]$
γ	Cost of penalization $[USD]$
y_h	Binary decision variable for EVCS installation at candidate node h. If $y_h = 1$ the EVCS is installed and $y_h = 0$ otherwise
x_{ghk}	Binary decision variable, taking the value of 1 if vehicle k goes from node g to node h and 0 otherwise
$P_{hk}^{fictitious}$	Missing autonomy to reach node h with vehicle k $[km]$
i_{mn}^{sqrt}	Square current flowing through line mn of PDS $[A^2]$
μ_{ghk}	Remaining merchandise when vehicle k leaves node g and goes to node h
pb_{hk}^1	Battery autonomy before vehicle k arrives node h $[km]$
pb_{gk}^2	Battery autonomy after vehicle k leaves node g $[km]$
P_{mn}	Active power flowing line mn of PDS $[kW]$
P_n^G	Active power generated at node n $[kW]$
PE_n	Active power drawn by an EVCS installed at node n $[kW]$
Q_{mn}	Reactive power flowing line mn of PDS $[kVar]$

Q_n^G	Reactive power generated at node n $[kVar]$
V_m^{sqr}	Square voltage at node m $[V^2]$

4.2.2 EVs-IPP Mathematical model

The mathematical model for EVs-IPP is presented in equations 4.1 to 4.29, considering O as the depot where the vehicles start the respective routes and O' is a depot copy where the vehicles will complete the routes. Note that equation 4.1 is the objective function and equations 4.2 to 4.29 are the set of constraints.

The objective function in 4.1 seeks to minimize the summation of four terms. The first term is the construction and maintenance cost of an EVCS at node h. The second term is the routing cost performed by the vehicle k from node g to node h. In this term the maintenance in terms of the distance traveled by the EV is also considered. The third term is a penalization created in case of need to increase the battery autonomy in EVs, in order to complete the routes and deliver the merchandise to customers. This term is the cost to make the problem feasible and is defined as the product between a positive variable (Increase of the battery autonomy at vehicle k to arrive node h) and the cost ap_k of the additional capacity of the battery. The last term represents the cost of the energy losses increase through the PDS lines compared with the energy losses when no EVCSs were installed (Benchmark case).

$$\min z = W_1 \cdot \alpha + W_2 \cdot \beta + W_3 \cdot \gamma + W_4 \cdot \omega \tag{4.1}$$

The four terms of the objective function are defined in equations 4.2 to 4.5 respectively, along a period equal to one year and shifted to future value. This latter depends on the number of years nt the cost will be shifted to future and the Consumer Price Index CPI.

$$\alpha = \sum_{h \in J} (f_h + fm_h) \cdot y_h \cdot (1 + CPI)^{nt} \tag{4.2}$$

$$\beta = 365 \cdot \sum_{g \in V} \sum_{h \in V} \sum_{k \in K} d_{gh} \cdot x_{ghk} \cdot (a_k + am_k) \cdot (1 + CPI)^{nt} \tag{4.3}$$

$$\gamma = 365 \cdot \sum_{h \in V} \sum_{k \in K} ap_k \cdot P_{hk}^{ficticious} \cdot (1 + CPI)^{nt} \tag{4.4}$$

$$\omega = 8760 \cdot b \sum_{mn \in L} \left(i_{mn}^{sqrt} \cdot R_{mn} - Loss_{\mathrm{w/oEVCSs}} \right) \cdot (1 + CPI)^{nt} \tag{4.5}$$

Weighting factors W_1, W_2, W_3 and W_4 in objective function provide a level of importance for each term, making the summation of all of them equals to the unity. The values assigned to these factors depend on strategic data managed by decision maker in the integrated planning. This information is related with financial availability to implement the routing, EVCSs construction, battery technology, among others. The values that best represent the deal between objectives can be obtained via a multi-objective approach, in order to build up an optimal front of solutions (which is not into the scope of this work). In the proposed model, punctual values for these factors are used in all instances and runs, distributing the relative importance of each term in objective function, in such a way that the need to increase the battery autonomy is largely penalized, followed by the routing cost, then, EVCSs installation cost and energy losses costs. Thus, in this proposal it is assumed that $W_3 > W_2 > W_1 = W_4$. Factor W_3 has the highest relevance, as it is attempted that a change of the battery capacity be not attractive. W_2 is greater than W_1 as the change in objective function value is more sensitive to the EVCSs installation cost than that with the routing cost.

The constraint in 4.6 requires every arc to be traveled only once, while constraint in 4.7 is an inequality to warranty that EVs only recharge their batteries at a located EVCS. Equation 4.8 is a constraint that assures the flow for each vehicle at each node. In 4.9, it is shown that the quantity of vehicles leaving the depot has to be the same as the number of vehicles entering the depot. Constraint in 4.10 requires each vehicle to do one trip at most. In 4.11, the cardinality of set K, assures that the maximum quantity of vehicles leaving the depot is limited by the quantity of vehicles available.

$$\sum_{g \in V \setminus \{o'\}, g \neq h} \sum_{k \in K} x_{ghk} = 1 \quad \forall h \in C \tag{4.6}$$

$$\sum_{g \in V \setminus \{o'\} g \neq h} \sum_{k \in K} x_{ghk} \leq M \cdot y_h \quad \forall h \in J \tag{4.7}$$

$$\sum_{h \in V \setminus \{o\}, h \neq g} x_{ghk} - \sum_{h \in V \setminus \{o'\}, h \neq g} x_{ghk} = 0 \tag{4.8}$$

$$\sum_{h \in V \setminus \{o\}} x_{ohk} - \sum_{h \in V \setminus \{o'\}} x_{ho'k} = 0 \quad \forall k \in K \tag{4.9}$$

$$\sum_{h \in V \setminus \{o\}} x_{ohk} \leq 1 \quad \forall k \in K \tag{4.10}$$

$$\sum_{k \in K} \sum_{h \in V \setminus \{o\}} x_{ohk} \leq |K| \tag{4.11}$$

When vehicles visit an EVCS without merchandise demand, $q_h = 0$, $h \in J$. Constraint in 4.12 represents that the summation of the remaining load u_{ghk} of an EV entering an EVCS is equal to the remaining load of the vehicle leaving an EVCS. This guarantees the vehicle capacity balance and indicates that an EVCS can be revisited more than once. The change in the remaining load of an EV when entering a customer node (with q_h >0) is calculated by constraint 4.13. If the vehicle k visits customer h, the remaining cargo is reduced by customer demand q_h. If the customer h is not visited by vehicle k, the constraint keeps valid. Both, constraints in 4.12 and 4.13 make an EV to pass by an EVCS more than once but visit a customer only once, and eliminate the generation of subtours. Constraint in 4.14 contains the range for u_{ghk} that can be at most, the total cargo capacity of the EV.

From the point of view of the EV battery, constraint in 4.15 records the EV battery autonomy in terms of distance. When the vehicle k with a battery autonomy Q, travels along the arc

gh, the battery autonomy before entering node h pb^1_{hk}, is the subtraction between the battery range after leaving node g pb^2_{gk} and the distance traveled d_{gh} along the arc.

$$\sum_{g \in V \backslash \{o', j\}} u_{ghk} = \sum_{g \in V \backslash \{o, j\}} u_{hgk} \quad \forall h \in J, \forall k \in K \tag{4.12}$$

$$\sum_{h \in V \backslash \{o, g\}} u_{ghk} \leq \sum_{h \in V \backslash \{o', g\}} (u_{hgk} - q_g \cdot x_{hgk}) + U_k \cdot \left(1 - \sum_{h \in V \backslash \{o', g\}} x_{hgk}\right) \quad \forall g \in C, \forall k \in K \tag{4.13}$$

$$0 \leq u_{ghk} \leq U_k \cdot x_{ghk} \quad \forall g \in V \backslash \{o'\}, h \in V \backslash \{o\}, g \neq h, k \in K \tag{4.14}$$

$$pb^1_{hk} \leq pb^2_{gk} - d_{gh} \cdot x_{ghk} + Q(1 - x_{ghk}) \quad \forall g \in V \backslash \{o'\}, h \in V \backslash \{o'\}, g \neq h, k \in K \tag{4.15}$$

Constraint 4.16 indicates that all the vehicles have to leave the depot with batteries completely charged. This also applies for the EVCSs, where constraint 4.17 describes that a vehicle will have its battery fully charged once leaving from the EVCS. Right before an EV enters a customer node, the battery autonomy will be the same once it leaves the node, which is established in constraint 4.18. If the vehicle does not have enough autonomy to arrive to the next node, a variable called $P^{fictitious}_{hk}$ is in charge to provide the missing autonomy. This latter is introduced in the objective function as a penalization, motivating the installation of EVCSs instead of to increase the EVs battery autonomy. In 4.19 the non-negativity of the battery autonomy is declared, and the binary decision variables are shown in 4.20.

$$pb^2_{ok} = Q \quad \forall k \in K \tag{4.16}$$

$$pb^2_{gk} = Q \cdot y_g \quad \forall g \in J \tag{4.17}$$

$$pb_{hk}^2 = pb_{hk}^1 + P_{hk}^{fictitios} \quad \forall h \in C \tag{4.18}$$

$$pb_{hk}^1 \geq 0 \quad \forall h \in V \tag{4.19}$$

$$y_j, x_{ghk} \in \{0, 1\} \quad \forall j \in J, \forall g \in V \backslash \{o'\}, h \in V \backslash \{o\}, k \in K \tag{4.20}$$

From 4.21 to 4.27 the status of the PDS is assessed. The balance of active and reactive power is done in 4.21 and 4.22 respectively. The voltage drop along the network segment mn is computed in 4.23 and the current square is obtained with constraint 4.24.

The constraints from 4.25 to 4.28 determine the voltage limits for each node, current flowing through the lines, active power generated and power consumed by the EVCSs, being $PEVCS$ the maximum power consumed by each EVCS. The non-negativity of the battery autonomy added to EV is formulated in 4.29.

$$\sum_{mn \in L} P_{mn} - \sum_{nr \in L} (P_{nr} + i_{nr}^{sqrt} \cdot R_{nr}) + P_n^G = P_n^d + PE_n \quad \forall m \in N, n \in N, r \in N \tag{4.21}$$

$$\sum_{mn \in L} Q_{mn} - \sum_{nr \in L} (Q_{nr} + i_{nr}^{sqrt} \cdot X_{nr}) + Q_n^G = Q_n^d \quad \forall m \in N, n \in N, r \in N \tag{4.22}$$

$$v_m^{sqr} - v_n^{sqr} = 2(R_{mn} \cdot P_{mn} + X_{mn} \cdot Q_{mn}) + Z_{mn}^2 \cdot i_{mn}^{sqr} \quad \forall mn \in L, m \in N, n \in N \tag{4.23}$$

$$v_n^{sqr} \cdot i_{mn}^{sqr} = P_{mn}^2 + Q_{mn}^2 \quad \forall mn \in L, n \in N \tag{4.24}$$

$$V_{\min}^2 \leq v_n^{sqr} \leq V_{\max}^2 \quad \forall n \in N \tag{4.25}$$

$$0 \leq i_{mn}^{sqr} \leq I_{\max}^{2} \quad \forall mn \in L \tag{4.26}$$

$$0 \leq P_{n}^{G} \leq P_{\max}^{G} \quad \forall n \in N \tag{4.27}$$

$$PE_{n} = PEVCS.y_{h} \quad \forall n \in N, \quad \forall h \in J \tag{4.28}$$

$$P_{hk}^{fictitios} \geq 0 \quad \forall h \in V, k \in K \tag{4.29}$$

4.2.3 Test systems

In order to validate the mathematical model proposed, three different instances composed by combination of transportation networks and power distribution systems from the specialized literature are proposed. The characteristics of the transportation, power distribution and hybrid networks, are featured below. Some tests are carried out on the uncoupled instances.

Transportation networks test systems

In this study, small-size instances for CVRP are used to examine the EVs-IPP mathematical model from the transportation network approach. As shown in (Yang and Sun, 2015), three instances are generated from the $Pn16k8$ instance, available in (Augerat, 2013). Instead of using all customers in the instance, each instance contains only a certain number of customers. For example, in this work, $Pn6k2$ presents the last 6 customers of $Pn16k8$, $Pn7k3$ presents the last 7 customers of $Pn16k8$ with 3 vehicles, and $Pn8k3$ contains the last 8 customers of $Pn16k8$ with 3 vehicles (see Table 4.2). According to the tests performed in (Yang and Sun, 2015), the autonomy Q for the EV's battery is set in $[1.2dmax]$, being $dmax$ the maximum Euclidean distance between any two nodes in the network. The cost associated with an EVCS construction is $[0.5Q]$. In this case, it is assumed that all the customer nodes are candidates for EVCSs.

Table 4.2: Small-size transportation network instances

Instance						Coord. X	Coord. Y
Pn6k2		Pn7k3		Pn8k3			
Customer node	EVCS candidate node	Customer node	EVCS candidate node	Customer node	EVCS candidate node		
				1	9	57	58
		1	8	2	10	62	42
1	7	2	9	3	11	42	57
2	8	3	10	4	12	27	68
3	9	4	11	5	13	43	67
4	10	5	12	6	14	58	48
5	11	6	13	7	15	58	27
6	12	7	14	8	16	37	69
Depot (0 and 0’)						1	-1

Table 4.3 provides the results obtained by EVs-IPP in $Pn6k2$, $Pn7k3$ and $Pn8k3$ instances, which can also be found in (Yang and Sun, 2015). Note that the candidate nodes where EVCSs were installed, are underlined along the EVs routes described in the column "Route".

Table 4.3: Results for three different transportation network instances

Instance	EVCSs installed	Objective function	Route			Time [s]
			k=1	k=2	k=3	
Pn6k2	2	426.8609	0-$\underline{10}$-4-5-0’	0-1-$\underline{9}$-3-6-2-0’		21
Pn7k3	2	428.5961	0-6-1-$\underline{12}$-5-0’	0-3-7-$\underline{14}$-4-2-0’		688
Pn8k3	2	597.1575	0-4-$\underline{16}$-8-5-3-0’	0-7-2-$\underline{14}$-0’	0-1-6-$\underline{14}$-0’	352

Power distribution test systems

By the side of power distribution networks, three test systems from the literature were used. The first system can be found in (Civanlar et al., 1988) and is presented in Tables B.1 and B.2. This instance is a three-feeder system with 16 nodes, which will be named *DS16N*. The second test system is a 34-nodes feeder (named in this work *DS34N*) available in (Ribeiro, 2013) and also presented in Tables B.3 and B.4. This system is rated at 11kV and utilized by other authors in optimal location of capacitors. The third case (named *DS23N* in this work), with 23 nodes, is a two-feeder distribution system proposed in (Miranda et al., 1994) rated at 28kV, and is shown in Tables B.5 and B.6.

Considering the effect of the power distribution system in EVs-IPP mathematical model, the electric feeders mentioned above are coupled with a transportation network. No matter which transportation network is used for this test, if a big autonomy Q for the EVs' batteries is used, the vehicles are able to complete the routes and meet the customers, without the need to install any EVCSs. In this sense, the results (voltage profile) from the point of view of the power distribution system will be quite similar as those that can be obtained with the conventional back-forward sweep algorithm, as there are no additional power loads. The error in p.u. between the voltage calculated by back-forward sweep algorithm and the EVs-IPP mathematical model is shown in Figures 4.1, 4.2 and 4.3 for *DS16N*, *DS34N*, *DS23N* test systems respectively.

Since the lower limit of voltage constraint in EVs-IPP mathematical model is not reached, the voltage at nodes are very similar compared with the voltage obtained with backward-forward sweep algorithm, as this latter is not able to restrict this variable. Figures 4.1 to 4.3 depict that the maximum error between the two methods is $1.9928x10^{-9}$.

Coupled systems

In order to examine the EVs-IPP's capability from a general perspective, both electric and transportation networks are coupled. Therefore, three new instances are created from the

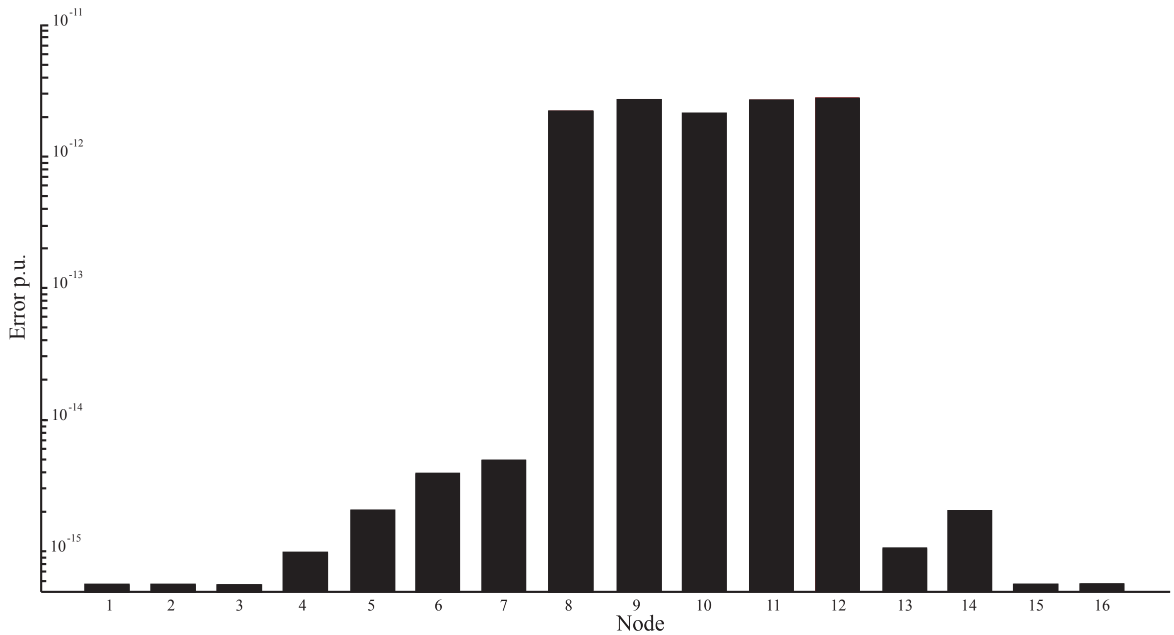

Figure 4.1: Voltages error in p.u. for *DS16N* test system

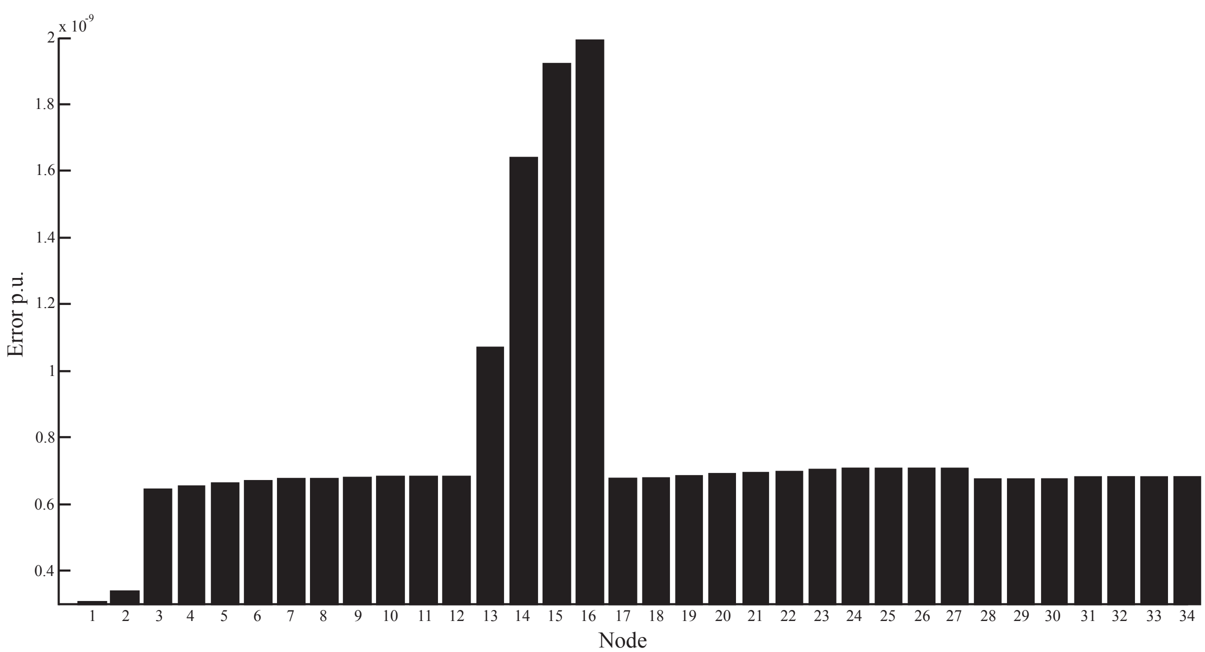

Figure 4.2: Voltages error in p.u. for *DS34N* test system

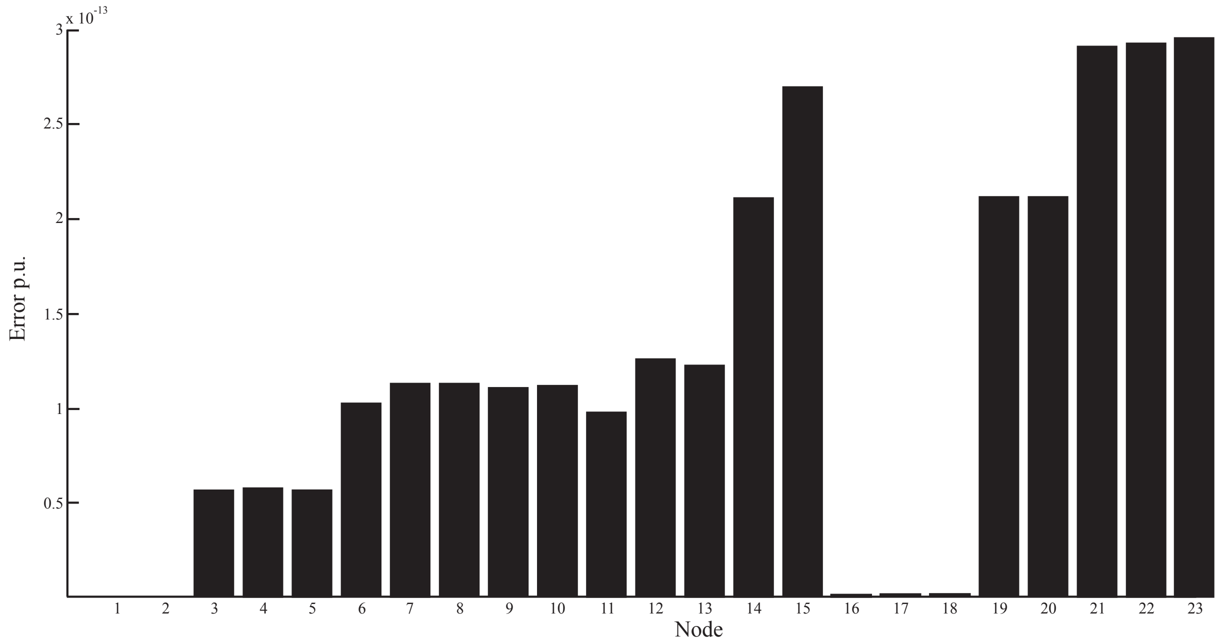

Figure 4.3: Voltages error in p.u. for *DS23N* test system

power networks and transportation instances shown before. These new instances are exposed in detail in Tables B.7, B.8 and B.9. Figure 4.4 shows the coupling between *Pn6k2* and *DS16N*. Note that nodes joined with continuous line represent the power distribution system, being nodes 7, 8 and 9 the distribution substations. The transportation network is portrayed by the square nodes. Figure 4.5 presents the coupling between *Pn7k3* and *DS34N*, where node 8 is the distribution substation. Finally, coupling of *Pn8k3* and *DS23N* is shown in Figure 4.6, with two distribution feeders around the transportation network compound by 8 nodes. In all three instances, it is assumed that none of the PDS nodes is located at the same coordinates of the customers. Therefore, EVCSs are not able to be installed on the customers' nodes (as EVCSs draw power from electric grid), which implies that the EV is required to visit a power network node (to an installed EVCS) once the battery is almost depleted and returns to still visiting the customers.

