UNIVERSIDADE ESTADUAL PAULISTA “JÚLIO DE MESQUITA FILHO”

FACULDADE DE ENGENHARIA DE ILHA SOLTEIRA

PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA ELÉTRICA

IGOOR MORRO MELLO

Spatial-temporal approach of electric vehicles in urban zones: traffic, infrastructure, decrease in local pollution, recharge, and impact on the electric network.

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Thesis presented to the Faculty of Engineering of the Campus of Ilha Solteira UNESP as part of the requirements for obtaining the title of Doctor in Electrical Engineering.
Area of concentration: Automation.

Prof. Dr. Antonio Padilha Feltrin
Orientador

Ilha Solteira
2022

FICHA CATALOGRÁFICA
Desenvolvido pelo Serviço Técnico de Biblioteca e Documentação

M527s

Mello, Igoor Morro.
Spatial-temporal approach of electric vehicles in urban zones: traffic, infrastructure, decrease in local pollution, recharge, and impact on the electric network / Igoor Morro Mello. -- Ilha Solteira: [s.n.], 2022
140 f. : il.

Tese (doutorado) - Universidade Estadual Paulista. Faculdade de Engenharia de Ilha Solteira. Área de conhecimento: Automação, 2022

Orientador: Antonio Padilha Feltrin
Inclui bibliografia

1. Análise geoespacial. 2. Infraestrutura E Mobilidade urbana. 3. Rede de tráfego e transportes. 4. Veículos elétricos. 5. Previsão espacial de carga. 6. Planejamento de sistemas de distribuição de energia.

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CRB/8 - 9999

UNIVERSIDADE ESTADUAL PAULISTA

Câmpus de Ilha Solteira

CERTIFICADO DE APROVAÇÃO

TÍTULO DA TESE: Spatial-temporal approach of electric vehicles in urban zones: traffic, infrastructure, decrease in local pollution, recharge, and impact on the electric network.

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Ilha Solteira, 23 de maio de 2022

AGRADECIMENTOS

À Deus, criador inefável, que é fonte da verdadeira luz e da ciência.

Agradeço aos meus pais Luciene Morro Mello e Márcio Orélio de Mello que rezaram por mim diariamente durante todos estes anos e estiveram em toda a minha jornada.

Agradeço à minha noiva Lílian de Fátima e Silva pela busca da santidade ao meu lado, com um sério caminho baseado na verdade, fé e amor para juntos chegarmos ao céu.

Agradeço ao meu orientador Dr. Antonio Padilha Feltrin pelo auxílio durante todo o trabalho de doutorado e ao Dr. Joel David Melo Trujillo pelas contribuições que enriqueceram a tese.

Agradeço ao meu diretor espiritual Dr. Luiz Henrique Brandão de Figueiredo, padre diocesano que me auxilia no caminho de santidade, com uma vida dedicada as coisas do alto, baseada na verdade e na fé.

Agradeço aos professores de Engenharia Elétrica da UNESP-FEIS e ao Laboratório de Planejamento de Sistemas de Energia Elétrica – LaPSEE e seus integrantes, em especial meu amigo Henrique Molina Barradas. Agradeço ao Instituto SENAI de Tecnologia em Automação (IST Automação) e colegas de trabalho.

O presente trabalho foi realizado com apoio da Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Código de Financiamento 001; Fundação de Amparo à Pesquisa do Estado de São Paulo (FAPESP) (Processos 2015/21972-6, 2017/01909-3, 2017/22577-9, 2019/00466-6); Conselho Nacional de Desenvolvimento Científico e Tecnológico-Brazil (CNPq) (processos: 307281/2016-7, 422044/2018-0); pelo Instituto Nacional de Ciência e Tecnologia de Energia Elétrica (INCT-INERGE). Agradecimentos à empresa AIMSUN pela licença concedida do *Aimsun Next Postgraduate License* para o desenvolvimento da tese de doutorado.

“Cumpre o pequeno dever de cada momento; faz o que deves e está no que fazes.”