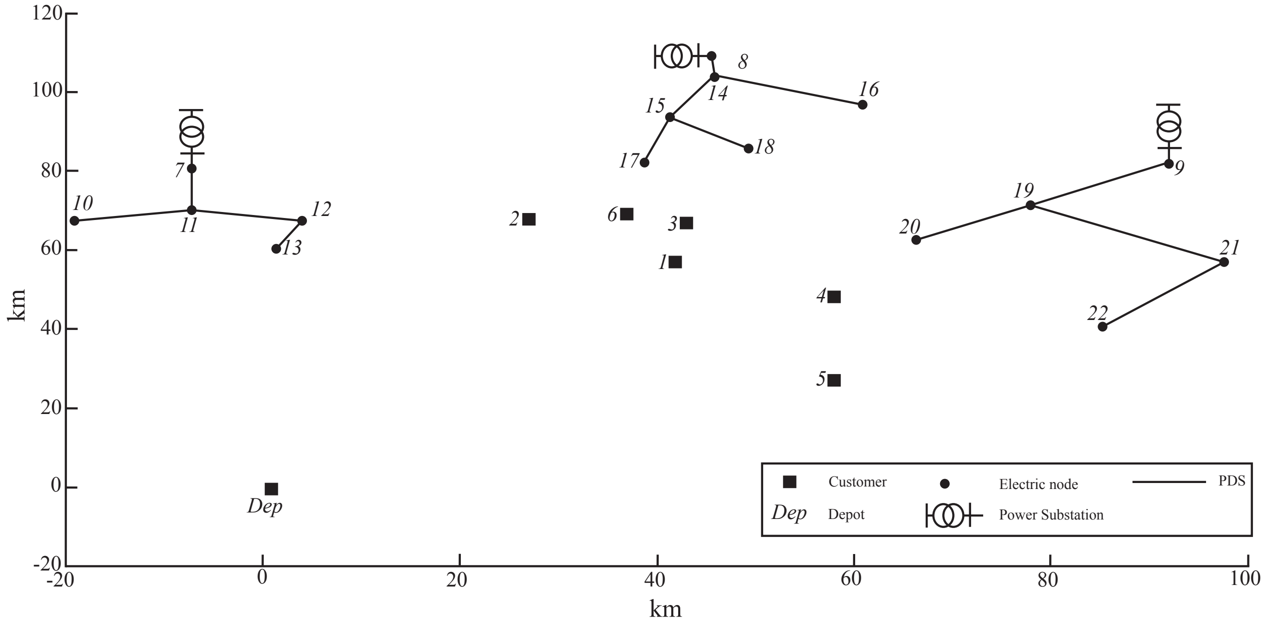

Figure 4.4: Coupling between $Pn6k2$ and $DS16N$

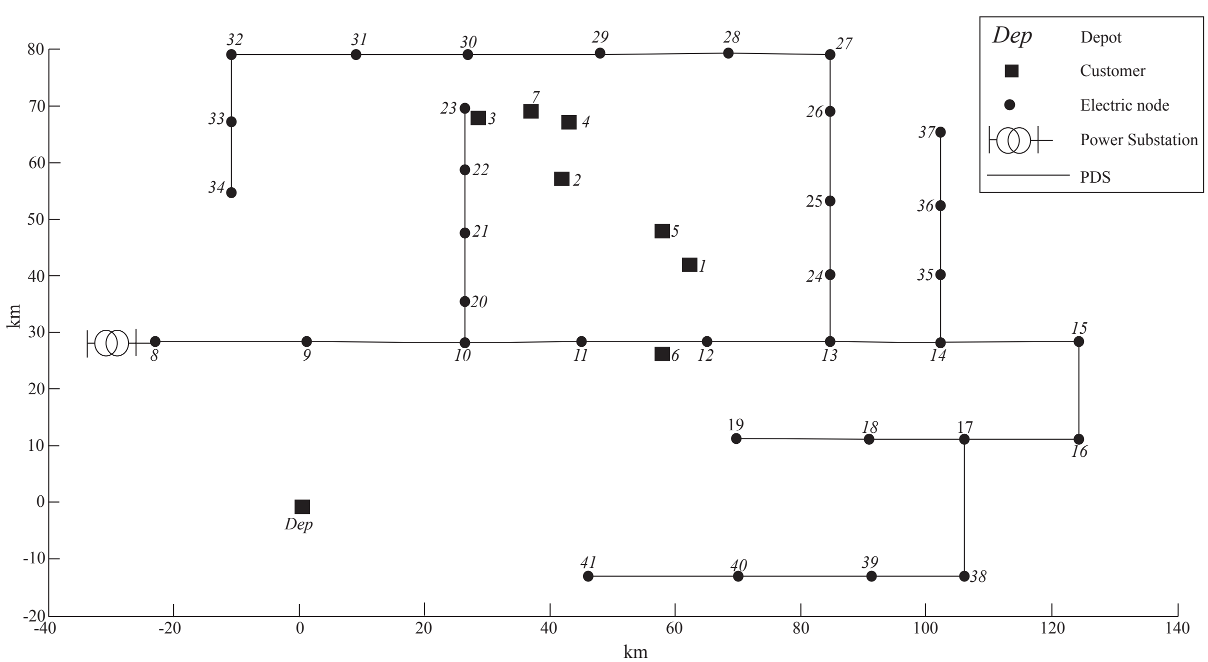

Figure 4.5: Coupling between $Pn7k3$ and $DS34N$

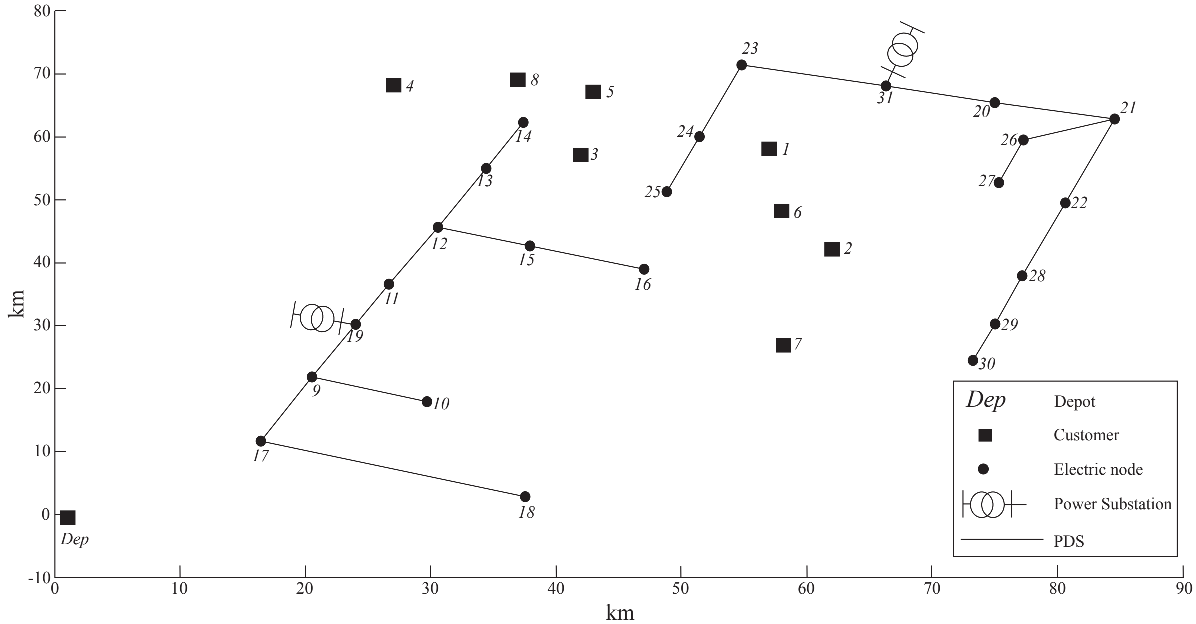

Figure 4.6: Coupling between $Pn8k3$ and $DS23N$

4.3 Results

Coupled systems shown in Figures 4.4, 4.5 and 4.6 are utilized to assess the performance of EVs-IPP. Parameters for all three instances were chosen consistently to the reality. According to (Motors, 2017), an EVCS may draw from the PDS up to 120 kW for a 272 km battery-range. In this work, PEVCS used is 60 kW, as the average range evaluated in the runs is around 130 km, considering a linear behavior between maximum power at EVCS and distance that can be traveled. The cost fh related with EVCS construction is assumed to be 22000 USD, as established in (Agenbroad, 2014), taking into account type of installation, materials, connectivity, data and other factors. Parameter fm_h, which is the maintenance cost associated with this infrastructure, is around 10% the installation cost. From the point of view of the EV operation, the average cost is 2.423 USD to travel 100 km, as reported by (of Energy, 2017), and an estimation of 86 USD for EV maintenance every 5000 km traveled. The parameter ap_k is chosen arbitrarily as 1000 times the cost per kilometer traveled, in order to strongly penalize the third term in the objective function. By the hand of PDS losses, the power losses cost used in all cases is 4.34 Cents per kWh. To shift the cost to future value,

CPI is set in 5%.

Weighting factors assigned in the objective function at all runs are: $W_1 = 0.1$, $W_2 = 0.2$, $W_3 = 0.6$ and $W_4 = 0.1$. The third term is multiplied by a high weight factor in objective function, compared with other terms, as the purpose is to obtain a solution where the EVCSs installation be encouraged instead of change the EVs' battery for a battery with larger autonomy. Notice that the weighting factor for routing cost is larger than that multiplying EVCSs installation cost, due to the installation of one EVCS can affect significantly the objective function value. Contrastingly, the change in routing caused by battery driving range, implies a slight affectation to the objective function, making this latter less sensitive to the routing cost change. By the other side, the term for change in energy losses cost, could have a high weighting factor, being appropriate to install EVCSs close the substations. However, this could result in a non-desired increment for the routing cost and eventually activate the third term in objective function, which is not attractive due to the reasons mentioned earlier. Therefore, energy losses cost (forth term in objective function) is highly dependent on the other objectives (EVCSs installation and EVs routing) due to its weighting factor and that the actions executed on the transportation network, greatly influence in the distribution system performance.

The proposed EVs-IPP model has been programmed and executed in the GAMS (General Algebraic Modeling System) environment on a HP desktop computer, Windows 64-bit operating system, with an Intel Core i3 @ 3.3 GHz processor and 4 GB of RAM. The presence of non-linearities and integer and continuous variables into equations, make the proposed EVs-IPP model be a MINLP, which is solved using the DICOPT solver (GAMS, 2017). In all runs, default values for DICOPT solver were used, i.e., 20 number of cycles for alternating solution of NLP subproblem and MIP master problem, and GAP of zero for MIP master problem solution.

4.3.1 *Pn6k2-DS16N*

The results for instance *Pn6k2-DS16N* are presented in Table 4.4, considering different values of battery autonomy Q and three values for parameter M described in equation 4.7. This parameter restricts the number of arcs entering and leaving an EVCS, limiting indirectly the number of vehicles that can visit the EVCS. For example, if $M = 1$, one EV is allowed to visit the EVCS. If $M = 2$, only two EVs are permitted to enter an EVCS, and if $M = 150$ (or a big number), all the EVs in the routing problem can visit the EVCS.

According to Table 4.4, as the battery autonomy (first column) is increased for a certain value of M (column 7), there is a reduction of the cost associated with EVCS installation, EVs routing and PDS energy losses (second, third and fourth columns respectively). Columns 5 and 6 show the nodes sequence traveled by the EVs, with the EVCSs identified in bold. When the battery autonomy Q is large enough (Q >180 km), no EVCSs are installed and the terms α and ω are zero, obtaining the same results as those presented in benchmark case.

Figure 4.7 depicts the EVs routes and the EVCSs installed along the PDS for instance *Pn6k2-DS16N*, with Q=80 km and $M = 1$. Note that the EVCSs are allowed to be visited by one EV. After visiting EVCS in 11, EV_1 has to visit another EVCS located at node 14, as the recharge acquired in 11 is not sufficient to visit all customers and come back to the depot. For values of Q greater or equal than 80 km, the third term γ of the objective function is always zero. For values of Q less than 80 km, i.e., Q=65 km in Table 4.4, the term γ is greater than zero. This situation suggests an upgrade in the battery, because along the routes, the autonomy for both EVs is not sufficient to complete some arcs and installing more EVCSs could incur in a relevant increase of energy losses (installation of EVCSs at nodes quite far from the substation). Specifically, for Q=65 km and $M = 150$, the route traveled by EV_1 is the longest path found in all the runs shown in Table 4.4. Due to M has a big number, there are more options to go back to depot after visiting customers and the routing length becomes longer than other cases. In contrast with this case, the routing length is smaller for Q=65 km and $M = 1$, as the EVCS revisit is not permitted, reducing the options for EVs to go back to depot.

Table 4.4: Results for instance $Pn6k2 - DS16N$

Q [km]	α [USD]	β [USD]	ω [USD]	Details of route k=1	Details of route k=2	M	Time [s]
65	154430	483983	3515056	0-5-**22**-**19**-1-**20**-4-0'	0-**13**-2-3-**17**-6-0'	1	809
80	247088	663491	4454116	0-**11**-**14**-3-6-2-**12**-0'	0-**10**-1-**20**-4-5-**22**-**19**-**13**-0'	1	1940
90	185316	600830	2862231	0-**13**-3-6-2-**12**-0'	0-**11**-1-**20**-4-5-**19**-**10**-0'	1	860
100	92658	423713	1355481	0-**12**-1-3-6-2-**10**-0'	0-5-**20**-4-0'	1	177
110	92658	450983	1112783	0-1-**20**-5-0'	0-4-**19**-3-6-2-**10**-0'	1	112
120	61772	419941	728485	0-2-6-3-**20**-4-0'	0-1-**19**-5-0'	1	70
130	61772	420425	728485	0-2-6-3-**19**-0'	0-1-**20**-4-5-0'	1	67
140	61772	413734	717722	0-4-**19**-5-0'	0-**10**-2-6-3-1-0'	1	114
150	61772	413734	717722	0-1-3-6-2-**10**-0'	0-5-**19**-4-0'	1	164
160	30886	356486	381939	0-4-5-0'	0-1-3-6-2-**10**-0'	1	10
170	30886	356486	381939	0-1-3-6-2-**10**-0'	0-4-5-0'	1	18
180	0	324905	0	0-5-4-0'	0-2-6-3-1-0'	1	5
200	0	324905	0	0-2-6-3-1-0'	0-5-4-0'	1	5
65	123544	566686	3171244	0-**13**-2-3-**17**-6-0'	0-**13**-**17**-1-**20**-**22**-5-**22**-**20**-4-0'	2	709
80	92658	571488	1355481	0-**10**-**20**-4-5-**20**-1-**10**-0'	0-**12**-3-6-2-**12**-0'	2	136
90	92658	571055	1355481	0-**10**-6-3-2-**12**-0'	0-**12**-1-**20**-5-4-**20**-**10**-0'	2	403
100	61772	426025	773007	0-4-**20**-5-0'	0-1-**20**-3-6-2-**10**-0'	2	41
110	61772	426025	773007	0-1-**20**-5-0'	0-**10**-2-6-3-**20**-4-0'	2	149
120	30886	394444	388708	0-4-**20**-5-0'	0-1-**20**-3-6-2-0'	2	31
130	30886	394444	388708	0-1-**20**-5-0'	0-4-**20**-3-6-2-0'	2	40
140	30886	394444	388708	0-1-**20**-3-6-2-0'	0-4-**20**-5-0'	2	47
150	30886	394444	388708	0-4-**20**-3-6-2-0'	0-1-**20**-5-0'	2	23
160	30886	356486	381939	0-5-4-0'	0-**10**-2-6-3-1-0'	2	19
170	30886	356486	381939	0-4-5-0'	0-1-3-6-2-**10**-0'	2	18
180	0	324905	0	0-1-3-6-2-0'	0-4-5-0'	2	5
200	0	324905	0	0-5-4-0'	0-1-3-6-2-0'	2	5
65	123544	649628	2133795	0-**13**-**12**-**20**-**22**-5-**22**-4-**20**-**12**-**13**-0'	0-**13**-**12**-1-**20**-3-6-2-**12**-**13**-0'	150	109
80	61772	542047	968403	0-**12**-**20**-4-5-**20**-1-**12**-0'	0-**12**-3-6-2-**12**-0'	150	54
90	61772	542047	968403	0-**12**-2-6-3-**12**-0'	0-12-1-**20**-4-5-**20**-0'	150	112
100	30886	449419	388708	0-**20**-3-6-2-1-**20**-0'	0-5-**20**-4-0'	150	28
110	30886	449419	388708	0-**20**-3-6-2-1-**20**-0'	0-4-**20**-5-0'	150	29
120	30886	394444	388708	0-2-6-3-**20**-1-0'	0-4-**20**-5-0'	150	21
130	30886	394444	388708	0-2-6-3-**20**-4-0'	0-5-**20**-1-0'	150	24
140	30886	394444	388708	0-4-**20**-5-0'	0-1-**20**-3-6-2-0'	150	33
150	30886	394444	388708	0-2-6-3-**20**-4-0'	0-1-**20**-5-0'	150	27
160	30886	356486	381939	0-4-5-0'	0-1-3-6-2-**10**-0'	150	13
170	30886	356486	381939	0-**10**-2-6-3-1-0'	0-4-5-0'	150	20
180	0	324905	0	0-1-3-6-2-0'	0-5-4-0'	150	3
200	0	324905	0	0-1-3-6-2-0'	0-4-5-0'	150	3

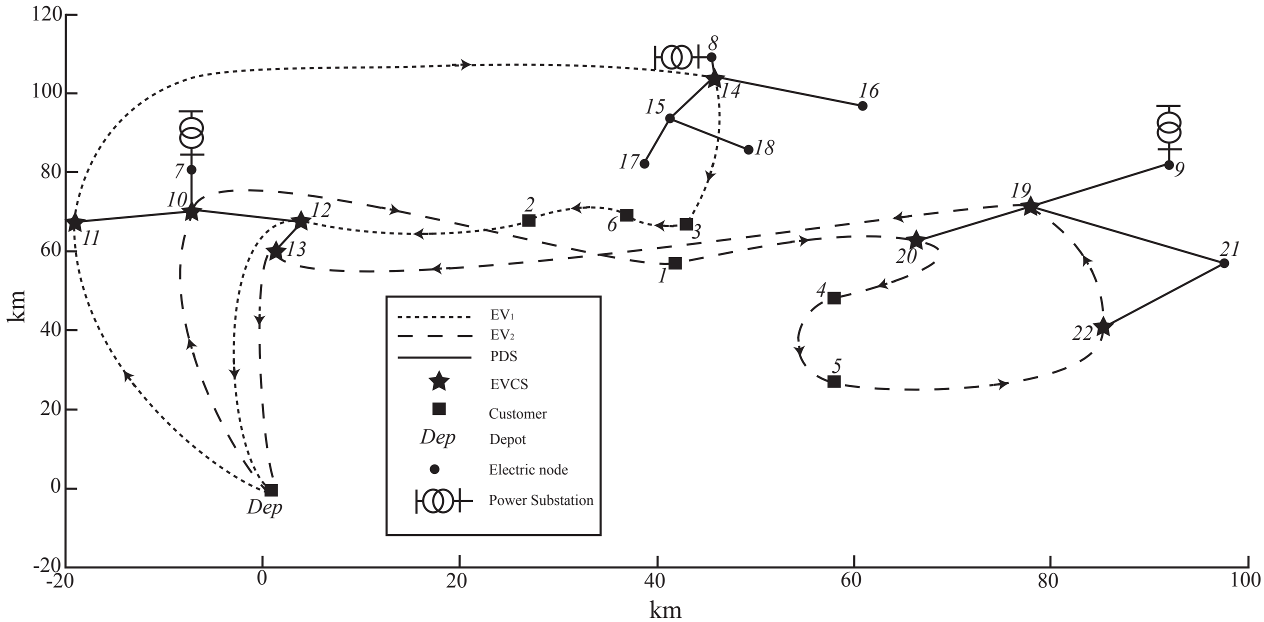

Figure 4.7: $Pn6k2 - DS16N$ with $M = 1$ and $Q = 80km$

For $M = 2$ and Q=80 km, the graphic result is shown in Figure 4.8. Due to $M = 2$, the number of arcs entering and leaving an EVCS installed can be less or equal than 2. Even if $M = 2$ some of the EVCSs receive one vehicle, which visits the EVCS, then goes to visit other customers and come back to the same EVCS to recharge the battery and continue with the travel. This case applies for EV_2, which once leaves from node 12 (EVCS installed), visits the customers at nodes 3, 6 and 2, and returns to node 12. The same situation happens for EV_1, when revisits EVCS installed at node 20 after visiting customers at nodes 4 and 5.

When $M = 150$ and Q=80 km, the behavior is pretty the same as that presented in Figure 4.8. While for $M = 2$, EV_1 visits the EVCS installed at node 10, the routing sequence (see this case in Table 4.4) changes slightly when $M = 150$, as EV_1 visits EVCS at node 12 (which is also visited by EV_2). This is the result of relaxing the parameter M with a big number, allowing the EVCS to receive several EVs. In this sense, the number of EVCSs is reduced, resulting in the decrease of energy losses in PDS.

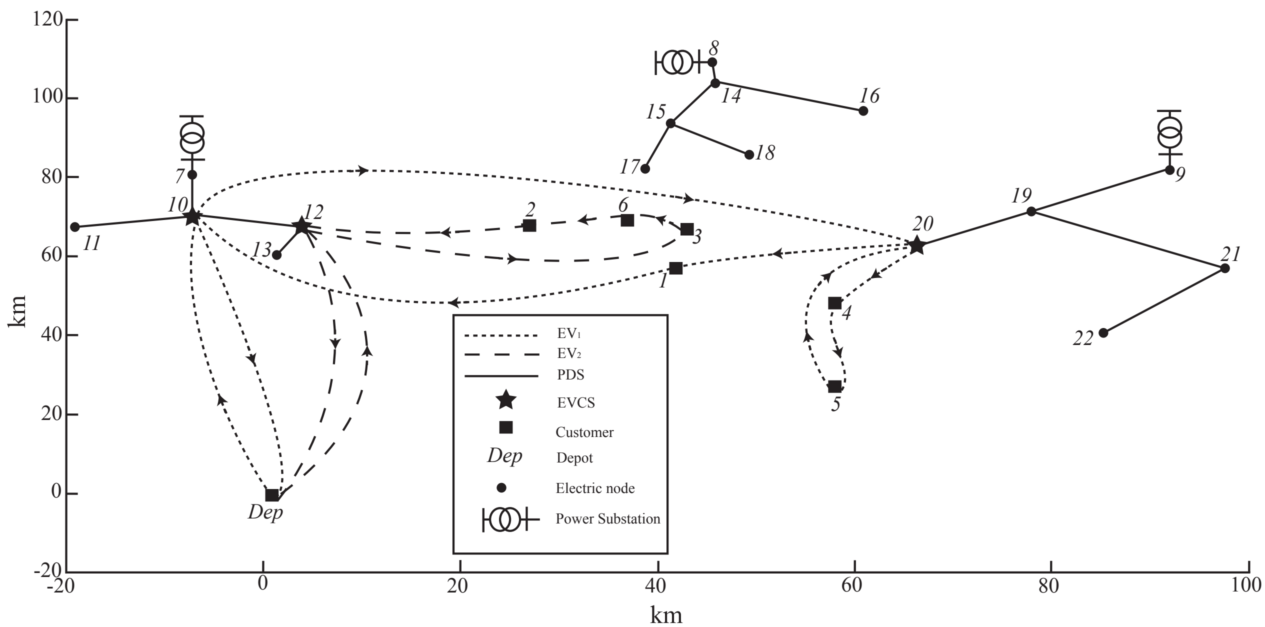

Figure 4.8: $Pn6k2 - DS16N$ with $M = 2$ and Q=80 km

4.3.2 *Pn7k3-DS34N*

Following the same dynamic with *Pn6k2-DS16N*, the results for *Pn7k3-DS34N* are presented in Table 4.5. In this latter, the execution time increases compared with *Pn6k2-DS16N* for the majority of the cases, because the introduction of more customers and vehicles (from the transportation approach), and the enlargement of the PDS contributes to a greater degree of the computational effort. In some cases all the three vehicles are used. For those runs where Q <120 km, Q <90 km and Q <30 km for $M = 1$, $M = 2$ and $M = 150$ respectively, the solver failed and was not able to find a feasible solution after too long.

Considering the situation in which $M = 150$ and $Q = 30$, the graphic solution is depicted in Figure 4.9. It is noted from this case that the EVCSs are installed as closest as possible to the power substation located at node 8, as a measure to reduce energy losses. By the other side, the revisit is done in all the ECVSs installed, due to relaxation of constraint in 4.7 by increasing parameter M. Note from Table 4.5 that this run has the longest computational time (around 8 hours) to obtain a solution, because the autonomy is slightly bigger than the distance between the depot and the closest electric node where an EVCS should be installed

Table 4.5: Results for instance $Pn7k3-DS34N$

Q [km]	α [USD]	β [USD]	ω [USD]	Details of route			M	Time [s]
				k=1	k=2	k=3		
120	61772	338027	2194760	0-6-1-5-**21**-0'	0-2-4-7-3-**22**-0'		1	11882
130	61772	327429	2073954	0-6-1-5-**10**-0'	0-3-7-4-2-**20**-0'		1	5691
140	61772	432216	1556729	0-3-7-**9**-2-4-0'	0-6-1-5-**10**-0'		1	5839
150	61772	330324	1556729	0-2-4-7-3-**9**-0'	0-**10**-5-1-6-0'		1	5730
160	30886	449912	537845	0-6-0'	0-2-4-7-3-**9**-0'	0-5-1-0'	1	626
170	0	466447	0	0-6-1-5-0'	0-3-0'	0-7-4-2-0'	1	27
180	0	326609	0	0-3-7-4-2-0'	0-6-1-5-0'		1	39
200	0	352291	0	0-7-3-2-4-0'	0-6-1-5-0'		1	11
90	61772	346245	2106560	0-**10**-6-1-5-**21**-0'	0-**21**-3-7-4-2-**10**-0'		2	32122
100	61772	337444	2073954	0-**10**-6-1-5-**10**-0'	0-**20**-2-4-7-3-**20**-0'		2	22598
110	61772	397053	1556729	0-**9**-3-7-4-2-**10**-0'	0-**9**-5-1-**10**-6-0'		2	27553
120	30886	339063	1084099	0-0'	0-6-1-5-**21**-0'	0-**21**-3-7-4-2-0'	2	1329
130	30886	329757	1051509	0-3-7-4-2-**20**-0'	0-6-1-5-**20**-0'		2	818
140	30886	327851	1017078	0-6-1-5-**10**-0'	0-3-7-4-2-**10**-0'		2	1002
150	30886	343577	537845	0-6-1-5-**9**-0'	0-2-4-7-3-**9**-0'		2	299
160	30886	343577	537845	0-**9**-3-7-4-2-0'	0-6-1-5-**9**-0'		2	103
170	0	466447	0	0-7-4-2-0'	0-5-1-6-0'	0-3-0'	2	82
180	0	326609	0	0-2-4-7-3-0'	0-5-1-6-0'		2	27
200	0	326609	0	0-0'	0-6-1-5-0'	0-3-7-4-2-0'	2	29
30	185316	509999	7986105	0-**9**-**20**-**11**-6-**12**-1-**12**-5-**12**-**11**-**20**-**9**-0'	0-**9**-**20**-**22**-2-**22**-3-**23**-4-**23**-7-**22**-**20**-**9**-0'		150	28010
60	61772	367532	2820349	0-**11**-5-1-6-**11**-0'	0-**21**-7-4-2-**21**-3-**21**-0'		150	6728
80	30886	426192	1084099	0-**21**-1-5-**21**-6-**21**-0'	0-**21**-2-4-7-3-**21**-0'		150	2683
90	30886	346314	1051509	0-**20**-2-4-7-3-**20**-0'	0-**20**-5-1-6-**20**-0'		150	411
100	30886	339333	1017078	0-**10**-6-1-5-**10**-0'	0-**10**-3-7-4-2-**10**-0'		150	1825
110	30886	339333	1017078	0-**10**-5-1-6-**10**-0'	0-**10**-2-4-7-3-**10**-0'		150	197
120	30886	339333	1017078	0-**10**-6-1-5-**10**-0'	0-**10**-2-4-7-3-**10**-0'		150	562
130	30886	453507	537845	0-**9**-2-4-7-3-**9**-0'	0-**9**-1-5-**9**-6-0'		150	177
140	30886	373938	537845	0-**9**-3-7-4-2-**9**-0'	0-**9**-6-1-5-**9**-0'		150	194
150	30886	343577	537845	0-6-1-5-**9**-0'	0-**9**-3-7-4-2-0'		150	88
160	30886	343577	537845	0-6-1-5-**9**-0'	0-2-4-7-3-**9**-0'		150	61
*160	30886	505182	3438866	0-3-7-4-**35**-1-0'	0-6-**35**-5-2-0'		150	9112
170	0	466447	0	0-6-1-5-0'	0-7-4-2-0'	0-3-0'	150	53
180	0	326609	0	0-5-1-6-0'	0-2-4-7-3-0'		150	35
200	0	326609	0	0-5-1-6-0'	0-2-4-7-3-0'		150	16

($dist(Dep, 9)$=29.33 km). This fact contributes that finding a feasible solution be hard as the battery autonomy is barely enough to complete the route.

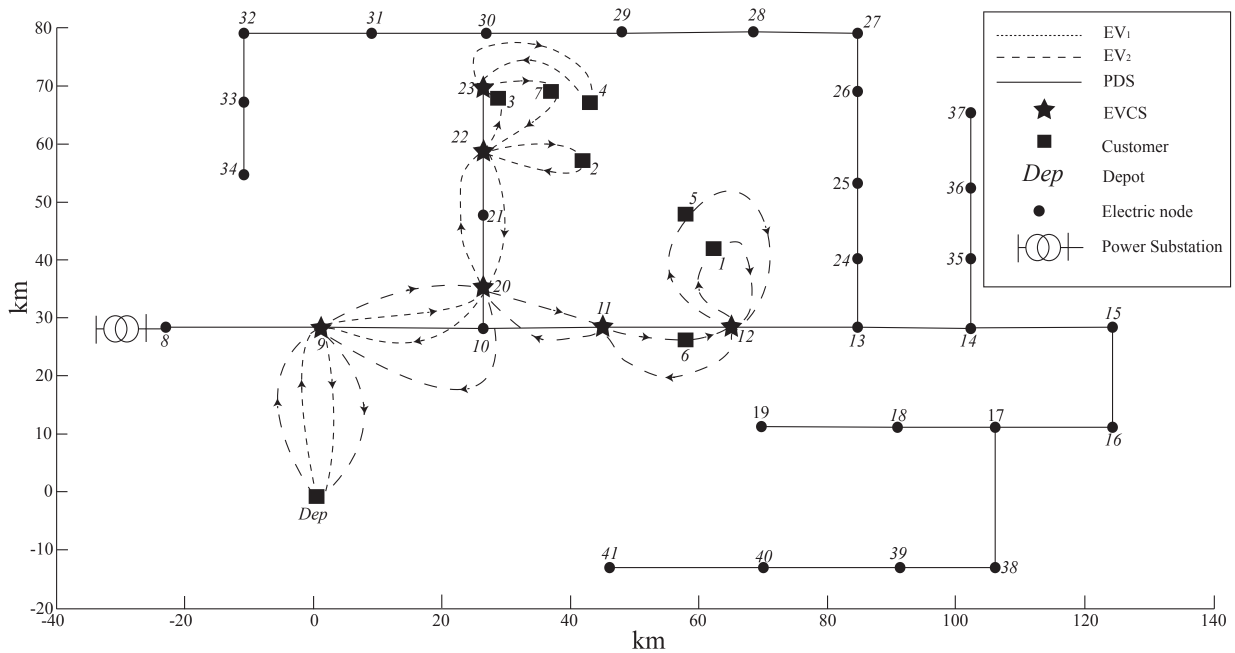

Figure 4.9: $Pn7k3 - DS34N$ with M = 150 and Q=30 km

Looking into a larger autonomy, figure 4.10 represents the solution with M = 150 and Q=160 km. In this situation, the behavior is consistent in regards with the location of the EVCS close to the power substation (at node 9). See that only one EVCS is installed to virtually increase the battery autonomy and meet the customers. However, other situations should be studied, for example: Figure 4.11 shows that a large portion of the nodes (area shaded) belonging PDS are not allowed to install EVCSs (nodes from 9 to 15 and from 20 to 30) due to other issues (limitations associated with terrain topology, public space, right of way, etc.) that are not addressed in this work. In this sense, the EVCS should be installed at the node where the energy losses be as reduced as possible. The solution shows that this can be reached by installing the EVCS at node 35, which is the next node out of the restricted area and with a less distance to the substation, compared with nodes 31, 32, 33 and 34. The costs and sequence of routes obtained for this solution are found in Table 4.5 at Q=*160 km.

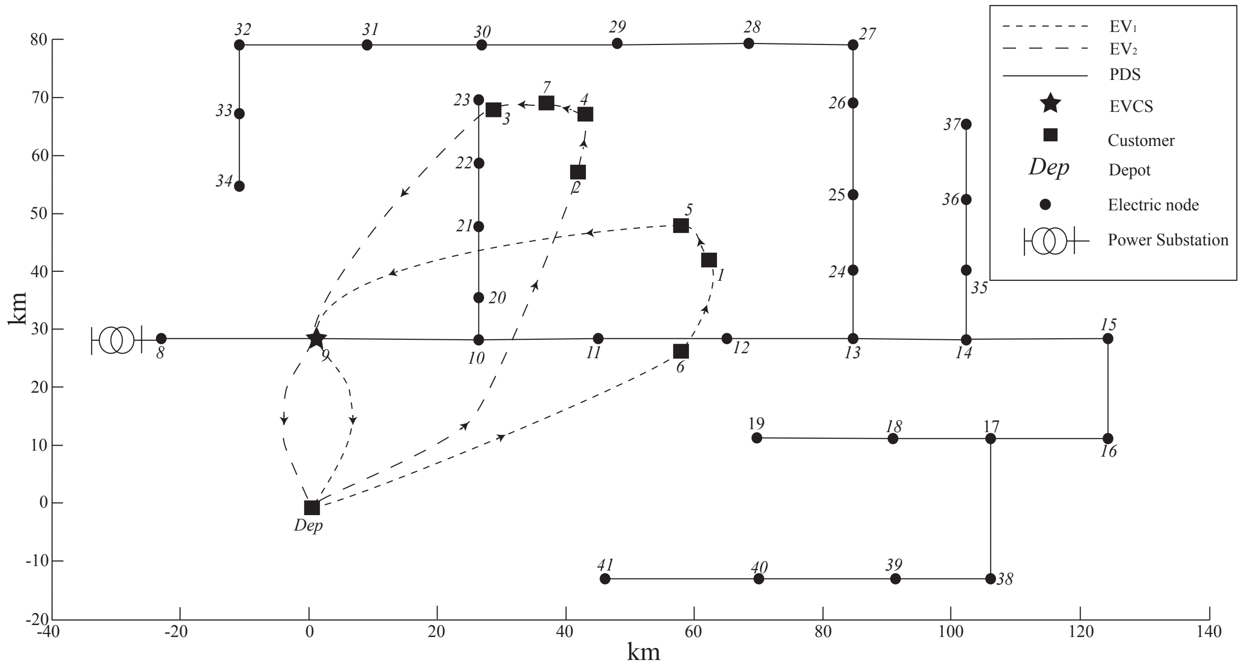

Figure 4.10: $Pn7k3 - DS34N$ with $M = 150$ and Q=160 km

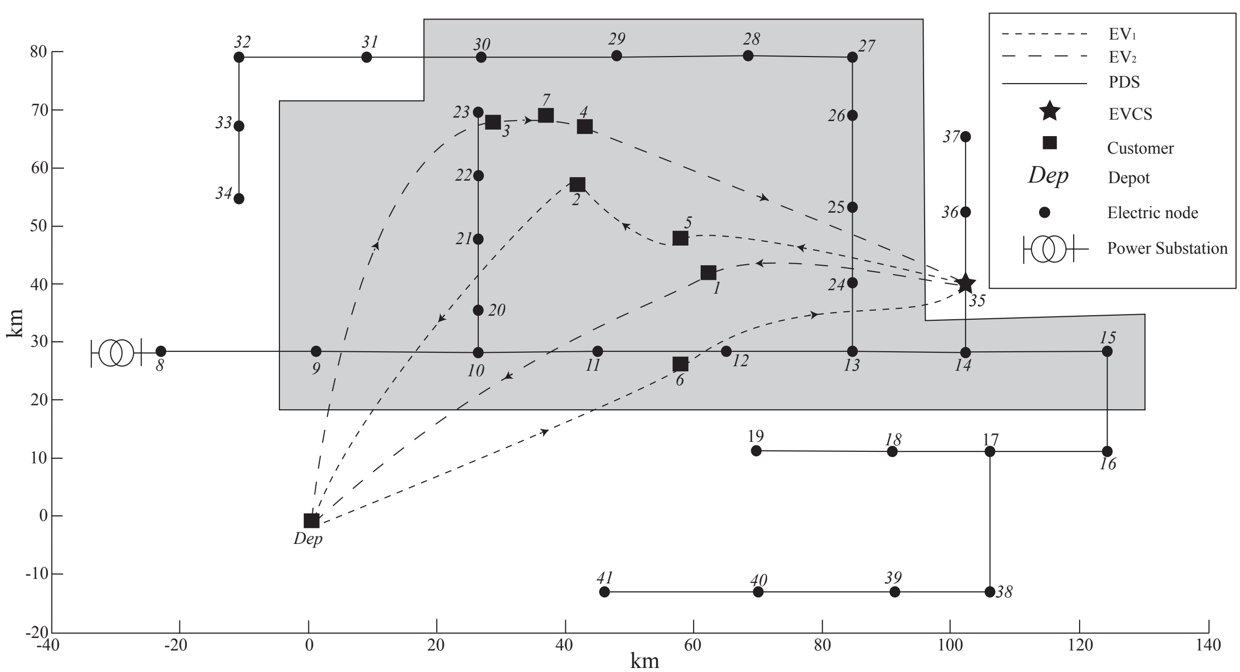

Figure 4.11: $Pn7k3 - DS34N$ with $M = 150$ and Q=160 km, restricting EVCSs at nodes 9-15 and 20-30

4.3.3 *Pn8k3-DS23N*

As mentioned before, the addition of a new customer to the transportation network, contributes to increase computational effort for finding a solution, which can be seen in Table 4.6 for instance *Pn8k3-DS23N*. Even if the mathematical model is relaxed with $M = 150$ for constraint in 4.7, run time is notably long compared with the instances *Pn6k2-DS16N* and *Pn7k3-DS34N* for similar cases of battery autonomy Q. It is not possible for solver to find a solution for cases when $M = 1$ (not presented in Table 4.6) and the installation of EVCSs is required, i.e., when the solution is different from the benchmark case. By the other side, when $M = 2$ and $Q < 160$ km no solution is found, because the number of customers and limitation in parameter M (which greatly restricts the mathematical model) makes impossible to get at least a feasible solution, due to an exact solution technique is being used.

Table 4.6: Results for instance $Pn8k3 - DS23N$

Q [km]	α [USD]	β [USD]	ω [USD]	Details of route			M	Time [s]
				k=1	k=2	k=3		
160	30886	492614	305791	0-**11**-1-6-0'	0-7-2-0'	0-**11**-3-8-5-4-0'	2	16280
170	0	489870	0	0-5-8-4-0'	0-6-2-7-0'	0-1-3-0'	2	218
180	0	482567	0	0-4-8-5-3-0'	0-1-6-0'	0-2-7-0'	2	245
60	61772	564356	996107	0-**11**-1-**25**-**11**-0'	0-**11**-7-**25**-3-4-**11**-0'	0-**11**-2-6-25-5-8-**11**-0'	150	19686
70	61772	605522	636591	0-**11**-3-**23**-1-**11**-0'	0-**11**-7-**11**-4-**11**-0'	0-**11**-2-6-**23**-5-8-**11**-0'	150	6999
80	30886	616619	305791	0-**11**-7-**11**-2-6-**11**-0'	0-**11**-3-5-8-**11**-4-**11**-0'	0-**11**-1-**11**-0'	150	7487
90	30886	510102	305791	0-**11**-1-**11**-0'	0-**11**-6-2-7-**11**-0'	0-**11**-4-8-5-3-**11**-0'	150	1133
100	30886	510102	305791	0-**11**-6-2-7-**11**-0'	0-**11**-1-**11**-0'	0-**11**-3-5-8-4-**11**-0'	150	718
110	30886	510102	305791	0-**11**-7-2-6-**11**-0'	0-**11**-1-**11**-0'	0-**11**-3-5-8-4-**11**-0'	150	1337
120	30886	494395	305791	0-7-2-6-**11**-0'	0-**11**-3-5-8-4-**11**-0'	0-1-**11**-0'	150	791
130	30886	490312	305791	0-6-1-**11**-0'	0-**11**-2-7-0'	0-4-8-5-3-**11**-0'	150	10297
140	30886	490312	305791	0-6-1-**11**-0'	0-4-8-5-3-**11**-0'	0-7-2-**11**-0'	150	189
150	30886	490312	305791	0-**11**-1-6-0'	0-**11**-3-5-8-4-0'	0-7-2-**11**-0'	150	3866
160	30886	483843	305791	0-2-7-0'	0-6-1-**11**-0'	0-4-8-5-3-**11**-0'	150	318
170	0	489870	0	0-6-2-7-0'	0-3-1-0'	0-4-8-5-0'	150	64

Routing solution with $M = 2$ and Q=160 km is shown in figure 4.12. See that Q is barely sufficient to complete a big portion of the routes length, being necessary the installation of only one EVCS for EV_2 and EV_3. EV_1 is able to meet its respective customers with autonomy assigned.

In contrast with case mentioned above, Figure 4.13 illustrates a different situation in which

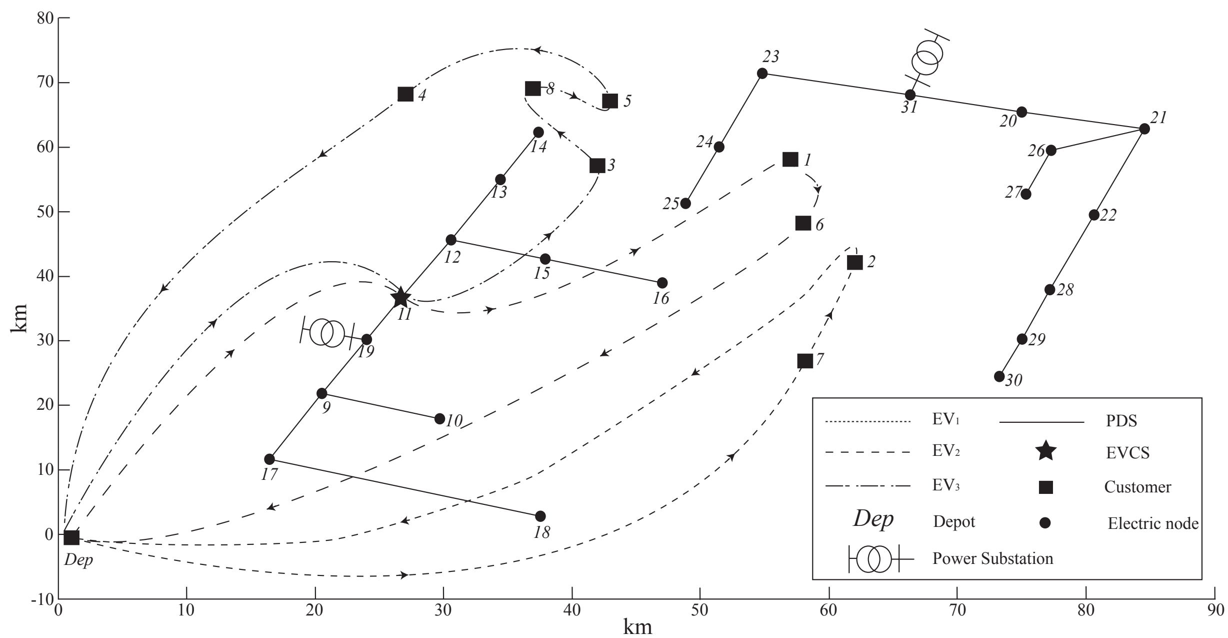

Figure 4.12: *Pn8k3-DS23N* with $M = 2$ and Q=160 km

M is increased (relaxed mathematical model) and autonomy is reduced. For $M = 150$ and Q=60 km, the installation of two EVCSs is required at both feeders of the PDS. According to Table 4.6, it is worth to mention that in this case the cost for energy losses is increased in three times compared with situation shown in Figure 4.12. Likewise, it is noted that both EVCSs are visited by all EVs to renew autonomy and meet customers.

Table 4.7 shows the average values of the objective function terms, for each value of parameter M in all three instances.

4.4 Conclusions

This chapter presented an electric vehicle integrated planning problem (EVs-IPP) model to improve the performance of transportation network and power distribution system PDS. A sensitivity analysis was performed by relaxing mathematical model and using different values of EVs' battery autonomy. In this manner, the number of EVs permitted to be recharged at a given EVCS was under control, examining different costs for each solution,

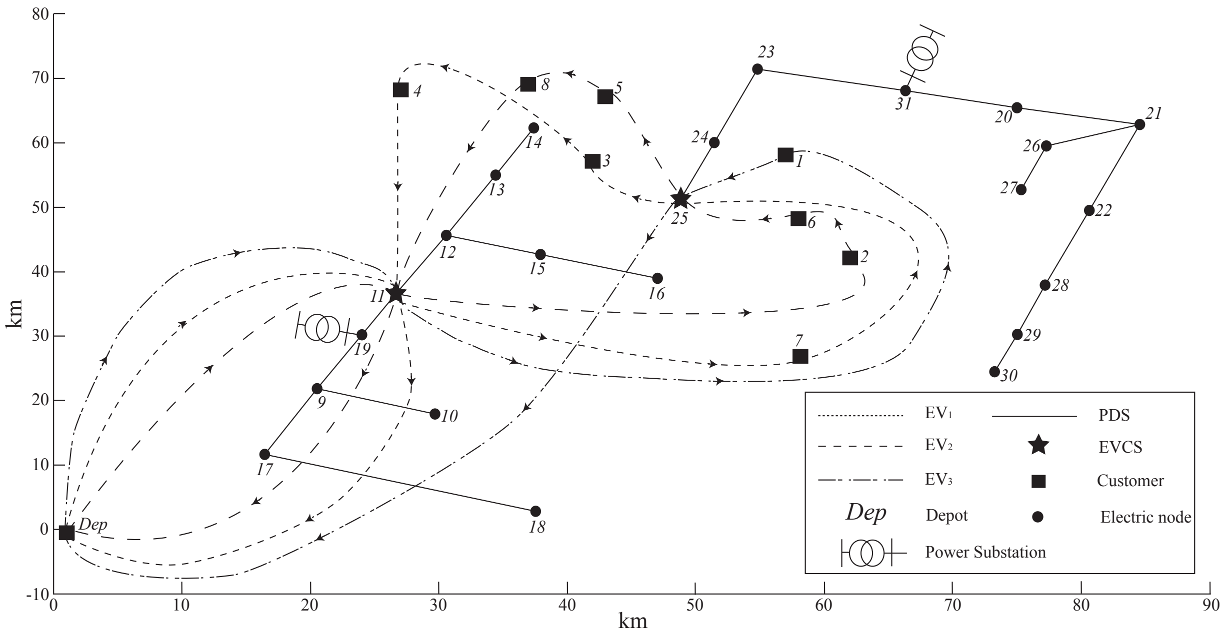

Figure 4.13: *Pn8k3-DS23N* with $M = 150$ and Q=60 km

Table 4.7: Summary of results in terms of average values

		Pn6k2-DS16N		
M	*α [USD]*	*β [USD]*	*ω [USD]*	*Time [s]*
1	83154	434893	1304304	334
2	47516	423218	749763	125
150	38013	428701	551286	36
		Pn7k3-DS34N		
1	34746	377906	990002	3730
2	30886	353112	905965	7814
150	37063	387165	1438902	3343
		Pn8k3-DS23N		
2	10295	488350	101930	5581
150	33459	521320	365401	4407

i.e., EVCSs installed along the PDS, EVs routing and energy losses. The cases in which was not necessary to install EVCSs due to the high battery autonomy, the results related with routing (transportation network approach) and power flow (PDS approach) were quite similar to those obtained in the benchmark case.

By restricting some nodes at the PDS, EVCSs were located as closest as possible to the power feeder substation, in order to make minimum the energy losses. The latter greatly contribute to objective function when the EVCSs are subjected to receive only one vehicle. In the cases, where a comparison with autonomy could be done, i.e., for *Pn6k2-DS16N* instance with $M = 1$, the energy losses cost was 16 times greater than those presented when the EVCSs are able to receive all the EVs ($M = 150$).

Due to the existence of several terms in objective function, the problem could be treated from the point of view of the multi-objective optimization. By varying weighting factors, a set of solutions can be built up, represented along a Pareto front. However, the proposed model can be solved by using meta-heuristic techniques such as NSGA II, SPEA, Epsilon Constraint, among others, to find a front of solutions with different weights for each objective. In this work, concrete values for weighting factors in the objective function were used, in order to represent consistently the priorities established by the decision maker, which would be the owner of both, the transportation and power distribution networks. Otherwise, the problem should be dealt as a bi-level problem, where the solution of the routing and EVCSs installation costs would be the input to find the energy losses on the power flow formulation.

Chapter 5

Electric vehicles routing and charging stations location: Second approach

5.1 Overview

In this chapter, the Charging Station Location Problem of Electric Vehicles for Freight Transportation (CSLP-EVFT) is presented, under the mobility patterns of freight EVs along the transportation network. The main aspects addressed in this approach are: First, the optimal location of EVCSs is performed, considering the impact on the power distribution system PDS; and second, travel patterns are focused on the mobility behavior of contracted and subcontracted fleet, which are framed respectively into the Capacitated Vehicle Routing Problem (CVRP) and the Shortest Path (SP) problem. A mixed integer linear mathematical model is proposed to portray the freight EVs travel patterns and the operation of the distribution system; the latter is achieved by using a novel power flow formulation which allows to include the effect of the grid by an affine constraint. This study is motivated by the low capacity that may be presented on the EVs' battery to provide enough autonomy to complete routes successfully, since the freight EVs are required to travel very long distances too often. EVCSs provide a virtual increase on EV's autonomy in case this latter is close to be depleted, warranting the deliveries to all the customers. On the other hand, the proper location of the EVCSs, represents a critical aspect when the energy losses of the PDS are addressed since these loads draw large quantities of energy during EV charging.

According to the works mentioned in section 2.2, the EVCSs planning in transportation networks and power distribution systems has not been widely investigated simultaneously, resulting in a real problem for the logistics firm and network operators. This works assumes that the transportation company and the distribution system belong the same owner, as objective functions and constraints of both networks are in the same mathematical model. Otherwise, the problem should be handled considering a bi-level approach, being the routing solution and EVCSs location, the input to find the energy consumption and energy losses with the power flow formulation.

Contributions of this chapter are summarized as follows:

- A new problem called CSLP-EVFT is proposed for optimal locating of EVCSs along the power distribution system and transportation network, finding optimal routes for contracted and subcontracted fleet conformed by EVs for freight transportation.
- Besides the Capacitated Vehicle Routing Problem (CVRP), the Shortest Path (SP) problem is introduced, to model EVs path that follows the route from a start point towards an end point throughout the transportation network.
- The operation with minimum power losses is evaluated by using a linear approach for the power flow on the distribution system.

5.2 CSLP-EVFT Mathematical formulation

CSLP-EVFT is divided into three subproblems: the CVRP and SP models for the mobility travels in the merchandise transportation, the strategy for optimal location of EVCSs, and the linear formulation of power flow equations in the distribution system. All of them are combined in a mathematical model, which is explained in the following subsections.