São Josemaría Escrivá

ABSTRACT

Electric vehicles have been encouraged in recent years as they have become widespread in society in terms of new technology, more efficient than combustion vehicles, and can reduce local pollution. However, due to the high price for purchase an electric vehicle, it is expected that their acquisition will occur gradually through financial incentives, price reduction, and diffusion of technology in society. With the increase in the purchase of these vehicles over the years, network infrastructure will meet the demand for recharging these vehicles in the urban zone and planning the distribution networks to meet the demand for recharging. Thus, this work proposes a complete methodology for the introduction of electric vehicles in an urban zone. First, a method is proposed for the acquisition of electric vehicles over time. With the introduction, a vehicle traffic methodology is proposed to find variables such as state of charge and driving patterns in the urban zone. With the results of vehicular traffic, charging stations are presented in the most critical locations. A module is created to find the local pollution reduction with the introduction of electric vehicles over the period. The increase in residential load from residential night charging is calculated, and finally, a methodology for connecting the charging stations to the distribution network is proposed. The method is applied in an urban zone of about 200,000 inhabitants using and integrating computational programming, traffic, geographic information systems, and energy distribution systems tools. The results are shown through spatial thematic maps over the study period. Helps to assist distribution companies in decision-making and planning, owners of charging stations, owners of electric vehicle dealerships, urban planners, and other public and private agents who will be involved in introducing electric vehicles in some stage urban zones.

Keywords: electric vehicles; geospatial analysis; power distribution system planning; spatial load forecasting; traffic and transport network; urban infrastructures and mobility.

RESUMO

Veículos elétricos têm sido incentivados nos últimos anos à medida que se tornam difundidos na sociedade em termos de uma nova tecnologia, por serem mais eficientes que os veículos a combustão e podendo reduzir a poluição local. No entanto, devido aos preços ainda elevados para aquisição dos veículos elétricos, espera-se que sua aquisição ocorra de forma gradual, através de incentivos financeiros, diminuição do preço, difusão da tecnologia na sociedade. Com o aumento, mesmo que gradual, da aquisição destes veículos ao longo dos anos, será necessária uma rede de infraestrutura para atender a demanda de recarga destes veículos na zona urbana e um planejamento das redes de distribuição para que se tenha demanda para a recarga. Assim, este trabalho propõe uma metodologia completa para a introdução dos veículos elétricos em uma zona urbana. Primeiramente, uma metodologia é proposta para a aquisição de veículos elétricos ao longo do tempo. Com a introdução, uma metodologia de tráfego veicular é proposta para encontrar as variáveis relacionadas aos veículos elétricos como estado da carga e padrões de condução na zona urbana. Com os resultados do tráfego veicular, são propostas estações de recarga nos locais mais críticos. Um módulo para obter a diminuição da poluição local com a introdução dos veículos elétricos ao longo do período é criada. Calcula-se o aumento de carga residencial oriundo da recarga residencial noturna e por fim uma metodologia para a conexão das estações de recarga na rede de distribuição é proposta. A metodologia é aplicada em uma zona urbana de cerca de 200 mil habitantes com o uso e integração de ferramentas de programação computacional, de tráfego, sistemas de informação geográfica e dos sistemas de distribuição de energia. Os resultados são mostrados através de mapas temáticos espaciais ao longo do período de estudo e auxiliam as empresas de distribuição na tomada de decisões e planejamento, donos de estações de recarga, donos de concessionárias de veículos elétricos, planejadores urbanos e demais agentes públicos e privados que estarão envolvidos em alguma etapa do processo de introdução dos veículos elétricos nas zonas urbanas.

Palavras Chaves: análise geoespacial; infraestrutura e mobilidade urbana; rede de tráfego e transportes; veículos elétricos; previsão espacial de carga; planejamento de sistemas de distribuição de energia.

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LIST OF ACRONYMS AND ABBREVIATIONS

BEB	Battery Electric Bus
BEV	Battery Electric Vehicle
CO_2	Carbon Dioxide
CS	Charging Station
CV	Coefficient of Variation
DNCEV	Distribution Network Connection Electric Vehicle
EREV	Extended-Range Electric Vehicles
EGT	Electric Garbage Truck
ET	Electric Taxi
EV	Electric Vehicle
FCEV	Fuel Cell Electric Vehicle
GHG	Greenhouse Gases
GIS	Geographic Information System
GWR	Geographically weighted regression
HEV	Hybrid Electric Vehicle
HSAR	Hierarchical spatial autoregressive
ICEV	Internal Combustion Engine Vehicle
LEM	London Emission Model
MCS	Monte Carlo Simulation
MHV	Mild hybrid vehicle
MIHV	Micro-Hybrid Vehicle
NOx	Nitrogen Oxides

O-D	Origins-destinations
PHEB	Plug-in Hybrid Electric Bus
PHEV	Plug-in Hybrid Electric Vehicle
PHGT	Plug-in Hybrid Garbage Truck
RI	Region of Influence
SOC	State of Charge
TSS	Transport Simulation Systems
V2G	Vehicle to Grid
WPT	Wireless Power Transfer

SUMMARY

1 INTRODUCTION

1.1 CONTEXT

The use of Electric vehicles (EVs) in urban zones has intensified in the last years in several countries as a part of new trends in the automotive sector, helping to reduce the emission of greenhouse gases (GHG) (ZIMM, 2020). Furthermore, besides helping reduce local pollution, the electrification of transportation contributes to reducing other environmental, social, and economic problems (PARDO-BOSCH *et al*., 2021).