The notations used in this chapter are listed as follows, for the sake of the mathematical formulation understanding:

Sets	
N	Set of customers on the transportation network
K	Set of vehicles in the CVRP formulation
E	Set of vehicles in the SP formulation
C	Set of candidate points to install EVCSs
Parameters	
$KVEHIC$	Number of vehicles for CVRP
dem_c	Demand of merchandise at customer c
Cap	Vehicle cargo capacity
$start_e$	Initial nodes for routes traveled by vehicles in SP problem
end_e	End nodes for routes traveled by vehicles in SP problem
$d_{c,o}$	Distance from node c to node o $[km]$
$d_{d,p}$	Distance from node d to node p $[km]$
V_{nom}	Nominal voltage of the distribution system $[V]$
$S_{np_{a,b,c}}$	Constant power load at electrical node n $[W]$
$S_{ni_{a,b,c}}$	Constant current load at electrical node n $[W]$
$S_{nz_{a,b,c}}$	Constant impedance load at electrical node n $[W]$
$T_{a,b,c}$	Three-phase unit vector
C_{km}	Cost per kilometer traveled $[USD/km]$
$C_{main-km}$	Maintenance cost in terms of kilometers traveled $[USD/km]$
f_a	Annualization factor
nt	Number of years in which the operation is considered, (routing and energy consumption)
CPI	Consumer Price Index
C_{const}	Construction cost of EVCS $[USD]$
P_{bat}	EVCS nominal power $[W]$

C_{energy}	Cost of energy $[USD/kWh]$
$Losses_{w/outEVs}$	Power losses in the distribution system without electric vehicles (Benchmark case) $[W]$

Variables

$Yvisit_{c,k}$	Binary decision variable for CVRP with value of 1 if vehicle k visits the customer at transportation node c, and 0 otherwise
$x_{c,o,k}$	Binary decision variable for CVRP, with value of 1 if vehicle k goes from node c to node o of the transportation network and 0 otherwise
$t_{c,o}$	Remaining merchandise to be delivered at arc $c - o$
$y_{d,p,e}$	Binary decision variable in SP problem, taking the value of 1 if vehicle e goes from node d to node p and 0 otherwise
$adist_{c,k}$	Distance traveled at node c by vehicle k in CVRP $[km]$
$Qbat_{cvrp}$	Battery autonomy of the vehicles in CVRP $[km]$
$adistaux_{o,k}$	Auxiliar variable for distance traveled at node o by vehicle k in CVRP $[km]$
$Ycvrp_o$	Binary decision variable in CVRP, taking the value of 1 if an EVCS is installed at node o and 0 otherwise
$adistSP_{d,e}$	Distance traveled at node d by vehicle e in SP problem $[km]$
$Qbat_{SP}$	Battery autonomy of the vehicles in SP problem $[km]$
$Ysp_{p,e}$	Binary decision variable in SP problem, taking the value of 1 if an EVCS is installed at node p, and 0 otherwise
$adistauxSP_{o,e}$	Auxiliar variable for distance traveled at node o by vehicle e in SP problem $[km]$
$Uaux_v$	Unification variable for $Ycvrp_o$ and $Ysp_{p,e}$ at node v
$I_{S_{a,b,c}}$	Three-phase current at slack node $[A]$
$I_{n_{a,b,c}}$	Three-phase current at electrical node n other than the slack node $[A]$
$V_{S_{a,b,c}}$	Three-phase voltage at slack node $[V]$
$V_{n_{a,b,c}}$	Three-phase voltage at electrical node n other than the slack node$[V]$
$Losses$	Power losses in the distribution system $[W]$

5.2.1 Capacitated Vehicle Routing Problem (CVRP)

Vehicles utilized in merchandise transportation, are in accordance with the mobility patterns assigned by the CVRP. This implies that a fleet of vehicles with limited cargo capacity leaves from a unique depot, deliver merchandise to several customers and come back to depot, following the behavior of a contracted fleet (belonging to the depot owner). The vehicles have to fully meet the merchandise demands, seeking a travelling minimal cost (Toth and Vigo, 2002). Equations 5.1 to 5.10 represent the CVRP formulation, taking into consideration a fixed number of EVs in the problem.

$$\sum_{k \in K} Yvisit_{c,k} = 1 \quad \forall c \in N \backslash \{Dep\} \tag{5.1}$$

$$\sum_{c \in N} \sum_{k \in K} x_{c,o,k} = 1 \quad \forall o \in N \backslash \{Dep\} \tag{5.2}$$

$$\sum_{c \in N} \sum_{k \in K} x_{o,c,k} = 1 \quad \forall o \in N \backslash \{Dep\} \tag{5.3}$$

$$\sum_{k \in K} \sum_{o \in N} x_{Dep,o,k} = KVEHIC \tag{5.4}$$

$$\sum_{k \in K} \sum_{o \in N} x_{o,Dep,k} = KVEHIC \tag{5.5}$$

$$\sum_{o \in N} x_{o,c,k} = Yvisit_{c,k} \quad \forall c \in N \forall k \in K \tag{5.6}$$

$$\sum_{\substack{q \in N \\ c \neq q}} t_{q,c} = \sum_{\substack{o \in N \\ c \neq o}} t_{c,o} + dem_c \quad \forall c \in N \backslash \{Dep\} \tag{5.7}$$

$$\sum_{\substack{c \in N \\ c \neq Dep}} t_{Dep,c} = \sum_{\substack{c \in N \\ c \neq Dep}} dem_c \tag{5.8}$$

$$t_{c,o} \leq \sum_{k \in K} Cap \cdot x_{c,o,k} \quad \forall c \in N, \forall o \in N \tag{5.9}$$

$$t_{c,Dep} = 0 \quad \forall c \in N \backslash \{Dep\} \tag{5.10}$$

Equation 5.1 imposes that one vehicle is assigned to one customer. Equations 5.2 and 5.3 are indegree and outdegree constraints, which impose that exactly one arc enters and leaves each vertex associated with each customer, respectively. Similarly, 5.4 and 5.5 show the degree requirements for the depot vertex, e.g., the number of vehicles leaving the depot has to be the same as the number of vehicles entering the depot. Equation 5.6 avoids the visit to a customer by several vehicles. The flow of merchandise through each arc is tracked by 5.7. In 5.8 the summation of the flows of merchandise leaving the depot should be equal to the total customers demand to be delivered. Equation 5.9 denotes that the remaining merchandise flowing through each arc is less than the cargo capacity of the vehicle. In 5.10, the remaining merchandise to be delivered is null just before completing the route.

5.2.2 Shortest Path (SP) problem

Other modes of freight transportation are developed in accordance with the SP problem, in which the vehicles have to travel from a start point to an end point, minimizing the travel distance (Pallottino and Scutella, 1998). This mode of transportation is in accordance with the subcontracted fleet, as the transportation company is only pending that merchandise is delivered at the destination point, no matters how or which route the vehicle (belonging the subcontracted fleet) takes to come back to the start point. Equations 5.11 to 5.13 depict the SP formulation, considering a fixed number of vehicles.

$$\sum_{p \in N} y_{d,p,e} - \sum_{p \in N} y_{p,d,e} = 1 \quad \forall d \in N, \forall e \in E, d = start_e \tag{5.11}$$

$$\sum_{p \in N} y_{d,p,e} - \sum_{p \in N} y_{p,d,e} = 0 \quad \forall d \in N, \forall e \in E, d \neq start_e, d \neq end_e \tag{5.12}$$

$$\sum_{p \in N} y_{d,p,e} - \sum_{p \in N} y_{p,d,e} = -1 \quad \forall d \in N, \forall e \in E, d = end_e \tag{5.13}$$

Equation 5.11 imposes that only one arc leaves from the start point of the route. In 5.12 the number of arcs leaving from an intermediate node has to be the same as the number of arcs entering the node. Equation 5.13 details that only one arc enters the end point of the route.

5.2.3 EVCSs location for CVRP

The EVCSs planning is related with the optimal location of these infrastructures along the transportation network. A key element on the EVCSs location is the battery autonomy consumption which is in terms of the distance being traveled on the route. Equation 5.14 describes the distance traveled at any node other than the depot and the candidate nodes to charging stations.

$$\begin{gathered} x_{Dep,o,k} \cdot d_{Dep,o} + \sum_{\substack{c \in N \\ c \neq Dep \\ c \neq o}} x_{c,o,k} \cdot (d_{c,o} + adist_{c,k}) = adist_{o,k} \\ \forall o \in N, \forall k \in K, o \neq Dep, o \notin C \end{gathered} \tag{5.14}$$

Notice that one of the expressions involved in 5.14 is a non-linear term, i.e., the product between a binary variable and continuous variable, $x_{c,o,k} \cdot adist_{c,k}$. This latter is linearized according to the mathematical approach depicted in 5.15, replacing the product $x_{c,o,k} \cdot adist_{c,k}$ by $gl_{c,o,k}$. In 5.16, the distance accumulated at node c is assigned to vehicle k for the arc $c - o$.

$$|gl_{c,o,k} - adist_{c,k}| \leq Qbat_{cvrp} \cdot (1 - x_{c,o,k}) \quad \forall c \in N, \forall o \in N, \forall k \in K, c \neq Dep \tag{5.15}$$

$$gl_{c,o,k} \leq Qbat_{cvrp} \cdot x_{c,o,k} \quad \forall c \in N, \forall o \in N, \forall k \in K, c \neq Dep \tag{5.16}$$

Equation 5.15 is equivalent to the expression in 5.17, considering the absolute value definition.

$$\begin{aligned} &-Qbat_{cvrp} \cdot (1 - x_{c,o,k}) \leq gl_{c,o,k} - adist_{c,k} \leq Qbat_{cvrp} \cdot (1 - x_{c,o,k}) \\ &\forall c \in N, \forall o \in N, \forall k \in K, c \neq Dep \end{aligned} \tag{5.17}$$

In this sense, 5.14 is written in a linear form as shown in 5.18.

$$\begin{aligned} &x_{Dep,o,k} \cdot d_{Dep,o} + \sum_{\substack{c \in N \\ c \neq Dep \\ c \neq o}} x_{c,o,k} \cdot d_{c,o} + gl_{c,o,k} = adist_{o,k} \\ &\forall o \in N, \forall k \in K, o \neq Dep, o \notin C \end{aligned} \tag{5.18}$$

The distance traveled at the depot once the route is completed, is given by 5.19.

$$\sum_{\substack{c \in N \\ c \neq Dep}} x_{c,Dep,k} \cdot d_{c,Dep} + gl_{c,Dep,k} = adist_{Dep,k} \quad \forall k \in K \tag{5.19}$$

The installation of an EVCS at the transportation node, involves the resetting of distance traveled so far, which is translated in making zero the value of $adist_{o,k}$. Note in 5.20 that when an ECVS is installed, this is, $Ycvrp_o = 1$, the variable $adist_{o,k}$ is reset. If $Ycvrp_o = 0$, then Equation 5.20 keeps valid.

$$adist_{o,k} \leq (1 - Ycvrp_o) \cdot Qbat_{cvrp} \quad \forall o \in C, \forall k \in K, o \neq Dep \tag{5.20}$$

An auxiliary variable $adistaux_{o,k}$ for the distance traveled $adist_{o,k}$ is required to avoid a conflict when the EVCS is installed and $adist_{o,k}$ becomes null. Equation 5.21 shows $adistaux_{o,k}$, which is calculated for all the nodes of the transportation network.

$$x_{Dep,o,k} \cdot d_{Dep,o} + \sum_{\substack{c \in N \\ c \neq Dep \\ c \neq o}} x_{c,o,k} \cdot d_{c,o} + gl_{c,o,k} = adistaux_{o,k} \quad \forall o \in N, \forall k \in K \tag{5.21}$$

Equation 5.22 synchronizes the connection between $adist_{o,k}$ and $adistaux_{o,k}$. If, $Ycvrp_o = 0$ (non-installation of an EVCS), the variables $adist_{o,k}$ and $adistaux_{o,k}$ are equal, otherwise, the equation keeps valid.

$$|adistaux_{o,k} - adist_{o,k}| \leq Qbat_{cvrp} \cdot Ycvrp_o \quad \forall o \in C, \forall k \in K, o \neq Dep \tag{5.22}$$

Equation 5.22 is equivalent to 5.23, in accordance with absolute value definition.

$$\begin{aligned} &-Qbat_{cvrp} \cdot Ycvrp_o \leq adistaux_{o,k} - adist_{o,k} \leq Qbat_{cvrp} \cdot Ycvrp_o \\ &\forall o \in C, \forall k \in K, o \neq Dep \end{aligned} \tag{5.23}$$

In Equations 5.24 and 5.25 the values for both $adist_{c,k}$ and $adistaux_{c,k}$ should not be greater than the battery autonomy . Equation 5.26 specifies the non-negativity of the EVCSs to be installed.

$$adist_{c,k} \leq Qbat_{cvrp} \cdot Yvisit_{c,k} \quad \forall c \in N, \forall k \in K, c \neq Dep \tag{5.24}$$

$$adistaux_{c,k} \leq Qbat_{cvrp} \cdot Yvisit_{c,k} \quad \forall c \in N, \forall k \in K, c \neq Dep \tag{5.25}$$

$$\sum_{c \in C} Ycvrp_c \geq 0 \tag{5.26}$$

5.2.4 EVCSs location for SP problem

For the EVs that follow the SP problem, the EVCSs location is quite similar to the strategy treated for CVRP, except that in this case there is no depot due to the nature of SP problem, instead, the start point for the EV's route is considered.

The distance traveled at any node is depicted in 5.27, since the node is not a candidate for charging station. However, the presence of the non-linearity $y_{d,p,e} \cdot adistSP_{d,e}$ leads to the linearization in 5.28, being $glSP_{d,p,e}$ the variable that replaces this product. Equation 5.28 is equivalent to 5.29 due to the absolute value concept. In 5.30, the distance accumulated in d is assigned to the vehicle e for the arc $d - p$.

$$\begin{aligned} &\sum_{\substack{d \in N \\ d = start_e}} y_{d,p,e} \cdot d_{d,p} + \sum_{\substack{d \in N \\ d \neq start_e}} y_{d,p,e} \cdot (d_{d,p} + adistSP_{d,e}) = adistSP_{p,e} \\ &\forall p \in N, \forall e \in E, \text{p} \notin C \end{aligned} \tag{5.27}$$

$$\begin{aligned} &|glSP_{d,p,e} - adistSP_{d,e}| \leq Qbat_{sp} \cdot (1 - y_{d,p,e}) \\ &\forall p \in N, \forall e \in E, \text{p} \notin C \end{aligned} \tag{5.28}$$

$$\begin{aligned} &-Qbat_{sp} \cdot (1 - y_{d,p,e}) \leq glSP_{d,p,e} - adistSP_{d,e} \leq Qbat_{sp} \cdot (1 - y_{d,p,e}) \\ &\forall d \in N, \forall p \in N, \forall e \in E, d \neq start_e \end{aligned} \tag{5.29}$$

$$glSP_{d,p,e} \leq Qbat_{sp} \cdot y_{d,p,e} \quad \forall d \in N, \forall p \in N, \forall e \in E, d \neq start_e \tag{5.30}$$

In this sense, 5.27 is replaced by 5.31.

$$\begin{aligned} &\sum_{\substack{d \in N \\ d = start_e}} y_{d,p,e} \cdot d_{d,p} + \sum_{\substack{d \in N \\ d \neq start_e}} y_{d,p,e} \cdot d_{d,p} + glSP_{d,p,e} = adistSP_{p,e} \\ &\forall p \in N, \forall e \in E, p \notin C \end{aligned} \tag{5.31}$$

Equation 5.32 performs the resetting of $adistSP_{p,e}$ when the EVCS is installed.

$$adistSP_{p,e} \leq (1 - Ysp_{p,e}) \cdot Qbat_{sp} \quad \forall p \in C, \forall e \in E \tag{5.32}$$

For the distance traveled $adistSP_{p,e}$, an auxiliary variable $adistauxSP_{p,e}$, computed in 5.33, is also necessary to avoid a mathematical conflict when the EVCS is installed and $adistSP_{p,e}$

becomes null. See in 5.34 the non-negativity of the number of EVCSs installed for the EVs that follow the SP mobility patterns.

$$\sum_{\substack{d \in N \\ d = start_e}} y_{d,p,e} \cdot d_{d,p} + \sum_{\substack{d \in N \\ d \neq start_e}} y_{d,p,e} \cdot d_{d,p} + glSP_{d,p,e} = adistauxSP_{p,e} \quad \forall p \in N, \forall e \in E \tag{5.33}$$

$$\sum_{d \in C} \sum_{e \in E} Ysp_{d,e} \geq 0 \tag{5.34}$$

5.2.5 Unifying variables of EVCSs installation

As noticed before, the installation of EVCSs is treated separately for CVRP and SP problem, due to the difference in EVs travel behaviors for each approach. With this in mind, both, $Ycvrp_c$ and $Ysp_{d,e}$ are merged into $Uaux_v$ in order to represent the installation of charging stations of EVs that follow either the CVRP or SP focuses. This unification is carried out in Equations 5.35 to 5.37.

$$\sum_{\substack{p \in N \\ p = v}} Ysp_{p,e} - 1 \leq Uaux_v - 1 \leq -\sum_{\substack{p \in N \\ p = v}} Ysp_{p,e} + 1 \quad \forall v \in N, \forall e \in E \tag{5.35}$$

$$\sum_{\substack{c \in N \\ c = v}} Ycvrp_c - 1 \leq Uaux_v - 1 \leq -\sum_{\substack{c \in N \\ c = v}} Ycvrp_c + 1 \quad \forall v \in N \tag{5.36}$$

$$-\sum_{\substack{c \in N \\ c = v}} Ycvrp_c - \sum_{\substack{p \in N \\ p = v}} \sum_{e \in E} Ysp_{p,e} \leq Uaux_v \leq \sum_{\substack{c \in N \\ c = v}} Ycvrp_c + \sum_{\substack{p \in N \\ p = v}} \sum_{e \in E} Ysp_{p,e} \quad \forall v \in N \tag{5.37}$$

5.2.6 Power flow linear formulation

The installation of an EVCS at a transportation node leads to the energy consumption from the power distribution network, as long as the transportation node is an EVCS candidate (located on the same coordinates as the power distribution node). The operation of the electric network is assessed through the methodology shown in (Garces, 2016), which addresses a linear approximation of power flow on the complex plane. Nodal voltages and currents are represented through the admittance matrix Y of the electric network, expressed in 5.38.

$$\begin{bmatrix} I_{S_{a,b,c}} \\ I_{n_{a,b,c}} \end{bmatrix} = \begin{bmatrix} Y_{SS_{a,b,c}} & Y_{Sn_{a,b,c}} \\ Y_{nS_{a,b,c}} & Y_{nn_{a,b,c}} \end{bmatrix} \begin{bmatrix} V_{S_{a,b,c}} \\ V_{n_{a,b,c}} \end{bmatrix} \tag{5.38}$$

where S is the Slack node and n are the remaining nodes. Loads on the power distribution system are represented in 5.39 according to the ZIP model.

$$S = S_n \left(\frac{V_n}{V_{nom}} \right)^{\alpha} \tag{5.39}$$

The exponent α takes the value of 0, 1 or 2 for the constant power, current and impedance load respectively. If a Wye connected load is at node n, V_n is the line to neutral voltage; otherwise it would be a line to line voltage for Delta-connected loads. Supported by the expression in 5.39, the voltage and current of a node can be associated in 5.40 as follows:

$$I_{n_{a,b,c}} = \frac{S^*_{np_{a,b,c}}}{V^*_{n_{a,b,c}}} + h \cdot S^*_{ni_{a,b,c}} + h^2 \cdot S^*_{nz_{a,b,c}} \cdot V_{n_{a,b,c}} \quad h = \frac{1}{V_{nom}} \tag{5.40}$$

Being n any node other than the Slack node; p, i, z, are the indices for the constant power, current and impedance load respectively. The a,b,c indices represent the three-phase system. Notice the ZIP model is linear in $V_{n_{a,b,c}}$ except for the constant power loads. This term is approximated in order to obtain a linear power flow.

A linear approximation is developed on the complex numbers (Flanigan, 1972) and not on the real set as in the conventional power flow formulations. The function $f(\Delta V) = 1/(1 - \Delta V)$ is analytic for all $\|\Delta V\| < 1$. By using Taylor series around zero, the expression in 5.41 is obtained.

$$\frac{1}{1-\Delta V} = \sum_{n=0}^{\infty} (\Delta V)^n \quad \|\Delta V\| < 1 \tag{5.41}$$

A linear form is shown in 5.42 by neglecting high order terms and defining $V = 1 - \Delta V$.

$$\frac{1}{V} = \frac{1}{1-\Delta V} \approx 1 + \Delta V = 2 - V \tag{5.42}$$

Notice that 5.42 is valid for values of V close to 1 p.u. for example, the error for $V = 0.8$, this is, $\Delta V = 0.2$, is around 5% and decreases as V approaches to 1.

Considering the Wye-connected loads, the first term of 5.40 is multiplied in the numerator and denominator by $T_{a,b,c}/V_{nom}$, where $T_{a,b,c} = [1, e^{-2\pi/3j}, e^{2\pi/3j}]^T$. Then, this term becomes linear as presented in 5.43.

$$\frac{S^*_{np_{a,b,c}}}{V^*_{n_{a,b,c}}} = \frac{S^*_{np_{a,b,c}}}{V^*_{n_{a,b,c}}} \cdot \frac{1/\left(T_{a,b,c}/V_{nom}\right)}{1/\left(T_{a,b,c}/V_{nom}\right)} = h \cdot S^*_{np_{a,b,c}} \circ \left(2 - h \cdot V^*_{n_{a,b,c}} \circ T_{a,b,c}\right) \circ T_{a,b,c} \tag{5.43}$$

See that $(\cdot)$ is the conventional product and $(\circ)$ is the Hadamard product. In this manner, 5.40 is converted into 5.44:

$$I_{n_{a,b,c}} = 2h \cdot S^*_{np_{a,b,c}} \circ T_{a,b,c} - h^2 \cdot S^*_{np_{a,b,c}} \circ V^*_{n_{a,b,c}} \circ T^2_{a,b,c} + h \cdot S^*_{ni_{a,b,c}} + h^2 \cdot diag\left(S^*_{nz_{a,b,c}}\right) \cdot V_{n_{a,b,c}} \tag{5.44}$$

In 5.38 the expression for $I_{k_{a,b,c}}$ can be rewritten as follows:

$$I_{n_{a,b,c}} = Y_{nS_{a,b,c}} \cdot V_{S_{a,b,c}} + Y_{nn_{a,b,c}} \cdot V_{n_{a,b,c}} \tag{5.45}$$

Then, making equal 5.44 and 5.45, and after arranging some terms, 5.46, 5.47 and 5.48 are obtained:

$$A = Y_{nS_{a,b,c}} \cdot V_{S_{a,b,c}} - 2h \cdot S^*_{np_{a,b,c}} \circ T_{a,b,c} - h \cdot S^*_{ni_{a,b,c}} \tag{5.46}$$

$$B = h^2 \cdot S^*_{np_{a,b,c}} \circ T^2_{a,b,c} \tag{5.47}$$

$$C = Y_{nn_{a,b,c}} - h^2 \cdot diag\left(S^*_{nz_{a,b,c}}\right) \tag{5.48}$$

Notice that the terms above are in accordance with $A + B \circ V^*_{n_{a,b,c}} + C \cdot V_{n_{a,b,c}} = 0$. This latter requires to be solved in rectangular representation, as shown in 5.49, to obtain the nodal voltages.

$$\begin{bmatrix} -A_r \\ -A_i \end{bmatrix} = \begin{bmatrix} B_r + C_r & B_i - C_i \\ B_i + C_i & -B_r + C_r \end{bmatrix} \begin{bmatrix} V_r \\ V_i \end{bmatrix} \tag{5.49}$$

where r and i indicate real and imaginary part, respectively.

5.2.7 Objective function

The equations 5.1 to 5.49 mentioned earlier, represent the constraints of the proposed CSLP-EVFT. The objective function is composed by the summation of six terms, shown in 5.50 to 5.55, in which the installation and operation costs are involved.

$$C_1 = \left(365 \cdot (C_{km} + C_{main-km}) \cdot \sum_{c\in N}\sum_{o\in N}\sum_{k\in K} x_{c,o,k} \cdot d_{c,o}\right) \cdot f_a \tag{5.50}$$

$$C_2 = \left(365 \cdot (C_{km} + C_{main-km}) \cdot \sum_{d\in N}\sum_{p\in N}\sum_{e\in E} y_{d,p,e} \cdot d_{d,p}\right) \cdot f_a \tag{5.51}$$

Equation 5.50 and 5.51 are the costs associated with the routing performed by the EVs that follow the mobility patterns of CVRP and SP problem respectively. It is assumed that the routes are repeated daily along one year and the maintenance cost is also considered within the cost per kilometer traveled. The cost of EVCSs installation are depicted in 5.52, and the operation costs related with EVCSs energy consumption, are established in 5.53 and 5.54 for the CVRP and SP problem respectively. Notice that the time that an EV (either for CVRP or SP problem) takes to fully charge its battery is considered to be 0.5 hours (fast charging), assuming that this time will not affect the time to perform the routing.

$$C_3 = C_{const} \cdot \sum_{v \in N} Uaux_v \tag{5.52}$$

$$C_4 = \left(365 \cdot 0.5 \cdot P_{bat} \cdot C_{energy} \cdot \sum_{c \in N} Ycvrp_c \right) \cdot f_a \tag{5.53}$$

$$C_5 = \left(365 \cdot 0.5 \cdot P_{bat} \cdot C_{energy} \cdot \sum_{p \in N} \sum_{e \in E} Ysp_{p,e} \right) \cdot f_a \tag{5.54}$$

Energy losses of the distribution system are computed in 5.55, based on the difference with respect to the benchmark case energy losses, e.g., without EVCSs. The term *Losses* is a non-linear expression that is deployed in 5.56 and 5.57.

$$C_6 = (365 \cdot 0.5 \cdot C_{energy}) \cdot \left(Losses - Losses_{w/outEVs} \right) \cdot f_a \tag{5.55}$$

$$Losses = V_R^T G_{BUS} V_R + V_I^T G_{BUS} V_I \tag{5.56}$$

$$Losses = \begin{pmatrix} V_{RS} G_{SS} V_{RS} + V_{RS} G_{Sk} V_{Rk} + \\ V_{Rn} G_{nS} V_{RS} + V_{Rn} G_{nn} V_{Rn} + \\ V_{IS} G_{SS} V_{IS} + V_{IS} G_{Sn} V_{In} + \\ V_{In} G_{SS} V_{IS} + V_{In} G_{nn} V_{In} \end{pmatrix} \tag{5.57}$$

where G_{BUS} is the real part of admittance matrix and, V_R and V_I are the real and imaginary parts of nodal voltages respectively.

All of the costs except C_3, are affected by a factor of annualization f_a to shift to present value the operation costs along the future years, which is computed according to 5.58. Notice that nt corresponds to the number of years in which the operation (routing and energy consumption) is considered and CPI is the Consumer Price Index.

$$f_a = \frac{nt}{(1 + CPI)^{nt}} \tag{5.58}$$

5.3 Test systems and CSLP-EVFT mathematical model validation

In order to validate the mathematical model proposed, two different test instances composed by combination of transportation networks and power distribution systems are proposed. Transportation and power networks are chosen from (Augerat, 2013) and (Feeders, 2013) respectively. Detailed information of these test systems can also be found in Section C.

The first system, shown in Figure 5.1, is formed by the CVRP instance $Pn19k2$ and the 34 node distribution test system, which is named $Pn19k2 - IEEE34$. Note that nodes joined with continuous line represent the power distribution system, being node 800 the distribution substation. Customers (drawn as solid squares) are identified by the numbers enclosed in squares, and electric nodes are in solid circles. Some nodes of the power network are made to coincide with the spatial location of all or part of the transportation network customers. These points are the candidate nodes for EVCSs.

A larger size test system is composed by the combination between the CVRP instance $En22k4$ and the 123 node distribution test system. The resulting test system is named $En22k4 - IEEE123$ and shown in Figure 5.2. Note that all the customers coincide with a node of the power network, except the depot node, which is identified with the number 1 enclosed in square. The distribution substation is located at node 150.

CSLP-EVFT mathematical model validation is carried out by providing a large enough amount of EV battery autonomy $Qbat_{CVRP}$ and $Qbat_{SP}$, in order to avoid the installation of EVCSs. In this sense the result for both transportation and power networks correspond to benchmark cases. Table 5.2 presents the objective function and the routes performed by the vehicles in each instance, considering only the transportation network.

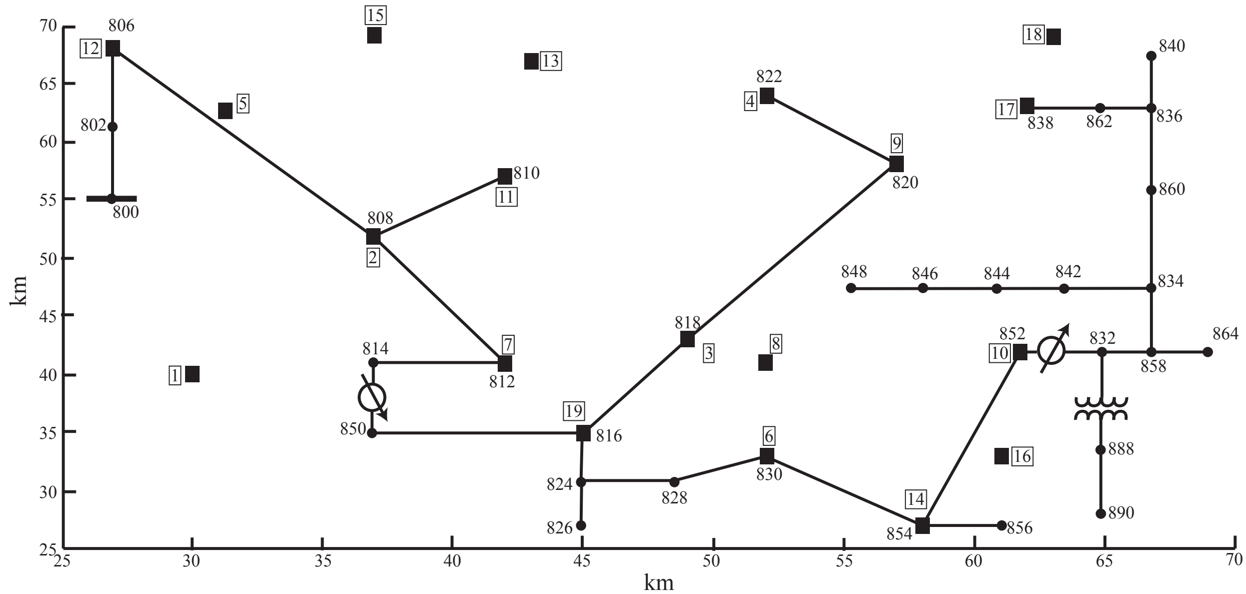

Figure 5.1: *Pn19k2-IEEE34* test system

Table 5.2: Benchmark case results with the transportation network approach

Instance	Objective function	Details of route	Time [s]
Pn19k2-IEEE34	212	1-7-9-17-18-4-13-15-12-5-1 1-19-6-14-16-10-8-3-11-2-1	416
En22k4-IEEE123	375	1-20-22-18-21-1 1-13-16-19-15-17-1 1-9-7-3-2-6-8-10-1 1-14-12-5-4-11-1	976

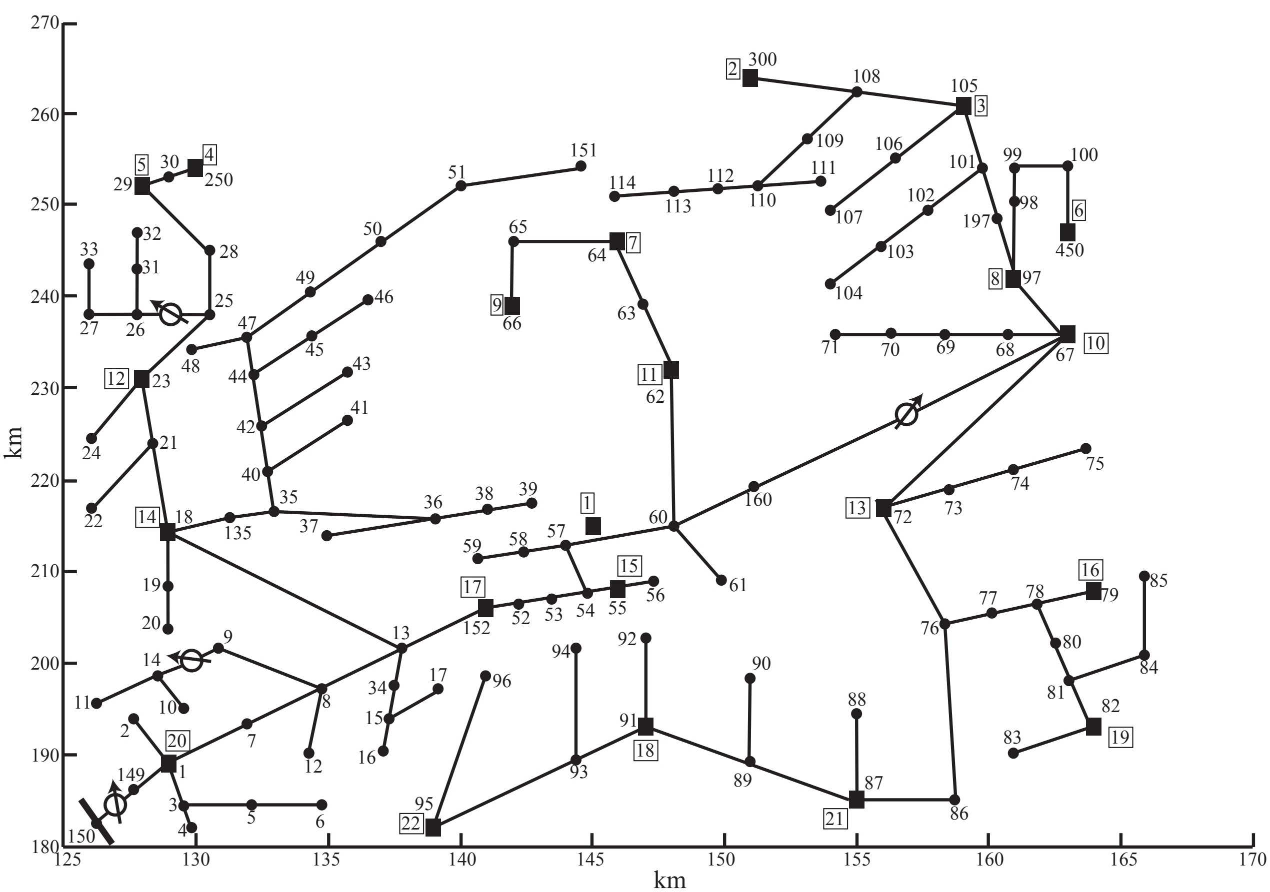

Figure 5.2: *En22k4-IEEE123N* test system

From the point of view of the power distribution system, the voltages at electric nodes should be very close (and not the same as the power flow formulation corresponds to a linear approach) to results reported on the IEEE database. Figure 5.3 and Figure 5.4 depict the difference in per unit of the voltages obtained with the CSLP-EVFT mathematical model, compared with the benchmark case voltages for $Pn19k2-IEEE34$ and $En22k4-IEEE123$ test systems respectively. The maximum difference in voltage is 1.3×10^{-3}.

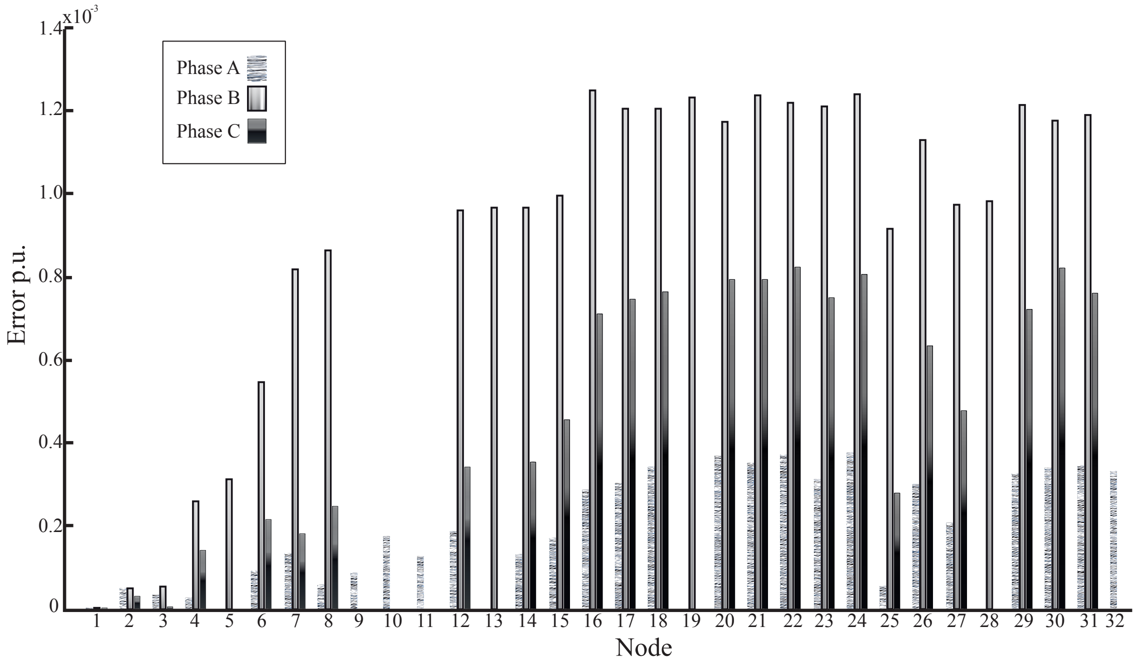

Figure 5.3: Difference in voltage of $Pn19k2 - IEEE34$ compared with benchmark case

The results shown before are based on the CSLP-EVFT mathematical model with the non-linear expression for the term *Losses*. In order to obtain a formulation that can be solved easily and with reduced computational times, the linearization of *Losses* is proposed in 5.59 to 5.62. This procedure is carried out by using Taylor series around a point of operation, which is chosen as the operation of the power distribution system without EVCSs.

$$Losses = \Delta_{Losses} + Losses_{op} \tag{5.59}$$

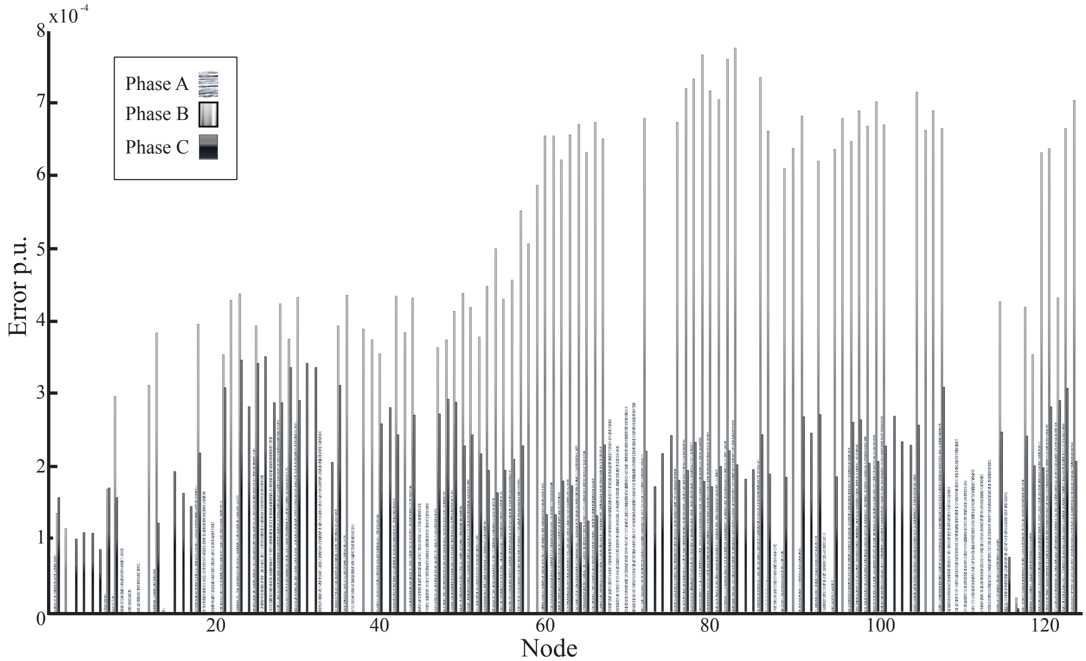

Figure 5.4: Difference in voltage of $En22k4 - IEEE123$ compared with benchmark case

$$\Delta_{Losses} = \begin{array}{c} V_{RS}G_{Sn}\Delta V_{Rn} + \Delta V_{Rn}G_{nS}V_{RS} + \Delta V_{Rn}G_{nn}V_{Rno} + V_{Rno}G_{nn}\Delta V_{Rn} + \\ V_{IS}G_{Sn}\Delta V_{In} + \Delta V_{In}G_{nS}V_{IS} + \Delta V_{In}G_{nn}V_{Ino} + V_{Ino}G_{nn}\Delta V_{In} \end{array} \tag{5.60}$$

$$V_{Rn} = \Delta V_{Rn} + V_{Rno} \tag{5.61}$$

$$V_{In} = \Delta V_{In} + V_{Ino} \tag{5.62}$$

At the operation point, power losses are identified as $Losses_{op}$, and real and imaginary parts of voltages at nodes (other than slack node S) are shown as V_{Rno} and V_{Ino} respectively.

5.4 Results

Coupled systems shown in Figures 5.1 and 5.2, are utilized to assess the performance of CSLP-EVFT problem, considering the linear formulation presented for the term $Losses$.

Parameters for $Pn19k2 - IEEE34$ and $En22k4 - IEEE123$ instances were chosen consistently to the reality. As reported by (Motors, 2017), an EVCS may draw up to 120 kW during 20 minutes from the electric distribution network for a 272 km battery range. In this work, the power demanded by the EV (for either the CVRP or SP problem) during the recharge is assumed to be 30 kW, as this value represents a suitable additional load for the distribution system and the duration of the recharge under this power would not affect the travel duration time. This value is introduced in the term $S^*_{ki_{a,b,c}}$ of the power flow equations, due to the recharge of the EVs can be represented as constant current load (Wang et al., 2013). The cost related with EVCS construction is 22000 USD, in accordance with (Agenbroad, 2014), considering type of installation, connectivity, materials, data and other factors. From the point of view of the EVs operation, the average cost is 2.423 USD to travel 100 km, as reported by (of Energy, 2017), and an estimation of 100 USD is used under the concept of EV maintenance for every 5000 km traveled. The operation cost of the EVCSs, e.g., cost for both, energy consumed from the distribution network and energy losses, is estimated in 0.2 USD/kWh. Consumer Price Index CPI for the annualization factor is set in 10%.

The proposed CSLP-EVFT model has been programmed and executed in the GAMS (General Algebraic Modeling System) environment (Gill et al., 2017). on a HP desktop computer, Windows 64-bit operating system, with an Intel Core i3 @ 3.3 GHz processor and 4 GB of RAM. The non-linear approach (non-linear expression for the term $Losses$) is solved using the DICOPT solver and the linearized mathematical model is solved with CPLEX solver.

5.4.1 *Pn19k2-IEEE34*

The results for instance $Pn19k2 - IEEE34$ are presented in Table 5.3, considering different values of battery autonomy, under the non-linearized approach of the mathematical model (non-linear expression for $Losses$). The first two columns show the values for autonomy Q_{CVRP} and Q_{SP} for CVRP and SP problems respectively. In the third column, the costs for each term at the objective function are presented. The routes sequence for each EV, following the respective mobility pattern (CVRP or SP), are shown in the sixth column. For all runs, the depot at CVRP is identified as 1 and the start and end points for the SP routes are the same. Numbers in bold are the EVCSs installed, which provide the recharge service for both type of EVs (CVRP and SP focuses). It is assumed that no more than one EV is able to be recharged at the same time.

Table 5.3: Results for $Pn19k2 - IEEE34$ with non-linearized mathematical model

Q_{CVRP} [km]	Q_{SP} [km]	Costs [USD]	Mobility pattern	Detail of routes	Time [s]	Q_{CVRP} [km]	Q_{SP} [km]	Costs [USD]	Mobility pattern	Detail of routes	Time [s]
30	20	C_1: 505872 C_2: 469413 C_3: 169400 C_4: 26042 C_5: 22787 C_6: 3985	CVRP	1-11-**2**-8-**10**-16-14-**6**-19-7-1 1-**3**-**9**-17-18-**4**-13-15-**12**-5-1	1238	90	44	C_1: 483085 C_2: 414724 C_3: 48400 C_4: 9765 C_5: 6510 C_6: 184	CVRP	1-2-**11**-3-8-10-16-14-6-19-1 1-7-9-17-18-4-13-15-**12**-5-1	870
			SP	12-5-**2**-7-**3**-8-10 1-**2**-11-**4**-18 15-**2**-7-**3**-8-6-14 17-9-**4**-11-**2**-5-12					SP	12-15-**11**-10 1-2-**11**-4-18 15-**11**-3-8-6-14 17-9-4-13-15-12	
40	24	C_1: 530938 C_2: 437511 C_3: 121000 C_4: 19531 C_5: 16276 C_6: 2494	CVRP	1-**11**-13-4-18-**17**-9-10-16-**14**-6-1 1-2-5-**12**-15-**3**-8-19-7-1	2870	100	48	C_1: 483085 C_2: 430675 C_3: 24200 C_4: 3255 C_5: 3255 C_6: 757	CVRP	1-7-9-17-18-**4**-13-15-12-5-1 1-19-6-14-16-10-8-3-11-2-1	117
			SP	12-15-**11**-**3**-8-10 1-2-**11**-4-18 15-**11**-**3**-8-6-14 17-9-**11**-15-12					SP	12-15-11-10 1-2-11-4-18 15-13-**4**-9-10-16-14 17-9-4-13-15-12	
50	28	C_1: 483085 C_2: 426118 C_3: 121000 C_4: 16276 C_5: 13021 C_6: 2125	CVRP	1-**19**-6-14-16-10-8-**3**-11-2-1 1-7-**9**-17-18-4-13-15-**12**-5-1	1779	110	52	C_1: 496760 C_2: 414720 C_3: 24200 C_4: 0 C_5: 3255 C_6: 19	CVRP	1-7-9-17-18-4-13-15-**12**-5-1 1-19-6-14-16-10-8-3-2-11-1	242
			SP	12-15-**11**-10 1-2-**11**-4-18 15-**11**-**3**-8-6-14 17-9-**11**-15-12					SP	12-15-11-10 1-2-11-4-18 15-11-3-8-6-14 17-9-4-13-15-12	
60	32	C_1: 483085 C_2: 426118 C_3: 72600 C_4: 16276 C_5: 6510 C_6: 1772	CVRP	1-19-6-14-16-**10**-8-3-11-2-1 1-7-9-17-18-**4**-13-15-12-5-1	1541	120	56	C_1: 483085 C_2: 414724 C_3: 0 C_4: 0 C_5: 0 C_6: 0	CVRP	1-19-6-14-16-10-8-3-11-2-1 1-7-9-17-18-4-13-15-12-5-1	500
			SP	12-15-**11**-10 1-2-**11**-4-18 15-**11**-**10**-16-14 17-9-**4**-13-15-12					SP	12-15-11-10 1-2-11-4-18 15-11-3-8-6-14 17-9-4-13-15-12	
70	36	C_1: 508151 C_2: 414724 C_3: 48400 C_4: 13021 C_5: 6510 C_6: 901	CVRP	1-7-8-3-**11**-13-15-12-5-2-1 1-19-6-14-16-10-**9**-17-18-4-1	1163	130	60	C_1: 483085 C_2: 414724 C_3: 0 C_4: 0 C_5: 0 C_6: 0	CVRP	1-2-11-3-8-10-16-14-6-19-1 1-5-12-15-13-4-18-17-9-7-1	425
			SP	12-15-**11**-10 1-2-**11**-4-18 15-**11**-3-8-6-14 17-**9**-4-13-15-12					SP	12-15-11-10 1-2-11-4-18 15-11-3-8-6-14 17-9-4-13-15-12	
80	40	C_1: 483085 C_2: 414724 C_3: 48400 C_4: 9765 C_5: 6510 C_6: 901	CVRP	1-7-**9**-17-18-4-13-15-12-5-1 1-19-6-14-16-10-8-3-**11**-2-1	411						
			SP	12-15-**11**-10 1-2-**11**-4-18 15-**11**-3-8-6-14 17-9-4-13-15-12							
			SP	12-15-11-10 1-2-11-4-18 15-11-3-8-6-14 17-9-4-13-15-12							

According to Table 5.3, as the battery autonomy is increased, there is a reduction of costs associated with EVCS installation (C_3) and energy consumption (C_4 and C_5). Notice that cost of delta of energy losses in C_6 is also decreased. Although this, the routing cost shown in C_1 and C_2 may not necessarily decrease with the increment of the battery autonomy, as the candidate points for EVCS coincide with the customers location, otherwise, a change in these costs would be noticeable. The last two runs only depict costs for EVs routing, being these cases the representation of the benchmark case results, as no EVCSs are installed and therefore the energy consumption and delta of losses are null.

As mentioned above, the non-linearized approach was developed using DICOPT solver in GAMS environment. This solver develops an alternating sequence of NLP subproblems (from the relaxed MINLP) and MIP master problem. The convergence in each MIP master problem is reached with the GAP feature, which is zero by default. The general algorithm has a convergence with the number of cycles (default: 20 cycles). In this work, the MIP master problem stops when the GAP is not decreased after several iterations, and the number of cycles is set in 5. This latter can commit the problem optimality, moreover, the main purpose is to validate and obtain at least a feasible solution. In Table 5.4, important aspects of the MIP master problem are shown, such as upper and lower bound, GAP and execution time. Notice that the last two runs where no EVCSs are installed, the global optimal solution is obtained, due to GAP is zero.

Table 5.4: GAP results for $Pn19k2-IEEE34$ with non linearized mathematical model

Q_{CVRP} [km]	*Q_{SP} [km]*	*Upper bound (Objective function)*	*Lower bound*	*GAP [%]*	*Time [s]*
30	20	1197499	1105148	7,712	1238
40	24	1127750	993333	11,919	2870
50	28	1061625	955463	10	1779
60	32	1006361	951615	5,44	1541
70	36	991707	929031	6,32	1163
80	40	963385	909821	5,56	411
90	44	962668	903271	6,17	870
100	48	945227	877265	7,19	117
110	52	938954	867030	7,66	242
120	56	897809	897809	0	500
130	60	897809	897809	0	425
Average		999163	935235	6,17	1014

In Table 5.5, the results for $Pn19k2-IEEE34$ are shown, under the context of the linearized mathematical model, considering the linear expression for the term *Losses*. This aspect makes the problem to be solved in less computational times compared with the non-linearized model. Besides of this, there is a reduction in the overall cost of the objective function, on behalf of the costs for CVRP and SP routing and delta of energy losses. This latter is strongly related with the EVCSs location, which are attempted to be installed as close as to the distribution substation or at three-phase nodes. The EVCSs installation at one-phase electric nodes may provide larger power losses in comparison to three-phase nodes.

Table 5.5: Results for $Pn19k2 - IEEE34$ with linearized mathematical model

Q_{CVRP} [km]	Q_{SP} [km]	Costs [USD]	Mobility pattern	Detail of routs	Time [s]	Q_{CVRP} [km]	Q_{SP} [km]	Costs [USD]	Mobility pattern	Detail of routs	Time [s]
30	20	C_1: 489921 C_2: 442069 C_3: 193600 C_4: 29297 C_5: 22787 C_6: 2417	CVRP	1-7-19-**6**-14-16-**10**-8-**11**-2-1 1-5-**12**-15-13-**4**-18-17-**9**-**3**-1	451	90	44	C_1: 483085 C_2: 414724 C_3: 48400 C_4: 9765 C_5: 6510 C_6: 293	CVRP	1-7-**9**-17-18-4-13-15-12-5-1 1-19-6-14-16-10-8-3-**11**-2-1	141
			SP	12-5-**2**-7-**3**-8-10 1-**2**-11-**4**-18 15-**11**-**3**-8-6-14 17-**9**-**11**-2-5-12					SP	12-15-**11**-10 1-2-**11**-4-18 15-**11**-3-8-6-14 17-9-4-13-15-12	
40	24	C_1: 483085 C_2: 437511 C_3: 145200 C_4: 19531 C_5: 16276 C_6: 1448	CVRP	1-7-**9**-17-18-**4**-13-15-**12**-5-1 1-19-6-**14**-16-10-8-**3**-11-2-1	399	100	48	C_1: 483085 C_2: 430675 C_3: 24200 C_4: 3255 C_5: 3255 C_6: 239	CVRP	1-5-12-15-13-4-18-17-**9**-7-1 1-2-11-3-8-10-16-14-6-19-1	163
			SP	12-15-**11**-**3**-8-10 1-2-**11**-4-18 15-11-**3**-8-6-14 17-9-**11**-15-12					SP	12-15-11-10 1-2-11-4-18 15-13-4-**9**-10-16-14 17-9-4-13-15-12	
50	28	C_1: 483085 C_2: 426118 C_3: 121000 C_4: 16276 C_5: 13021 C_6: 1015	CVRP	1-7-**9**-17-18-4-13-15-**12**-5-1 1-**19**-6-14-16-10-8-**3**-11-2-1	624	110	52	C_1: 483085 C_2: 414724 C_3: 24200 C_4: 0 C_5: 3255 C_6: 19	CVRP	1-5-**12**-15-13-4-18-17-9-7-1 1-19-6-14-16-10-8-3-11-2-1	332
			SP	12-15-**11**-10 1-2-**11**-4-18 15-**11**-**3**-8-6-14 17-9-**11**-15-12					SP	12-15-11-10 1-2-11-4-18 15-11-3-8-6-14 17-9-4-13-15-12	
60	32	C_1: 483085 C_2: 414724 C_3: 96800 C_4: 13021 C_5: 6510 C_6: 1368	CVRP	1-5-12-15-13-**4**-18-17-9-7-1 1-2-11-3-8-**10**-16-14-6-19-1	95	120	56	C_1: 483085 C_2: 414724 C_3: 0 C_4: 0 C_5: 0 C_6: 0	CVRP	1-5-12-15-13-4-18-17-9-7-1 1-2-11-3-8-10-16-14-6-19-1	177
			SP	12-15-**11**-10 1-2-**11**-4-18 15-11-**3**-8-6-14 17-9-**4**-13-15-12					SP	12-15-11-10 1-2-11-4-18 15-11-3-8-6-14 17-9-4-13-15-12	
70	36	C_1: 483085 C_2: 414724 C_3: 72600 C_4: 13021 C_5: 6510 C_6: 522	CVRP	1-5-12-15-13-**4**-18-17-9-7-1 1-2-11-**3**-8-10-16-14-6-19-1	188	130	60	C_1: 483085 C_2: 414724 C_3: 0 C_4: 0 C_5: 0 C_6: 0	CVRP	1-7-9-17-18-4-13-15-12-5-1 1-2-11-3-8-10-16-14-6-19-1	286
			SP	12-15-**11**-10 1-2-**11**-4-18 15-**11**-3-8-6-14 17-9-**4**-13-15-12					SP	12-15-11-10 1-2-11-4-18 15-11-3-8-6-14 17-9-4-13-15-12	
80	40	C_1: 483085 C_2: 414724 C_3: 48400 C_4: 9765 C_5: 6510 C_6: 299	CVRP	1-5-12-15-13-**4**-18-17-9-7-1 1-19-6-14-16-10-8-3-**11**-2-1	287						
			SP	12-15-**11**-10 1-2-**11**-4-18 15-**11**-3-8-6-14 17-9-4-13-15-12							

The linearized mathematical model is solved using CPLEX solver. The algorithm is stopped when the GAP value is not decreased after certain number of iterations. This information is shown in Table 5.6, with the lower and upper bound for each run, besides the execution time.

Table 5.6: GAP results for $Pn19k2 - IEEE34$ with linearized mathematical model

Q_{CVRP} [km]	Q_{SP} [km]	Upper bound (Objective function)	Lower bound	GAP [%]	Time [s]
30	20	1180091	1081553	8,35	451
40	24	1103051	964067	12,6	399
50	28	1060515	957645	9,7	624
60	32	1015508	967779	4,7	95
70	36	990462	927072	6,4	188
80	40	962783	893944	7,15	287
90	44	962777	912135	5,26	141
100	48	944709	880374	6,81	163
110	52	925283	875318	5,4	332
120	56	897809	897809	0	177
130	60	897809	897809	0	286
Average		994617	932318	6,03	285

5.4.2 *En22k4-IEEE123*

The increment in customers and electric nodes on transportation and power distribution networks respectively, contributes to increase computational effort for finding a solution, which can be seen in Table 5.7 for instance $En22k4 - IEEE123$. As the battery autonomy is increased, the installation of EVCSs is less required and hence the energy drawn by EVs from the distribution system is reduced, as noted in C_3, C_4 and C_5. Cost associated with delta of energy losses also follows a descending behavior to reach a point, in which no EVCSs must be installed, e.g., the objective function is only affected by the routing costs established in C_1 and C_2 for CVRP and SP approaches respectively. Table 5.8 presents information related with GAP value and execution time for the MIP master problem in DICOPT solver. Number of cycles in each run is set in 5.

Table 5.7: Results for $En22k4 - IEEE123$ with non-linearized mathematical model

Q_{CVRP} [km]	Q_{SP} [km]	Costs [USD]	Mobility pattern	Detail of routes	Time [s]	Q_{CVRP} [km]	Q_{SP} [km]	Costs [USD]	Mobility pattern	Detail of routes	Time [s]
30	30	C_1: 881860 C_2: 619810 C_3: 338800 C_4: 26042 C_5: 45574 C_6: 2333	CVRP	1-**12**-**5**-4-**2**-3-**7**-**9**-1 1-15-**18**-22-**21**-19-**16**-1 1-**13**-8-**6**-10-**11** 1-**17**-**20**-**14**-1	24793	90	60	C_1: 900090 C_2: 617530 C_3: 48400 C_4: 6510 C_5: 3255 C_6: 370	CVRP	1-9-7-**3**-2-4-5-12-1 1-14-20-22-18-1 1-10-8-6-11-13-1 1-17-15-21-19-16-1	1313
			SP	5-4-**9**-11-**13**-16-19 12-9-**11**-13-16 14-**9**-**11**-8-10 20-**17**-1-**11**-8-**6**-3					SP	5-4-9-**11**-13-16-19 12-14-17-15-16 14-9-11-8-10 20-17-1-**11**-8-3	
40	35	C_1: 890970 C_2: 617530 C_3: 266200 C_4: 22787 C_5: 32553 C_6: 1694	CVRP	1-**15**-22-**20**-17-1 1-**16**-19-21-**18**-13-1 1-**10**-8-6-3-**2**-**11**-1 1-**14**-12-**5**-4-7-**9**-1	16433	100	65	C_1: 916040 C_2: 617530 C_3: 48400 C_4: 6510 C_5: 6510 C_6: 364	CVRP	1-15-17-21-19-16-1 1-14-20-22-18-1 1-**11**-8-6-3-2-7-9-1 1-13-**10**-4-5-12-1	2377
			SP	5-4-9-**11**-13-**16**-19 12-14-**17**-15-16 14-**9**-11-8-10 20-**17**-1-11-8-3					SP	5-4-9-**11**-13-16-19 12-9-11-13-16 14-9-11-8-10 20-17-1-**11**-8-3	
50	40	C_1: 863630 C_2: 617530 C_3: 217800 C_4: 19532 C_5: 19532 C_6: 1348	CVRP	1-15-17-22-**20**-1 1-7-**2**-3-**6**-8-10-1 1-13-16-**19**-21-18-1 1-**14**-12-4-**5**-9-11-1	9304	110	70	C_1: 900090 C_2: 617530 C_3: 48400 C_4: 6510 C_5: 3255 C_6: 371	CVRP	1-13-16-19-21-18-1 1-17-15-20-22-1 1-3-**2**-6-8-10-1 1-14-12-5-4-7-9-11-1	1361
			SP	5-4-9-**11**-**13**-16-19 12-9-**11**-13-16 14-9-**11**-8-10 20-**17**-1-**11**-8-3					SP	5-4-9-**11**-13-16-19 12-9-11-13-16 14-9-11-8-10 20-17-1-**11**-8-3	
60	45	C_1: 893250 C_2: 633480 C_3: 145200 C_4: 16276 C_5: 13021 C_6: 927	CVRP	1-10-8-6-**3**-2-1 1-11-9-7-5-**4**-12-14-1 1-17-15-22-**20**-1 1-13-**16**-19-21-18-1	3128	120	75	C_1: 881860 C_2: 631200 C_3: 24200 C_4: 3255 C_5: 0 C_6: 110	CVRP	1-10-8-6-3-2-7-1 1-14-20-22-18-15-1 1-12-5-4-9-11-13-1 1-17-21-19-16-1	956
			SP	5-4-9-**11**-13-16-19 12-9-11-13-16 14-17-1-**11**-8-10 20-17-1-13-8-3					SP	5-4-9-11-13-16-19 12-14-17-15-16 14-9-11-8-10 20-**14**-9-7-2-3	
70	50	C_1: 856790 C_2: 617530 C_3: 145200 C_4: 13021 C_5: 13021 C_6: 1038	CVRP	1-11-**4**-5-12-14-1 1-13-**16**-19-21-18-1 1-10-8-6-3-**2**-7-9-1 1-15-22-**20**-17-1	3209	150	80	C_1: 881860 C_2: 631200 C_3: 24200 C_4: 3255 C_5: 0 C_6: 196	CVRP	1-13-16-19-21-18-1 1-11-2-3-6-8-10-1 1-14-12-5-4-7-9-1 1-20-22-15-17-1	1690
			SP	5-4-9-**11**-13-16-19 12-14-17-**15**-16 14-9-**11**-8-10 20-17-1-**11**-8-3					SP	5-4-9-11-13-16-19 12-14-17-15-16 14-9-11-8-10 20-14-**9**-7-2-3	
80	55	C_1: 888700 C_2: 617530 C_3: 72600 C_4: 9765 C_5: 6510 C_6: 580	CVRP	1-20-14-17-1 1-9-7-**3**-2-4-5-12-1 1-11-6-8-10-13-1 1-16-19-21-**22**-18-15-1	1526	200	130	C_1: 854520 C_2: 617530 C_3: 0 C_4: 0 C_5: 0 C_6: 0	CVRP	1-7-2-3-6-8-10-1 1-14-12-5-4-9-11-1 1-13-16-19-21-18-1 1-15-22-20-17-1	976
			SP	5-4-9-**11**-13-16-19 12-14-17-15-16 14-9-**11**-8-10 20-17-1-**11**-8-3					SP	5-4-9-11-13-16-19 12-14-17-15-16 14-9-11-8-10 20-17-1-11-8-3	

Table 5.8: GAP results for $En22k4 - IEEE123$ with non-linearized mathematical model

Q_{CVRP} [km]	Q_{SP} [km]	Upper bound (Objective function)	Lower bound	GAP [%]	Time [s]
30	30	1914419	1696366	11,39	24793
40	35	1831734	1531146	16,41	16433
50	40	1739372	1497947	13,88	9304
60	45	1702154	1465895	13,88	3128
70	50	1646600	1435835	12,8	2109
80	55	1595685	1436116	10	1526
90	60	1576155	1418539	10	1313
100	65	1595354	1435818	10	2377
110	70	1576156	1418540	10	1361
120	75	1540625	1386562	10	956
150	80	1540711	1386639	10	1690
200	130	1472050	1324845	10	976
Average		1644251	1452854	11,53	5497

As performed with the first instance, runs with the linearized mathematical model are also implemented. In Table 5.9 the runs for different values of battery autonomy are shown. Under the linearized approach, the majority of the executions present a reduced cost of CVRP and SP routing, and EVCSs installation. The latter does not apply to the first case (Q_{CVRP}=30 km and Q_{SP}=30 km) in which the EVCS installation cost is greater compared with the non-linearized model. Notice in Table 5.9 that the EVCS installed at customer 17 serves the EVs associated with SP problem, in contrast with the non-linearized case where the same EVCS serves both type of EVs. In regards with delta of energy losses, it is supposed that this cost should be reduced as the battery autonomy increases. However, this cost is increased in some cases, i.e., when the autonomy changes from Q_{CVRP}=120 km and Q_{SP}=75 km to Q_{CVRP}=150 km and Q_{SP}=80 km. Although the number of EVCSs installed is the same for both cases, the cost of energy losses is greater in the second case (Q_{CVRP}=150 km and Q_{SP}=80 km) because the electrical path from the distribution substation to the EVCS installed at customer 14 is less than that for the customer at 9. From the point of view of the computational effort, the run times for most of the cases decrease notably in comparison to results shown in Table 5.7.

Table 5.9: Results for $En22k4 - IEEE123$ with linearized mathematical model

Q_{CVRP} [km]	Q_{SP} [km]	Costs [USD]	Mobility pattern	Detail of routes	Time [s]	Q_{CVRP} [km]	Q_{SP} [km]	Costs [USD]	Mobility pattern	Detail of routes	Time [s]
30	30	C_1: 856790 C_2: 617530 C_3: 363000 C_4: 26042 C_5: 48829 C_6: 2477	CVRP	1-**9**-7-**2**-3-6-**8**-**10**-1 1-**14**-**12**-5-**4**-**11**-1 1-**18**-21-**19**-16-**13**-1 1-**15**-**22**-**20**-17-1	3460	90	60	C_1: 854520 C_2: 617530 C_3: 48400 C_4: 6510 C_5: 6510 C_6: 367	CVRP	1-15-22-20-17-1 1-18-21-19-16-13-1 1-10-**8**-6-3-2-7-1 1-14-12-5-4-9-**11**-1	376
			SP	5-4-**9**-11-**13**-16-19 12-9-**11**-13-16 14-**9**-**11**-8-10 20-**17**-1-**11**-**8**-3					SP	5-4-9-**11**-13-16-19 12-9-11-13-16 14-9-11-8-10 20-17-1-**11**-8-3	
40	35	C_1: 856790 C_2: 622090 C_3: 242000 C_4: 19532 C_5: 32553 C_6: 1593	CVRP	1-**9**-7-2-**3**-6-8-**10**-1 1-**14**-12-**5**-4-**11**-1 1-17-**20**-22-**15**-1 1-13-**16**-19-**21**-18-1	698	100	65	C_1: 861350 C_2: 617530 C_3: 48400 C_4: 6510 C_5: 6510 C_6: 375	CVRP	1-15-22-20-17-1 1-13-16-19-21-18-1 1-**9**-7-2-3-6-8-10-1 1-**11**-5-4-12-14-1	144
			SP	5-4-9-**11**-13-**16**-19 12-9-**11**-13-16 14-**9**-11-8-10 20-17-**15**-1-**11**-8-3					SP	5-4-**9**-11-13-16-19 12-9-11-13-16 14-9-11-8-10 20-17-1-**11**-8-3	
50	40	C_1: 888700 C_2: 631200 C_3: 193600 C_4: 19532 C_5: 19532 C_6: 1265	CVRP	1-10-**8**-6-3-**2**-11-1 1-**13**-16-19-**21**-22-1 1-17-**20**-18-15-1 1-**14**-**12**-5-4-7-**9**-1	2994	110	70	C_1: 868190 C_2: 617530 C_3: 24200 C_4: 6510 C_5: 3255 C_6: 176	CVRP	1-**11**-2-3-6-8-10-1 1-14-12-5-4-7-9-1 1-15-17-20-22-1 1-13-16-19-21-18-1	1056
			SP	5-4-**9**-11-**13**-16-19 12-**14**-17-15-16 14-**9**-11-8-10 20-**14**-**9**-7-2-3					SP	5-4-9-**11**-13-16-19 12-9-11-13-16 14-9-11-8-10 20-17-1-**11**-8-3	
60	45	C_1: 872740 C_2: 617530 C_3: 145200 C_4: 16276 C_5: 16276 C_6: 999	CVRP	1-7-2-**3**-6-8-10-1 1-20-**22**-21-18-1 1-**11**-9-4-5-**12**-14-1 1-17-15-19-**16**-13-1	71	120	75	C_1: 909200 C_2: 617530 C_3: 24200 C_4: 3255 C_5: 0 C_6: 176	CVRP	1-14-12-5-4-7-9-1 1-13-20-17-1 1-10-8-6-3-2-11-1 1-16-19-21-22-18-15-1	2002
			SP	5-4-9-**11**-13-16-19 12-9-**11**-13-16 14-9-**11**-8-10 20-**17**-1-**11**-8-3					SP	5-4-9-11-1316-19 12-14-17-15-16 14-9-11-8-10 20-17-1-**11**-8-3	
70	50	C_1: 925150 C_2: 617530 C_3: 121000 C_4: 13021 C_5: 13021 C_6: 729	CVRP	1-7-2-**3**-6-8-10-1 1-16-19-**21**-22-18-15-1 1-17-**20**-14-1 1-13-4-**5**-12-9-11-1	3189	150	80	C_1: 854520 C_2: 617530 C_3: 24200 C_4: 3255 C_5: 0 C_6: 90	CVRP	1-10-8-6-3-2-7-1 1-11-9-4-5-12-14-1 1-17-20-22-15-1 1-18-21-19-16-13-1	1113
			SP	5-4-9-**11**-13-16-19 12-9-**11**-13-16 14-9-**11**-8-10 20-17-1-**11**-8-3					SP	5-4-9-11-13-16-19 12-9-11-13-16 14-9-11-8-10 20-**17**-1-11-8-3	
80	55	C_1: 854520 C_2: 617530 C_3: 96800 C_4: 9765 C_5: 9765 C_6: 767	CVRP	1-7-2-3-6-**8**-10-1 1-15-22-20-17-1 1-14-12-5-4-**9**-11-1 1-18-21-19-16-**13**-1	990	200	130	C_1: 854520 C_2: 617530 C_3: 0 C_4: 0 C_5: 0 C_6: 0	CVRP	1-18-21-19-16-13-1 1-7-2-3-6-8-10-1 1-11-9-4-5-12-14-1 1-17-20-22-15-1	46
			SP	5-4-9-**11**-13-16-19 12-14-17-15-16 14-9-**11**-8-10 20-17-1-**11**-8-3					SP	5-4-9-11-13-16-19 12-9-11-13-16 14-9-11-8-10 20-17-1-11-8-3	

As performed in instances above, the linearized model is solved using CPLEX solver and, GAP values, computational times and the respective average for each run are presented in Table 5.10.

Table 5.10: GAP results for $En22k4 - IEEE123$ with linearized mathematical model

Q_{CVRP} [km]	Q_{SP} [km]	Upper bound (Objective function)	Lower bound	GAP [%]	Time [s]
30	30	1914668	1633958	14,66	3460
40	35	1774558	1539056	13,27	698
50	40	1753829	1536512	12,39	2994
60	45	1669021	1464382	12,26	71
70	50	1690451	1426554	15,61	3189
80	55	1589147	1375231	13,46	990
90	60	1533837	1380453	10	376
100	65	1540675	1386607	10	144
110	70	1519861	1367874	10	1056
120	75	1554361	1398924	10	2002
150	80	1499595	1349635	10	1113
200	130	1472050	1324845	10	46
Average		1626004	1432002	11,8	1344

In order to assess the linearized model in terms of the power flow formulation, the maximum voltage difference respect to the non-linearized model (non-linear term for Losses) is found in Table 5.11 for both instances.

Table 5.11: Maximum voltage difference between non-linearized and linearized models

Pn19k2-IEEE34			*En22k4-IEEE123*		
Q_{CVRP} [km]	Q_{SP} [km]	Max. Dif. [$p.u$]	Q_{CVRP} [km]	Q_{SP} [km]	Max. Dif. [$p.u$]
30	20	0.016366226	30	30	0.000402307
40	24	0.010846248	40	35	0.000276445
50	28	0.010447972	50	40	0.0003341
60	32	0.006739884	60	45	0.000331383
70	36	0.003773189	70	50	0.000753311
80	40	0.005995303	80	55	0.000879476
90	44	0.002535781	90	60	6.82391×10^{-5}
100	48	0.006798513	100	65	6.82391×10^{-5}
110	52	0.00358965	110	70	0.000589611
120	56	7.96501×10^{-11}	150	80	0.000715173
130	60	7.96501×10^{-11}	200	130	2.6835×10^{-10}

According to Table 5.11, as the battery autonomy is reduced, the voltage difference between two models is increased, because the installation of EVCSs makes the power distribution point of operation to move away from the point over which the linearization was carried out (without EVCSs installed). Notice that this linearization shown better results for $En22k4-IEEE123$ instance, due to the robustness of this distribution system to receive more loads, compared with results of $Pn19k2-IEEE34$ instance.

5.5 Conclusions

Many companies have had facility location and vehicle routing as two of the most crucial decisions to reduce logistics cost. For a logistics corporation, equipped with a fleet of electric vehicles, the routing cost is directly affected by the location strategy for charging stations.

On the other hand, this aspect leads to impact the power distribution network, from the point of view of the electric utility. Therefore, this chapter studied the Charging Station Location Problem of Electric Vehicles for Freight Transportation CSLP-EVFT to improve the performance of transportation network and power distribution system.

The distance traveled by the EVs, introduced along the mathematical model, represented an appropriate alternative to optimally locate Electric Vehicle Charging Stations EVCSs on the transportation network with the equivalent nodes on the distribution system. By the other side, the battery autonomy is considered as a critical factor in the EVCSs location, as this is described in terms of the distance that can be traveled.

When no EVCSs were installed, as a consequence of too large battery autonomy, the linear formulation of power flow, depicted in the mathematical model, had favorable results compared with benchmark case results, showing a maximum difference of 1.3×10^{-3}.

Due to the presence of a non-linear expression for the term *Losses* in the objective function, a Taylor series based linearization was used to obtain a mathematical model completely linearized. This focus leads not only to handle this nonlinearity, but also reduce the overall objective function, which involves the cost of EVs routing, installation and energy consumption of EVCSs, and delta of energy losses. In many cases, the computational times of runs was improved notably.

For any case, non-linearized or linearized mathematical model, the EVCSs location involves a change in the term for delta of Energy losses. This term is reduced whether by means the EVCS is installed as close as to the distribution substation or at a one-phase or three-phase distribution node.

In regards with the power distribution system operation, the voltage difference between the linearized and non-linearized mathematical models is increased as the battery autonomy is reduced. This is because the installation of EVCSs makes the power distribution point of operation to move away from the point over which the linearization was carried out (without EVCSs installed). The robustness of the distribution system incurs in the results shown by the linearization.

The mathematical model addressed in this chapter, suggests a unique owner of the transportation company and the distribution system. Otherwise, the problem should be handled considering a bi-level approach, being the routing solution and EVCSs location, the input to find the energy consumption and energy losses with the power flow formulation.

Chapter 6

General conclusions

The research in this thesis primarily deals with the optimal location of Electric Vehicle Charging Stations (EVCSs) in transportation networks, considering the impact on the power distribution systems. In this sense, three mathematical models were proposed in the context of demand management for EVs and optimal siting and sizing of charging facilities, in accordance with the interests of network operators, logistic companies and end-consumers.

6.1 Summary

The main contents and conclusions of this thesis can be summarized as follows:

- In chapter 2, a detailed and updated review (until the end of 2017) of the state of the art was presented, considering the interaction of EVs and power distribution systems and transportation networks. Thus, the large deployment during the last decades of EVs and the research around the impact on the distribution network, has led to split up the literature review developed in this thesis in several topics, such as: power quality, study of scenarios, electricity markets, demand response, demand management, power system stability, vehicle to grid technology and, optimal location of EVCSs. This latter deserved a separate section, due to its relevance in terms of the operation, not only of the distribution system, but also of the transportation network. The research growth of optimal location of EVCSs, has been demonstrated with the increment during the last seven years (from the end of 2017), on the number of publications identified in highly ranked specialized literature databases, i.e., IEEE Xplore, Science Direct, Springer and Scopus. The optimal location of EVCSs play an important role for the efficient operation of the transportation network and power distribution system (as the EVCS is considered the connection between both networks). This is widely related with the "city logistics" concept, which is about finding efficient and effective ways to transport goods in urban areas while taking into account the negative effects on congestion, safety and environment. Along the review of EVCSs location, some of the problem formulations found are based on graph and queuing theory, integer programming, flow capturing optimization model, flow refueling location model and peak load shifting. By the other side, the models proposed in the literature contain characteristics that involve traffic flow, cost of EVCS, customer waiting fees, urban restrictions and, EVCS cost of service and coverage. The algorithms used to solve the mathematical models, cover from exact techniques to approximated techniques (meta-heuristics), such as particle swarm optimization, greedy algorithm, genetic algorithms, ant colony algorithm and Cuckoo search.

- Chapter 3 presented a mathematical model for a demand management strategy in distribution systems with different insertion levels of EVs, considering the probabilistic behavior of variables that affect the operation of the distribution network, i.e., driving patterns (arrival and departure times) and state of charge of EVs' batteries. Under the framework of variation of energy price based on charging priority subperiods, the optimal operation point of the distribution network was obtained in terms of statistics, such as, the expected value and probability density function of the optimal rate of the EVs recharge in the system. With the freedom of EVs' owners to choose the charging subperiod, according to their needs, the mathematical model is sensitive with the variability of energy price, as demonstrated when charging power was provided at hours when the energy price is lower. Additionally, cost of energy losses in the distribution network were minimized and other important terms in the objective function were considered, that account for penalization of the incomplete EVs recharge and a reward term to maximize the amount of EVs to be recharged. In this context, the study contributes to risk analysis, defining the uncertainty level of the results and supporting the process of appropriate decision making, mainly for location and installation of EVCSs. Furthermore, other processes could be supported, e.g., electricity generation dispatch, contingency criteria and distribution system planning.

- Chapter 4 presented and discussed a novel mathematical optimization model for the optimal location of EVCSs in transportation networks, considering the impact on the power distribution system (PDS). The developed mathematical model (MINLP formulation) incorporates in the objective function the cost of EVCSs installation and cost of routing for EVs utilized in merchandise delivery, following the Capacitated Vehicle Routing Problem (CVRP) approach. Other terms correspond to the increment of energy losses cost in PDS, respect to the benchmark case (No EVCSs installed), and a penalization term used to make feasible the solution. This latter was activated in case that the EVCSs installed were not sufficient for EVs to complete the routes and meeting the customers demand merchandise. Otherwise, a change of the current batteries used in the EVs would have been necessary, for others with a larger driving range. The weight factors presented in the objective function, were chosen consistently with the relative importance of each term. This is, the need to increase the battery autonomy was largely penalized in comparison with the other terms (change of battery is not attractive); and routing cost is of greater importance than EVCSs installation and energy losses cost. By the other side, the parameter M permitted to control the revisit to an EVCS. Accordingly, the amount of EVCSs installed, routing and energy losses cost were affected, since parameter M represented a sensitive factor in the problem, besides the battery autonomy.

- In chapter 5 a mathematical model is formulated for the charging station location problem of EVs used by logistics companies, which involves the direct impact on the routing cost and power distribution system performance. Transportation operation was in regards with the CVRP formulation and Shortest Path (SP) problem, given the mobility patterns of logistics companies. Power distribution network assessment was proposed by using a power flow linear formulation, which allowed to include the effect of the grid by an affine set of constraints. In the model proposed, the objective function was conformed by the following objectives: cost of EVCSs, routing cost for the freight EVs that followed the travel patterns of CVRP and SP formulations, cost of energy consumption in the EVCSs and the increment of the energy losses cost respect to the benchmark case (No EVCSs installed). The battery autonomy, featured in terms of the distance that can be traveled, represented a suitable sensitive factor for the EVCSs location, with a relevant impact in the EVCSs installation cost, EVs energy consumption and energy losses. Furthermore, energy losses cost was also affected by how close the EVCS was located from the substation and if it was installed at a one-phase or three-phase distribution node. By the other side, the linearized mathematical (MIP formulation) model presented better results, in comparison with the initial approach (MINLP formulation), where the energy losses term was not linear.

- Notice that approach used in model 2 presented in chapter 4, seeks similar objectives compared with model 3 proposed in chapter 5, from the point of view of distribution system performance, EVCSs investment and transportation network operation. It is necessary to clarify that in both models, the transportation company and distribution system belong the same owner. Otherwise, the problem should be handled considering a bi-level approach, being the routing solution and EVCSs location, the input to find the energy consumption and energy losses with the power flow formulation.

- The mathematical approach proposed in model 3, incorporated a set of constraints that were not addressed in model 2, and made the general problem more adjusted to the reality. Some of these aspects are framed in the unbalance characteristic of the distribution network and the introduction of another type of transportation pattern (Shortest Path formulation), in the mobility scheme of the logistics companies. Nevertheless, model 2 adopted special features, which were not included in model 3. For example, the EV is able to be recharged more than once in the same EVCS and, transportation and distribution network nodes are allowed to be in different spatial coordinates. These attributes have a direct impact on the cost of EVCSs installation, routing and energy losses. Lastly, if the EVCSs installed are not enough to make possible for EVs to meet customers demand merchandise, the model could suggest an improvement in the driving range battery.

6.2 Contributions and future works

In the framework of the EVs, and the notable interaction with the power distribution systems and transportation networks, the following contributions have been performed along the development of this thesis:

- A comprehensive and detail revision of the prominent works was presented, related with the EVs charging management strategies and the impact of the distribution networks, covering different points of view, e.g., power quality, electricity markets, demand response, power system stability and vehicle to grid assessments. Furthermore, the study also contributed on the review of EVs charging facilities location methodologies, providing a substantial frame of reference for future efforts around this topic. References cited in the literature review correspond to classic and recent papers (until the end of 2017), with explanatory graphics that help to present the information by type, amount of papers, publication year and database consulted.
- A novel EV charging strategy was formulated in distribution systems. Unlike the works published in other papers, the mathematical model developed in this thesis, considers different aspects from the stochastic point of view, i.e, conventional demand, initial state of charge of battery and, arrival and departure times for EVs. In this manner, different output variables, such as the optimal rate of EV charging power can be obtained, in terms of the probability density function. Other works found in this regards, address some or all of these characteristics by using deterministic approaches, which limits the development of risk analysis and decision making tools.

- Two mathematical models (described in chapter 4 and chapter 5) were proposed and developed for the optimal location of EVCSs. The main aspect that makes different these models in contrast with other works published in the literature, is based on the integration of the power distribution and transportation networks in the same framework, taking into account that the EVCS is the link between both networks. Additionally and given the low capacity of the EVs batteries, these mathematical models promote an alternative to provide a virtual increase of the EV driving range (by the approach of the EVCSs installation). This concept avoids to change the current batteries with larger-capacity ones, that could decrease the EV performance due to weight increment.

- New test systems were proposed in the context of validation, covering power distribution and transportation networks published in the literature. Accordingly, other proposals of mathematical modeling and solution algorithms can be verified and compared with the results obtained in this thesis.

- The development of this thesis contributes to the the area of operations research, focused on smart grids and mobility electrification for logistics companies, with the consequent improvement of power distribution and transportation network operation and reduction of pollution levels.

Based on the research presented in this thesis, the ideas and directions for further research are suggested as follows:

- The two mathematical models for the optimal location of EVCSs, considered a flat transportation network, and that the driving range is estimated with the current state of charge of battery, expressed in terms of the distance traveled by the EV. However, other factors should be taken into account for this estimation, such as average driving speed, average power consumption and slopes of the trip.

- An improved and more sophisticated mathematical model can be structured, encompassing the novel features involved in models 2 and 3. These items are:

unbalance distribution network, EVCS revisit component and, different location for EVCS candidate nodes and customers nodes. In addition to this, different modes for merchandise delivery travel patterns can be introduced, such as multi-depot vehicle routing problem. This latter corresponds to one of the expansion strategies of the freight transportation companies.

- As part of a wider approach, the implementation of solution methodologies based on meta-heuristic techniques and set partitioning, will be considered in future research to validate the proposed mathematical models in larger instances, considering the introducing of index t. This latter represents the behavior over the course of the time of these models and their respective variables and parameters. Consequently, the work developed in this thesis will be adjusted for real-world applications, from the planning and operation point of view.

- The introduction of energy storage and renewable energy resources could be implemented with the optimal location of EVCSs, based on the new tests systems proposed in this thesis and other approaches in which several owners are involved. These approaches can be focused on master-slave techniques and iterative cascade algorithms.

Appendix A

Test systems for optimal probabilistic charging of EVs

Table A.1: 19 nodes test system

Line	Initial node	End node	R [Ohm]	Ω [Ohm]	Penetration level		Priority degree	
					16%	63%	16%	63%
1	1	2	0.0415	0.0415	1	1	Medium	Medium
2	2	3	0.0424	0.0189	0	0	N/A	N/A
3	3	4	0.0444	0.0198	0	1	N/A	Medium
4	4	5	0.0369	0.0165	0	0	N/A	N/A
5	5	6	0.052	0.0232	0	1	N/A	Low
6	6	7	0.0524	0.0234	0	1	N/A	Low
7	7	8	0.3123	0.0311	0	1	N/A	High
8	7	9	0.2002	0.0199	0	0	N/A	N/A
9	7	10	1.734	0.1729	0	1	N/A	Medium
10	6	11	0.2607	0.026	0	1	N/A	High
11	6	12	1.3605	0.1357	0	0	N/A	N/A
12	4	13	0.14	0.014	0	1	N/A	Low
13	3	14	0.7763	0.0774	0	0	N/A	N/A
14	2	15	0.5977	0.0596	1	1	High	Medium
15	1	16	0.1423	0.0496	0	0	N/A	N/A
16	16	17	0.0837	0.0292	1	1	Low	Low
17	17	18	0.3123	0.0311	0	1	N/A	High
18	1	19	0.0163	0.0062	0	1	N/A	Low

Table A.2: 35 nodes test system

Line	Initial node	End node	R [Ohm]	Ω [Ohm]	Penetration level		Priority degree	
					16%	63%	16%	63%
1	1	2	0.0415	0.0415	1	1	High	Low
2	2	3	0.0424	0.0189	0	0	N/A	N/A
3	3	4	0.0444	0.0198	0	1	N/A	High
4	4	5	0.0369	0.0165	0	0	N/A	N/A
5	5	6	0.052	0.0232	1	1	Low	Medium
6	6	7	0.0524	0.0234	0	1	N/A	High
7	7	8	0.3123	0.0311	0	1	N/A	Low
8	7	9	0.2002	0.0199	0	0	N/A	N/A
9	7	10	1.734	0.1729	0	1	N/A	Low
10	6	11	0.2607	0.026	0	1	N/A	Low
11	6	12	1.3605	0.1357	0	1	N/A	Medium
12	4	13	0.14	0.014	1	1	Medium	Low
13	3	14	0.7763	0.0774	0	1	N/A	Medium
14	2	15	0.5977	0.0596	0	1	N/A	Medium
15	1	16	0.1423	0.0496	0	1	N/A	Low
16	16	17	0.0837	0.0292	0	1	N/A	High
17	17	18	0.3123	0.0311	0	1	N/A	Medium
18	1	19	0.0163	0.0062	0	1	N/A	Low
19	15	20	0.5977	0.0596	0	1	N/A	Low
20	13	21	0.14	0.014	0	0	N/A	N/A
21	19	22	0.2607	0.026	0	0	N/A	N/A
22	3	23	1.734	0.1729	0	0	N/A	N/A
23	18	24	1.3605	0.1357	1	0	Low	N/A
24	14	25	0.7763	0.0774	0	0	N/A	N/A
25	16	26	0.1423	0.0496	0	0	N/A	N/A
26	22	27	0.2607	0.026	1	1	Low	Medium
27	20	28	0.5977	0.0596	0	0	N/A	N/A
28	4	29	0.14	0.014	1	1	Medium	Medium
29	5	30	0.14	0.014	0	0	N/A	N/A
30	24	31	1.3605	0.1357	0	1	N/A	Low
31	22	32	0.2607	0.026	0	1	N/A	High
32	27	33	0.2607	0.026	0	0	N/A	N/A
33	23	34	1.734	0.1729	0	1	N/A	Low
34	30	35	0.14	0.014	0	1	N/A	Low

Appendix B

Test systems for EVCSs location: First approach

Table B.1: 16 nodes test system: R and X parameters. Substations at nodes 1, 2 and 3

Line	Initial node	End node	R [Ohm]	X [Ohm]
1	1	4	0.39675	0.529
2	4	5	0.4232	0.5819
3	4	6	0.4761	0.9522
4	6	7	0.2116	0.2116
5	2	8	0.5819	0.5819
6	8	9	0.4232	0.5819
7	8	10	0.5819	0.5819
8	9	11	0.5819	0.5819
9	9	12	0.4232	0.5819
10	3	13	0.5819	0.5819
11	13	14	0.4761	0.6348
12	13	15	0.4232	0.5819
13	15	16	0.2116	0.2116

Table B.2: 16 nodes test system: loads

Node	S [VA]	P [W]	Q [Var]
1	0	0	0
2	0	0	0
3	0	0	0
4	2561250	2000000	1600000
5	3026549	3000000	400000
6	2039608	2000000	-400000
7	1920937	1500000	1200000
8	4825971	4000000	2700000
9	5314132	5000000	1800000
10	1345362	1000000	900000
11	721110	600000	-400000
12	4810405	4500000	-1700000
13	1345362	1000000	900000
14	1486607	1000000	-1100000
15	1345362	1000000	900000
16	2247221	2100000	-800000

Table B.3: 34 nodes test system: R and X parameters. Substation at node 1

Initial node	End node	R [Ohm]	X [Ohm]
1	2	0.117	0.048
2	3	0.1073	0.044
3	4	0.1645	0.0457
4	5	0.1495	0.0415
5	6	0.1495	0.0415
6	7	0.3144	0.054
7	8	0.2096	0.036
8	9	0.3144	0.054
9	10	0.2096	0.036
10	11	0.131	0.0225
11	12	0.1048	0.018
3	13	0.1572	0.027
13	14	0.2096	0.036
14	15	0.1048	0.018
15	16	0.0524	0.009
6	17	0.1794	0.0498
17	18	0.1645	0.0457
18	19	0.2079	0.0473
19	20	0.189	0.043
20	21	0.189	0.043
21	22	0.262	0.045
22	23	0.262	0.045
23	24	0.3144	0.054
24	25	0.2096	0.036
25	26	0.131	0.0225
26	27	0.1048	0.018
7	28	0.1572	0.027
28	29	0.1572	0.027
29	30	0.1572	0.027
10	31	0.1572	0.027
31	32	0.2096	0.036
32	33	0.1572	0.027
33	34	0.1048	0.018

Table B.4: 34 nodes test system: loads

Node	S [VA]	P [W]	Q [Var]
1	0	0	0
2	459963	391000	242250
3	0	0	0
4	459963	391000	242250
5	459963	391000	242250
6	0	0	0
7	0	0	0
8	459963	391000	242250
9	459963	391000	242250
10	0	0	0
11	459963	391000	242250
12	273193	232900	142800
13	144340	122400	76500
14	144340	122400	76500
15	144340	122400	76500
16	26254	22950	12750
17	459963	391000	242250
18	459963	391000	242250
19	459963	391000	242250
20	459963	391000	242250
21	459963	391000	242250
22	459963	391000	242250
23	459963	391000	242250
24	459963	391000	242250
25	459963	391000	242250
26	459963	391000	242250
27	274085	232900	144500
28	151376	127500	81600
29	151376	127500	81600
30	151376	127500	81600
31	115990	96900	63750
32	115990	96900	63750
33	115990	96900	63750
34	115990	96900	63750

Table B.5: 23 nodes test system: R and X parameters. Substations at nodes 1 and 2

Line	Initial node	End node	R[Ohm]	X[Ohm]
1	1	3	0.820801	0.692946
2	3	4	1.14036	0.78624
3	1	5	0.636778	0.537588
4	5	6	1.14036	0.78624
5	6	7	1.14036	0.78624
6	7	8	0.91375	0.63
7	6	9	0.91375	0.63
8	9	10	1.14036	0.78624
9	3	11	1.253665	0.86436
10	11	12	2.62429	1.80936
11	2	13	1.027055	0.70812
12	13	14	1.14036	0.78624
13	14	15	1.597235	1.10124
14	2	16	1.370625	0.945
15	16	17	1.370625	0.945
16	17	18	1.027055	0.70812
17	14	19	0.91375	0.63
18	19	20	0.79679	0.54936
19	15	21	1.370625	0.945
20	21	22	0.91375	0.63
21	22	23	0.683485	0.47124

Table B.6: 23 nodes test system: loads

Node	S [VA]	P [W]	Q [Var]
1	0	0	0
2	0	0	0
3	4140048,31	3300000	2500000
4	1375000	1100000	825000
5	500000	400000	300000
6	1750000	1400000	1050000
7	2500000	2000000	1500000
8	750000	600000	450000
9	250000	200000	150000
10	1875000	1500000	1125000
11	2375000	1900000	1425000
12	2500000	2000000	1500000
13	250000	200000	150000
14	1250000	1000000	750000
15	1125000	900000	675000
16	1000000	800000	600000
17	1250000	1000000	750000
18	1625000	1300000	975000
19	625000	500000	375000
20	625000	500000	375000
21	0	0	0
22	1250000	1000000	750000
23	750000	600000	450000

Table B.7: $Pn6k2 - DS16N$ Vehicle capacity: 40 No. of vehicles:2

Node in transportation network	Node in Power network	X	Y	Customer demand	CVRP:1 PDS:2
1	N/A	42	57	8	1
2	N/A	27	68	7	1
3	N/A	43	67	14	1
4	N/A	58	48	6	1
5	N/A	58	27	19	1
6	N/A	37	69	11	1
7	1	-7.14	80.22	0	2
8	2	45.5	109.02	0	2
9	3	92.03	81.87	0	2
10	4	-7.14	70.22	0	2
11	5	-19.01	67.06	0	2
12	6	3.95	67.06	0	2
13	7	1.28	60.18	0	2
14	8	45.9	103.73	0	2
15	9	41.41	93.73	0	2
16	10	60.9	97.5	0	2
17	11	38.75	82.23	0	2
18	12	49.34	85.9	0	2
19	13	77.97	71.31	0	2
20	14	66.41	62.37	0	2
21	15	97.57	57.01	0	2
22	16	85.19	40.77	0	2
23	N/A	1	-1	Dep	1
24	N/A	1	-1	Dep’	1

Table B.8: $Pn7k3 - DS34N$ Vehicle capacity: 40 No. of vehicles:3

Node in transportation network	Node in Power network	X	Y	Customer demand	CVRP:1 PDS:2
1	N/A	62	42	8	1
2	N/A	42	57	8	1
3	N/A	27	68	7	1
4	N/A	43	67	14	1
5	N/A	58	48	6	1
6	N/A	58	27	19	1
7	N/A	37	69	11	1
8	1	-23.11	28.33	0	2
9	2	1.14	28.33	0	2
10	3	26.51	28.33	0	2
11	4	45.14	28.33	0	2
12	5	65	28.33	0	2
13	6	84.75	28.33	0	2
14	7	102.35	28.33	0	2
15	8	124.5	28.33	0	2
16	9	124.5	11.14	0	2
17	10	106.26	11.14	0	2
18	11	90.88	11.14	0	2
19	12	69.67	11.14	0	2
20	13	26.51	35.41	0	2
21	14	26.51	47.48	0	2
22	15	26.51	58.47	0	2
23	16	26.51	69.55	0	2
24	17	84.75	40.43	0	2
25	18	84.75	53.22	0	2
26	19	84.75	68.86	0	2
27	20	84.75	79.67	0	2
28	21	68.48	79.67	0	2
29	22	48.12	79.67	0	2
30	23	26.91	79.67	0	2
31	24	8.86	79.67	0	2
32	25	-10.87	79.67	0	2
33	26	-10.87	67.38	0	2
34	27	-10.87	54.6	0	2
35	28	102.35	40.22	0	2
36	29	102.35	52.38	0	2
37	30	102.35	65.49	0	2
38	31	106.26	-13.14	0	2
39	32	91.47	-13.14	0	2
40	33	69.94	-13.14	0	2
41	34	46.15	-13.14	0	2
42	N/A	1	-1	Dep	1
43	N/A	1	-1	Dep'	1

Table B.9: $Pn8k3 - DS23N$ Vehicle capacity: 40 No. of vehicles:3

Node in transportation network	Node in Power network	X	Y	Customer demand	CVRP:1 PDS:2
1	N/A	57	58	28	1
2	N/A	62	42	8	1
3	N/A	42	57	8	1
4	N/A	27	68	7	1
5	N/A	43	67	14	1
6	N/A	58	48	6	1
7	N/A	58	27	19	1
8	N/A	37	69	11	1
9	3	20.55	21.78	0	2
10	4	29.77	17.96	0	2
11	5	26.67	36.53	0	2
12	6	30.5	45.75	0	2
13	7	34.32	54.97	0	2
14	8	37.39	62.36	0	2
15	9	37.89	42.69	0	2
16	10	47.11	38.86	0	2
17	11	16.35	11.64	0	2
18	12	37.57	2.84	0	2
19	1	24	30.09	0	2
20	13	74.95	65.56	0	2
21	14	84.53	62.75	0	2
22	15	80.59	49.33	0	2
23	16	54.8	71.47	0	2
24	17	51.43	59.95	0	2
25	18	48.89	51.32	0	2
26	19	77.27	59.37	0	2
27	20	75.31	52.68	0	2
28	21	77.21	37.81	0	2
29	22	74.96	30.14	0	2
30	23	73.28	24.4	0	2
31	2	66.32	68.09	0	2
32	N/A	1	-1	Dep	1
33	N/A	1	-1	Dep'	1

Appendix C

Test systems for EVCSs location: Second approach

Table C.1: 34 nodes test system topology and associated transportation nodes.

Initial node	End node	Length [ft].	Config.	Transportation node at end node	Initial node	End node	Length [ft].	Config.	Transportation node at end node
800	802	2580	1	0	907	860	1010	2	0
802	891	865	1	0	834	842	280	2	0
891	806	865	1	12	836	909	430	2	0
806	808	32230	1	2	909	840	430	2	0
808	892	2902	4	0	836	862	280	2	0
892	810	2902	4	11	842	904	675	2	0
808	812	37500	1	7	904	923	674	2	0
812	814	29730	1	0	923	844	1	2	0
814	850	10	2	0	844	905	1820	2	0
816	818	1710	3	0	905	846	1820	2	0
816	895	5105	2	0	846	906	265	2	0
895	824	5105	2	0	906	925	264	2	0
818	893	24075	3	3	925	848	1	2	0
893	820	24075	3	9	850	816	310	2	19
820	894	6870	3	0	852	832	10	2	0
894	822	6870	3	4	854	899	11665	4	0
824	896	1515	4	0	899	856	11665	4	0
896	826	1515	4	0	854	852	36830	2	10
824	897	420	2	0	858	901	810	3	0
897	828	420	2	0	901	864	810	3	0
828	898	10220	2	6	858	902	2915	2	0
898	830	10220	2	0	902	834	2915	2	0
830	854	520	2	14	860	908	1340	2	0
832	900	2450	2	0	908	836	1340	2	0
900	858	2450	2	0	862	910	2430	5	0
834	907	1010	2	0	910	838	2430	5	17

Table C.2: 34 nodes test system configuration.

Parameters	Configuration				
	1	2	3	4	5
R_{11}	1.3368	1.9300	2.7995	0.0000	0.0000
R_{12}	0.2101	0.2327	0.0000	0.0000	0.0000
R_{13}	0.2130	0.2359	0.0000	0.0000	0.0000
R_{22}	1.3238	1.9157	0.0000	2.7995	1.9217
R_{23}	0.2066	0.2288	0.0000	0.0000	0.0000
R_{33}	1.3294	1.9219	0.0000	0.0000	0.0000
X_{11}	1.3343	1.4115	1.4855	0.0000	0.0000
X_{12}	0.5779	0.6442	0.0000	0.0000	0.0000
X_{13}	0.5015	0.5691	0.0000	0.0000	0.0000
X_{22}	1.3569	1.4281	0.0000	1.4855	1.4212
X_{23}	0.4591	0.5238	0.0000	0.0000	0.0000
X_{33}	1.3471	1.4209	0.0000	0.0000	0.0000
B_{11}	5.3350	5.1207	4.2251	0.0000	0.0000
B_{12}	-1.5313	-1.4364	0.0000	0.0000	0.0000
B_{13}	-0.9943	-0.9402	0.0000	0.0000	0.0000
B_{22}	5.0979	4.9055	0.0000	4.2251	4.3637
B_{23}	-0.6212	-0.5951	0.0000	0.0000	0.0000
B_{33}	4.8880	4.7154	0.0000	0.0000	0.0000

Table C.3: Loads at 34 nodes test system. *Capacitive load

Node	Connection Wye=1, Delta=0	Load modeling (α) PQ=0, I=1, Z=2	Phase 1		Phase 2		Phase 3	
			P [kW]	Q [kVar]	P [kW]	Q [kVar]	P [kW]	Q [kVar]
860	1	0	20	16	20	16	20	16
840	1	1	9	7	9	7	9	7
844	1	2	135	105	135	105	135	105
848	0	0	20	16	20	16	20	16
832	0	1	150	75	150	75	150	75
830	0	2	10	5	10	5	25	10
891	1	0	0	0	30	15	25	14
892	1	1	0	0	16	8	0	0
893	1	2	34	17	0	0	0	0
894	1	0	135	70	0	0	0	0
895	0	1	0	0	5	2	0	0
896	1	1	0	0	40	20	0	0
897	1	0	0	0	0	0	4	2
898	1	0	7	3	0	0	0	0
899	1	0	0	0	4	2	0	0
900	0	2	7	3	2	1	6	3
901	1	0	2	1	0	0	0	0
902	0	0	4	2	15	8	13	7
907	0	2	16	8	20	10	110	55
908	0	0	30	15	10	6	42	22
909	0	1	18	9	22	11	0	0
910	1	0	0	0	28	14	0	0
904	1	0	9	5	0	0	0	0
905	1	0	0	0	25	12	20	11
906	1	0	0	0	23	11	0	0
*923	1	2	0	-100	0	-100	0	-100
*925	0	2	0	-150	0	-150	0	-150

Table C.4: Benchmark case results at 34 nodes test system.

Node	V_a	θ_a	V_b	θ_b	V_c	θ_c
800	1.05	0	1.05	-120	1.05	120
802	1.0475	-0.05	1.0484	-120.07	1.0484	119.95
806	1.0457	-0.08	1.0474	-120.11	1.0474	119.92
808	1.0136	-0.75	1.0296	-120.95	1.0289	119.3
810	0	0	1.0294	-120.95	0	0
812	0.9763	-1.57	1.01	-121.92	1.0069	118.59
814	0.9467	-2.26	0.9945	-122.7	0.9893	118.01
816	1.0172	-2.26	1.0253	-122.71	1.02	118.01
818	1.0163	-2.27	0	0	0	0
820	0.9926	-2.32	0	0	0	0
822	0.9895	-2.33	0	0	0	0
824	1.0082	-2.37	1.0158	-122.94	1.0116	117.76
826	0	0	1.0156	-122.94	0	0
828	1.0074	-2.38	1.0151	-122.95	1.0109	117.75
830	0.9894	-2.63	0.9982	-123.39	0.9938	117.25
832	1.0359	-3.11	1.0345	-124.18	1.036	116.33
834	1.0309	-3.24	1.0295	-124.39	1.0313	116.09
836	1.0303	-3.23	1.0287	-124.39	1.0308	116.09
838	0	0	1.0285	-124.39	0	0
840	1.0303	-3.23	1.0287	-124.39	1.0308	116.09
842	1.0309	-3.25	1.0294	-124.39	1.0313	116.09
844	1.0307	-3.27	1.0291	-124.42	1.0311	116.06
846	1.0309	-3.32	1.0291	-124.46	1.0313	116.01
848	1.031	-3.32	1.0291	-124.47	1.0314	116
850	1.0176	-2.26	1.0255	-122.7	1.0203	118.01
852	0.9581	-3.11	0.968	-124.18	0.9637	116.33
854	0.989	-2.64	0.9978	-123.4	0.9934	117.24
856	0	0	0.9977	-123.41	0	0
858	1.0336	-3.17	1.0322	-124.28	1.0338	116.22
860	1.0305	-3.24	1.0291	-124.39	1.031	116.09
862	1.0303	-3.23	1.0287	-124.39	1.0308	116.09
864	1.0336	-3.17	0	0	0	0

Additional characteristics for 34 nodes distribution network characteristics:

- Slack node: 800
- V_{nom}=24.9 kV
- S_{transf}=2.5 MVA
- Regulators at:

  Line 814-850: tap_a : 12, tap_b : 5, tap_c : 5

  Line 852-832: tap_a : 13, tap_b : 11, tap_c : 12

Table C.5: $Pn19k2$ instance and candidate nodes for EVCSs.

Customer	Coord. X	Coord. Y	Candidate for EVCS	Demand
1	30	40	0	0
2	37	52	1	19
3	49	43	1	30
4	52	64	1	16
5	31	62	0	23
6	52	33	1	11
7	42	41	1	31
8	52	41	0	15
9	57	58	1	28
10	62	42	1	14
11	42	57	1	8
12	27	68	1	7
13	43	67	0	14
14	58	27	1	19
15	37	69	0	11
16	61	33	0	26
17	62	63	1	17
18	63	69	0	6
19	45	35	1	15

Table C.6: Connectivity matrix for SP problem in $Pn19k2$ instance.

Node	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	0	1	0	0	1	0	1	0	0	0	0	1	0	1	0	0	0	0	1
2	1	0	0	0	1	0	1	0	0	0	1	0	0	0	1	0	0	0	0
3	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	1
4	0	0	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	1	0
5	1	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0
6	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	1	0	0	1
7	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
8	0	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0
9	0	0	0	1	0	0	0	0	0	1	1	0	0	0	0	0	1	1	0
10	0	0	0	0	0	1	0	1	1	0	1	0	0	0	0	1	1	1	0
11	0	1	1	1	0	0	1	0	1	1	0	0	1	0	1	0	0	0	0
12	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0
13	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	1	0
14	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0
15	0	1	0	0	1	0	0	0	0	0	1	1	1	0	0	0	0	1	0
16	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	0	0
17	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0
18	0	0	0	1	0	0	0	0	1	1	0	0	1	0	1	0	1	0	0
19	1	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0

Additional characteristics for transportation network in $Pn19k2$ instance:

- CVRP:

  Vehicle capacity: 160

  Number of vehicles: 2

- SP problem:

  Vehicle 1: Start point: 12, End point: 10

  Vehicle 2: Start point: 1, End point: 18

  Vehicle 3: Start point: 15, End point: 14

  Vehicle 4: Start point: 17, End point: 12

Table C.7: 123 nodes test system topology and associated transportation nodes.

Initial node	End node	Length [ft.]	Config.	Transportation node at end node	Initial node	End node	Length [ft.]	Config.	Transportation node at end node
149	1	400	1	20	64	65	425	12	0
1	2	175	10	0	65	66	325	12	9
1	3	250	11	0	160	67	350	6	10
3	4	200	11	0	67	68	200	9	0
3	5	325	11	0	68	69	275	9	0
5	6	250	11	0	69	70	325	9	0
1	7	300	1	0	70	71	275	9	0
7	8	200	1	0	67	72	275	3	13
8	9	225	9	0	72	73	275	11	0
14	10	250	9	0	73	74	350	11	0
14	11	250	9	0	74	75	400	11	0
8	12	225	10	0	72	76	200	3	0
8	13	300	1	0	76	77	400	6	0
9	14	425	9	0	77	78	100	6	0
34	15	100	11	0	78	79	225	6	16
15	16	375	11	0	78	80	475	6	0
15	17	350	11	0	80	81	475	6	0
13	18	825	2	14	81	82	250	6	19
18	19	250	9	0	82	451	249	6	0
19	20	325	9	0	451	83	1	6	0
18	21	300	2	0	81	84	675	11	0
21	22	525	10	0	84	85	475	11	0
21	23	250	2	12	76	86	700	3	0
23	24	550	11	0	86	87	450	6	21
23	25	275	2	0	87	452	174	9	0
25	26	350	7	0	452	88	1	9	0
26	27	275	7	0	87	89	275	6	0
25	28	200	2	0	89	453	224	10	0
28	29	300	2	5	453	90	1	10	0
29	30	350	2	0	89	91	225	6	18
26	31	225	11	0	91	454	299	11	0
31	32	300	11	0	454	92	1	11	0
27	33	500	9	0	91	93	225	6	0
13	34	150	11	0	93	94	275	9	0
135	35	375	4	0	93	95	300	6	22
35	36	650	8	0	95	96	200	10	0
36	37	300	9	0	67	97	250	3	8
36	38	250	10	0	97	98	275	3	0
38	39	325	10	0	98	99	550	3	0
35	40	250	1	0	99	100	300	3	0
40	41	325	11	0	197	101	250	3	0
40	42	250	1	0	101	102	225	11	0
42	43	500	10	0	102	103	325	11	0
42	44	200	1	0	103	104	700	11	0
44	45	200	9	0	101	105	275	3	3
45	46	300	9	0	105	106	225	10	0
44	47	250	1	0	106	107	575	10	0
47	48	150	4	0	105	108	325	3	0
47	49	250	4	0	108	109	450	9	0
49	50	250	4	0	109	110	300	9	0
50	51	250	4	0	110	111	575	9	0
152	52	400	1	0	110	112	125	9	0
52	53	200	1	0	112	113	525	9	0
53	54	125	1	0	113	114	325	9	0
54	55	275	1	15	51	151	500	4	0
55	56	275	1	0	30	250	200	2	4
54	57	350	3	0	108	300	1000	3	2
57	58	250	10	0	100	450	800	3	6
58	59	250	10	0	18	135	10	4	0
57	60	750	3	0	150	149	10	1	0
60	61	550	5	0	13	152	10	1	17
60	62	250	12	11	60	160	10	6	0
62	63	175	12	0	97	197	10	3	0
63	64	350	12	7					

Table C.8: 123 nodes test system configuration.

Parameters	Configuration											
	1	2	3	4	5	6	7	8	9	10	11	12
R_{11}	0.4576	0.4666	0.4615	0.4615	0.4666	0.4576	0.4576	0.4576	1.3292	0.0000	0.0000	1.5209
R_{12}	0.1560	0.1580	0.1535	0.1580	0.1560	0.1535	0.0000	0.1535	0.0000	0.0000	0.0000	0.5198
R_{13}	0.1535	0.1560	0.1580	0.1535	0.1580	0.1560	0.1535	0.0000	0.0000	0.0000	0.0000	0.4924
R_{22}	0.4666	0.4615	0.4576	0.4666	0.4576	0.4615	0.0000	0.4615	0.0000	1.3292	0.0000	1.5329
R_{23}	0.1580	0.1535	0.1560	0.1560	0.1535	0.1580	0.0000	0.0000	0.0000	0.0000	0.0000	0.5198
R_{33}	0.4615	0.4576	0.4666	0.4576	0.4615	0.4666	0.4615	0.0000	0.0000	0.0000	1.3292	1.5209
X_{11}	1.0780	1.0482	1.0651	1.0651	1.0482	1.0780	1.0780	1.0780	1.3475	0.0000	0.0000	0.7521
X_{12}	0.5017	0.4236	0.3849	0.4236	0.5017	0.3849	0.0000	0.3849	0.0000	0.0000	0.0000	0.2775
X_{13}	0.3849	0.5017	0.4236	0.3849	0.4236	0.5017	0.3849	0.0000	0.0000	0.0000	0.0000	0.2157
X_{22}	1.0482	1.0651	1.0780	1.0482	1.0780	1.0651	0.0000	1.0651	0.0000	1.3475	0.0000	0.7162
X_{23}	0.4236	0.3849	0.5017	0.5017	0.3849	0.4236	0.0000	0.0000	0.0000	0.0000	0.0000	0.2775
X_{33}	1.0651	1.0780	1.0482	1.0780	1.0651	1.0482	1.0651	0.0000	0.0000	0.0000	1.3475	0.7521
B_{11}	5.6765	5.9809	5.3971	5.3971	5.9809	5.6765	5.1154	5.1154	4.5193	0.0000	0.0000	67.2242
B_{12}	-1.8319	-1.1645	-0.6982	-1.1645	-1.8319	-0.6982	0.0000	-1.0549	0.0000	0.0000	0.0000	0.0000
B_{13}	-0.6982	-1.8319	-1.1645	-0.6982	-1.1645	-1.8319	-1.0549	0.0000	0.0000	0.0000	0.0000	0.0000
B_{22}	5.9809	5.3971	5.6765	5.9809	5.6765	5.3971	0.0000	5.1740	0.0000	4.5193	0.0000	67.2242
B_{23}	-1.1645	-0.6982	-1.8319	-1.8319	-0.6982	-1.1645	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
B_{33}	5.3971	5.6765	5.9809	5.6765	5.3971	5.9809	5.1704	0.0000	0.0000	0.0000	4.5193	67.2242

Table C.9: Loads at 123 nodes test system. *Capacitive load

Node	Connection Wye=1, Delta=0	Load modeling (α) PQ=0, I=1, Z=2	Phase 1		Phase 2		Phase 3		Node	Connection Wye=1, Delta=0	Load modeling (α) PQ=0, I=1, Z=2	Phase 1		Phase 2		Phase 3	
			P [kW]	Q [kVar]	P [kW]	Q [kVar]	P [kW]	Q [kVar]				P [kW]	Q [kVar]	P [kW]	Q [kVar]	P [kW]	Q [kVar]
1	1	0	40	20	0	0	0	0	63	1	0	40	20	0	0	0	0
2	1	0	0	0	20	10	0	0	64	1	1	0	0	75	35	0	0
4	1	0	0	0	0	0	40	20	65	0	2	35	25	35	25	70	50
5	1	1	0	0	0	0	20	10	66	1	0	0	0	0	0	75	35
6	1	2	0	0	0	0	40	20	68	1	0	20	10	0	0	0	0
7	1	0	20	10	0	0	0	0	69	1	0	40	20	0	0	0	0
9	1	0	40	20	0	0	0	0	70	1	0	20	10	0	0	0	0
10	1	1	20	10	0	0	0	0	71	1	0	40	20	0	0	0	0
11	1	2	40	20	0	0	0	0	73	1	0	0	0	0	0	40	20
12	1	0	0	0	20	10	0	0	74	1	2	0	0	0	0	40	20
16	1	0	0	0	0	0	40	20	75	1	0	0	0	0	0	40	20
17	1	0	0	0	0	0	20	10	76	0	1	105	80	70	50	70	50
19	1	0	40	20	0	0	0	0	77	1	0	0	0	40	20	0	0
20	1	1	40	20	0	0	0	0	79	1	2	40	20	0	0	0	0
22	1	2	0	0	40	20	0	0	80	1	0	0	0	40	20	0	0
24	1	0	0	0	0	0	40	20	82	1	0	40	20	0	0	0	0
28	1	1	40	20	0	0	0	0	83	1	0	0	0	0	0	20	10
29	1	2	40	20	0	0	0	0	84	1	0	0	0	0	0	20	10
30	1	0	0	0	0	0	40	20	85	1	0	0	0	0	0	40	20
31	1	0	0	0	0	0	20	10	86	1	0	0	0	20	10	0	0
32	1	0	0	0	0	0	20	10	87	1	0	0	0	40	20	0	0
33	1	1	40	20	0	0	0	0	88	1	0	40	20	0	0	0	0
34	1	2	0	0	0	0	40	20	90	1	1	0	0	40	20	0	0
35	0	0	40	20	0	0	0	0	92	1	0	0	0	0	0	40	20
37	1	2	40	20	0	0	0	0	94	1	0	40	20	0	0	0	0
38	1	1	0	0	20	10	0	0	95	1	0	0	0	20	10	0	0
39	1	0	0	0	20	10	0	0	96	1	0	0	0	20	10	0	0
41	1	0	0	0	0	0	20	10	98	1	0	40	20	0	0	0	0
42	1	0	20	10	0	0	0	0	99	1	0	0	0	40	20	0	0
43	1	2	0	0	40	20	0	0	100	1	2	0	0	0	0	40	20
45	1	1	20	10	0	0	0	0	102	1	0	0	0	0	0	20	10
46	1	0	20	10	0	0	0	0	103	1	0	0	0	0	0	40	20
47	1	1	35	25	35	25	35	25	104	1	0	0	0	0	0	40	20
48	1	2	70	50	70	50	70	50	106	1	0	0	0	40	20	0	0
49	1	0	35	25	70	50	35	20	107	1	0	0	0	40	20	0	0
50	1	0	0	0	0	0	40	20	109	1	0	40	20	0	0	0	0
51	1	0	20	10	0	0	0	0	111	1	0	20	10	0	0	0	0
52	1	0	40	20	0	0	0	0	112	1	1	20	10	0	0	0	0
53	1	0	40	20	0	0	0	0	113	1	2	40	20	0	0	0	0
55	1	2	20	10	0	0	0	0	114	1	0	20	10	0	0	0	0
56	1	0	0	0	20	10	0	0	451	1	2	0	-200	0	-200	0	-200
58	1	1	0	0	20	10	0	0	452	1	2	0	-50	0	0	0	0
59	1	0	0	0	20	10	0	0	453	1	2	0	0	0	-50	0	0
60	1	0	20	10	0	0	0	0	454	1	2	0	0	0	0	0	-50
62	1	2	0	0	0	0	40	20									

Table C.10: Benchmark case results at 123 nodes test system.

Node	V_a	θ_a	V_b	θ_b	V_c	θ_c	Node	V_a	θ_a	V_b	θ_b	V_c	θ_c
1	1.0311	-0.66	1.0412	-120.33	1.0348	119.6	63	0.9866	-3.49	1.0236	-121.97	1.0022	117.74
2	0	0	1.041	-120.33	0	0	64	0.9863	-3.47	1.0217	-121.93	1	117.7
3	0	0	0	0	1.0331	119.57	65	0.9856	-3.48	1.0214	-121.89	0.997	117.7
4	0	0	0	0	1.0326	119.56	66	0.9858	-3.51	1.0216	-121.87	0.9955	117.7
5	0	0	0	0	1.0318	119.55	67	1.0355	-3.77	1.0311	-122.19	1.0345	117.61
6	0	0	0	0	1.0311	119.53	68	1.034	-3.79	0	0	0	0
7	1.0218	-1.13	1.0395	-120.57	1.0291	119.35	69	1.0322	-3.83	0	0	0	0
8	1.0158	-1.44	1.0382	-120.74	1.0253	119.18	70	1.031	-3.85	0	0	0	0
9	1.0144	-1.47	0	0	0	0	71	1.0303	-3.86	0	0	0	0
10	1.006	-1.5	0	0	0	0	72	1.0359	-3.86	1.0302	-122.29	1.0343	117.5
11	1.0057	-1.51	0	0	0	0	73	0	0	0	0	1.0321	117.46
12	0	0	1.0379	-120.74	0	0	74	0	0	0	0	1.0303	117.42
13	1.0079	-1.87	1.036	-120.97	1.0196	118.9	75	0	0	0	0	1.0293	117.4
14	1.0063	-1.5	0	0	0	0	76	1.0358	-3.92	1.0297	-122.38	1.0349	117.45
15	0	0	0	0	1.0183	118.87	77	1.037	-3.99	1.0308	-122.46	1.0358	117.37
16	0	0	0	0	1.0173	118.85	78	1.0373	-4.01	1.0312	-122.48	1.036	117.35
17	0	0	0	0	1.0178	118.86	79	1.037	-4.02	1.0313	-122.48	1.0359	117.36
18	0.9988	-2.29	1.0319	-121.22	1.0122	118.83	80	1.0394	-4.07	1.0329	-122.54	1.0368	117.24
19	0.9975	-2.31	0	0	0	0	81	1.0415	-4.14	1.0352	-122.57	1.0374	117.14
20	0.9967	-2.33	0	0	0	0	82	1.0424	-4.18	1.0364	-122.6	1.0382	117.11
21	0.9983	-2.34	1.032	-121.22	1.0111	118.81	83	1.0436	-4.2	1.0375	-122.63	1.039	117.07
22	0	0	1.0305	-121.25	0	0	84	0	0	0	0	1.0348	117.09
23	0.9979	-2.39	1.0323	-121.2	1.01	118.79	85	0	0	0	0	1.0336	117.07
24	0	0	0	0	1.0085	118.77	86	1.0349	-3.95	1.0279	-122.55	1.0364	117.42
25	0.9972	-2.45	1.0328	-121.2	1.0091	118.8	87	1.0342	-3.97	1.0272	-122.63	1.0369	117.39
26	0.997	-2.48	0	0	1.0023	118.79	88	1.0342	-4	0	0	0	0
27	0.9966	-2.49	0	0	1.0022	118.79	89	1.0338	-3.96	1.027	-122.68	1.0373	117.38
28	0.9968	-2.48	1.033	-121.19	1.0087	118.8	90	0	0	1.0269	-122.72	0	0
29	0.9967	-2.5	1.0332	-121.19	1.0083	118.79	91	1.0336	-3.96	1.0266	-122.69	1.0376	117.36
30	0.9969	-2.5	1.0331	-121.18	1.0078	118.77	92	0	0	0	0	1.0375	117.31
31	0	0	0	0	1.0017	118.77	93	1.0333	-3.97	1.0265	-122.71	1.0377	117.37
32	0	0	0	0	1.0013	118.77	94	1.0326	-3.98	0	0	0	0
33	0.9953	-2.52	0	0	0	0	95	1.0332	-3.96	1.0261	-122.73	1.0378	117.37
34	0	0	0	0	1.0187	118.88	96	0	0	1.0258	-122.73	0	0
35	0.996	-2.38	1.0293	-121.31	1.0112	118.77	97	1.0345	-3.82	1.0306	-122.21	1.0338	117.6
36	0.9951	-2.4	1.0288	-121.36	0	0	98	1.0343	-3.83	1.0303	-122.22	1.0336	117.59
37	0.9943	-2.41	0	0	0	0	99	1.0346	-3.82	1.0295	-122.23	1.0332	117.55
38	0	0	1.0282	-121.37	0	0	100	1.0348	-3.82	1.0294	-122.21	1.0328	117.53
39	0	0	1.0278	-121.38	0	0	101	1.0337	-3.86	1.0303	-122.22	1.0332	117.59
40	0.9945	-2.42	1.0282	-121.36	1.0101	118.72	102	0	0	0	0	1.0318	117.56
41	0	0	0	0	1.0097	118.71	103	0	0	0	0	1.0301	117.53
42	0.9929	-2.45	1.027	-121.41	1.0092	118.68	104	0	0	0	0	1.0283	117.49
43	0	0	1.0257	-121.43	0	0	105	1.0323	-3.9	1.0301	-122.27	1.0335	117.61
44	0.9918	-2.48	1.0263	-121.44	1.0084	118.65	106	0	0	1.029	-122.29	0	0
45	0.9913	-2.49	0	0	0	0	107	0	0	1.0275	-122.32	0	0
46	0.9909	-2.5	0	0	0	0	108	1.0309	-3.97	1.0308	-122.28	1.0334	117.65
47	0.9908	-2.5	1.0253	-121.47	1.0074	118.61	109	1.0267	-4.05	0	0	0	0
48	0.9905	-2.51	1.025	-121.47	1.0072	118.6	110	1.0248	-4.09	0	0	0	0
49	0.9905	-2.51	1.0247	-121.48	1.0071	118.58	111	1.024	-4.1	0	0	0	0
50	0.9905	-2.52	1.0247	-121.47	1.0067	118.57	112	1.0241	-4.1	0	0	0	0
51	0.9903	-2.53	1.0248	-121.47	1.0067	118.58	113	1.022	-4.14	0	0	0	0
52	1.0018	-2.26	1.0348	-121.22	1.0164	118.64	114	1.0216	-4.15	0	0	0	0
53	0.9991	-2.43	1.034	-121.34	1.0148	118.51	135	0.9988	-2.29	1.0318	-121.23	1.0122	118.83
54	0.9976	-2.53	1.0334	-121.41	1.0138	118.43	149	1.0436	-0.02	1.0437	-120.02	1.0436	119.98
55	0.9974	-2.54	1.0334	-121.42	1.0139	118.43	150	1	0	1	-120	1	120
56	0.9974	-2.53	1.0332	-121.43	1.014	118.43	151	0.9903	-2.53	1.0248	-121.47	1.0067	118.58
57	0.9945	-2.83	1.0306	-121.61	1.0113	118.21	152	1.0078	-1.88	1.036	-120.98	1.0196	118.89
58	0	0	1.03	-121.63	0	0	160	0.988	-3.52	1.0256	-122.01	1.0052	117.75
59	0	0	1.0296	-121.63	0	0	197	1.0345	-3.82	1.0306	-122.21	1.0338	117.59
60	0.988	-3.51	1.0256	-122	1.0052	117.76	250	0.9969	-2.5	1.0331	-121.18	1.0078	118.77
61	0.988	-3.51	1.0256	-122	1.0052	117.76	300	1.0309	-3.97	1.0308	-122.28	1.0334	117.65
62	0.9872	-3.5	1.0245	-121.98	1.0032	117.75	450	1.0348	-3.82	1.0294	-122.21	1.0328	117.53

Additional characteristics for 123 nodes distribution network characteristics:

- Slack node: 150
- V_{nom}=4.16 kV
- S_{transf}=5 MVA
- Regulators at:

  Line 9-14: $tap_a : -1$

  Line 25-26: $tap_c : -1$

  Line 160-67: $tap_a : 8$, $tap_b : 1$, $tap_c : 5$

  Line 150-149: $tap_a : 7$, $tap_b : 7$, $tap_c : 7$

Table C.11: $En22k4$ instance and candidate nodes for EVCSs.

Customer	Coord. X	Coord. Y	Candidate for EVCS	Demand
1	145	215	0	0
2	151	264	1	1100
3	159	261	1	700
4	130	254	1	800
5	128	252	1	1400
6	163	247	1	2100
7	146	246	1	400
8	161	242	1	800
9	142	239	1	100
10	163	236	1	500
11	148	232	1	600
12	128	231	1	1200
13	156	217	1	1300
14	129	214	1	1300
15	146	208	1	300
16	164	208	1	900
17	141	206	1	2100
18	147	193	1	1000
19	164	193	1	900
20	129	189	1	2500
21	155	185	1	1800
22	139	182	1	700

Table C.12: Connectivity matrix for SP problem in $En22k4$ instance.

Node	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	1	0	0	0	0	0
2	0	0	1	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
6	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
7	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
8	0	1	1	0	0	1	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0
9	0	0	0	1	0	0	1	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0
10	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
11	1	0	0	0	0	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0
12	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0
13	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	1	0	0
15	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0
16	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	1	0	0	0
17	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	1	0	1
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0

Additional characteristics for transportation network in $En22k4$ instance:

- CVRP:

  Vehicle capacity: 6000

  Number of vehicles: 4

- SP problem:

  Vehicle 1: Start point: 5, End point: 19

  Vehicle 2: Start point: 12, End point: 16

  Vehicle 3: Start point: 14, End point: 10

  Vehicle 4: Start point: 20, End point: 3

Appendix D

Publications

The works presented as follows, were published (or currently under review) in specialized journals and conferences during the development of this thesis:

- Title: Optimal probabilistic charging of electric vehicles in distribution systems

  Authors: Andrés Arias, Mauricio Granada, Carlos A. Castro

  Journal: IET Electrical Systems in Transportation

  http://ieeexplore.ieee.org/document/8019958/

- Title: Integrated planning of electric vehicles routing and charging stations location considering transportation networks and power distribution systems

  Authors: Andrés Arias, Juan D. Sánchez, Mauricio Granada

  Journal: International Journal of Industrial Engineering Computations

  http://www.growingscience.com/ijiec/IJIEC_2017_33.pdf

- Title book: Vehículos eléctricos, energía y movilidad

  Authors: Mauricio Granada, Andrés Arias, Juan D. Sánchez

  Editorial: UTP

https://www.researchgate.net/publication/322698118_Vehiculos_electricos_energia_y_movilidad

- Title: Optimal placement of freight electric vehicles charging stations and their impact on the power distribution network (under review)

  Authors: Andrés Arias, Alejandro Garcés, Mauricio Granada

  Journal: NETWORKS. An international journal

- Title: Vehículos eléctricos para el transporte de carga: planeación integrada considerando el sistema de distribución de energía (under review)

  Authors: Juan D. Sánchez, Andrés Arias, Mauricio Granada

  Journal: IEEE Latin America Transactions

- Title: Optimal Charging Schedule of Electric Vehicles Considering Variation of Energy Price

  Authors: Andrés Arias, Geovanny Marulanda, Camila Puentes, Ricardo Hincapié and Mauricio Granada

  Conference: Transmission & Distribution Conference and Exposition - Latin America, 2014 IEEE PES

  http://ieeexplore.ieee.org/document/6955238/

- Title: An IEEE Xplore database literature review regarding the interaction between electric vehicles and power grids

  Authors: Andrés Arias, Juan D. Sánchez, Luis H. Martínez, Ricardo Hincapié, Mauricio Granada

  Conference: Innovative Smart Grid Technologies Latin America (ISGT LATAM), 2015 IEEE PES

  http://ieeexplore.ieee.org/document/7381237/

- Title: An efficient approach to solve the combination between Battery Swap Station Location and CVRP by using the MTZ formulation

Authors: Andrés Arias, Juan D. Sánchez, Luis H. Martínez, Ricardo Hincapié, Mauricio Granada

Conference: Innovative Smart Grid Technologies Latin America (ISGT LATAM), 2015 IEEE PES

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