The high-income public initially acquired the high price to purchase an EV in developed countries. However, with the increase in multi-level recharge infrastructure, maintenance, regulations, tax incentives, advertising, public awareness, a decrease in price, and the introduction of different EVs, the number of them has expanded in these countries.

Over these years of changes in the transportation system in developed countries, with the introduction of new technologies and challenges, developing countries have become almost passive observers of transportation electrification. Moreover, the high price for EVs acquisition, lack of infrastructure, and other varied problems have made their introduction difficult. However, with the recent increase in environmental concern, the need to reduce local pollution in urban zones, combined with the search for new technologies, is becoming a reality (BAMISILE *et al*., 2021).

These countries will detect several challenges in the coming years to electrify transportation. They will have technological, economic, social, environmental, cultural challenges that can make it difficult for EVs to enter their markets (GOEL; SHARMA; RATHORE, 2021). To mitigate such problems, the present work proposes introducing EVs in urban zones considering several aspects that will gradually help use EVs. Moreover, this work tries to cause a minor problem on the systems. As an example, this work will help distribution companies to find connection points in the network, prioritizing the connection in the current elements and consequently reducing expansion costs. The systems that will be impacted are considered in this work, to help the most significant number of agents participating in some stage.

This work presents a different model that will be integrated to consider the dynamic of EVs in the urban zones. The proposed methodology is composed by five modules. First, an approach proposes the gradual introduction of several EVs in the urban zones over the years. Second, an urban traffic model considering the EVs and their characteristics is presented. Third, this work creates criteria to introduce different infrastructures for EVs. Fourth, a model that locates and quantifies the decrease in local pollution with the introduction of EVs is presented. And finally, the fifth, the impact in the distribution network is studied and mitigated, with a model that explores the possibilities of connection of EVs in the network using home and charging stations (CS) modes of recharging.

In the following, each of these modules will be covered in its most varied aspects. A theoretical and state-of-the-art approach will be shown with the main features of each of the modules. Finally, it is essential to emphasize the multidisciplinary of this work, contemplating several aspects related to EVs and their infrastructure.

1.2 INTRODUCTION OF EVS IN URBAN ZONES

The introduction of EVs in urban zones must consider financial, economic, social, infrastructure, incentive advertisements, and exemptions. For this penetration, it is necessary to identify acquisition patterns for the various types of existing EVs. They can be divided into the following categories (DENTON, 2018):

i) **Battery electric vehicle (BEV):** EV whose power is provided only by the battery as a source of electrical energy.

ii) **Plug-in hybrid electric vehicle (PHEV):** A vehicle with a battery connected to the electrical network and an internal combustion engine (ICE). It generally changes its operation after the electrical autonomy is exhausted.

iii) **Extended-range electric vehicle (EREV):** A vehicle powered by a battery that receives power from a generator coupled to an internal combustion engine. Similar to BEV but with low autonomy. The autonomy increases through a generator. The electric motor always provides movement, and this system can be called a series hybrid.

iv) **Hybrid electric vehicle (HEV):** Execute traction by a battery and/or by ICE. The vehicle selects the power source automatically, depending on speed, battery state of charge (SOC), and engine load. The battery is recharged using a regenerative braking system without using the power network (sometimes called parallel EV).

v) **Mild hybrid vehicle (MHV):** Similar to HEV but do not operate only in electric mode. Generally, it uses the electric motor in acceleration moments.

vi) **Micro hybrid vehicle (MIHV):** Has a start-stop system (the system that turns off the vehicles at short stops and automatically turns on when accelerating the vehicle), and the regenerative braking system is used to recharge the 12V battery.

vii) **Motorcycle and electric quad:** powered by batteries that can connect to the distribution network.

viii) **Fuel cell electric vehicle (FCEV)**: EV which uses a fuel cell, instead of a battery, or in combination with a battery or supercapacitor, to power its onboard electric motor. Fuel cells in vehicles generate electricity to power the engine, mostly oxygen from the air and compressed hydrogen.

ix) **Vehicle to grid (V2G)**: Enables energy stored in EVs to be fed back into the electricity network to help supply energy at times of peak demand.

x) **Electric Taxi (ET)**: EV that can be subcategorized in i) to viii) but have different driving patterns because of its almost constant operation.

xi) **Trolleybus:** A vehicle powered by electricity drawn from two overhead wires by trolley poles. Currently, trolleybuses can have batteries if the coupling system fails.

xii) **Battery Electric Bus (BEB):** whose power is provided only by the battery as a source of electrical energy.

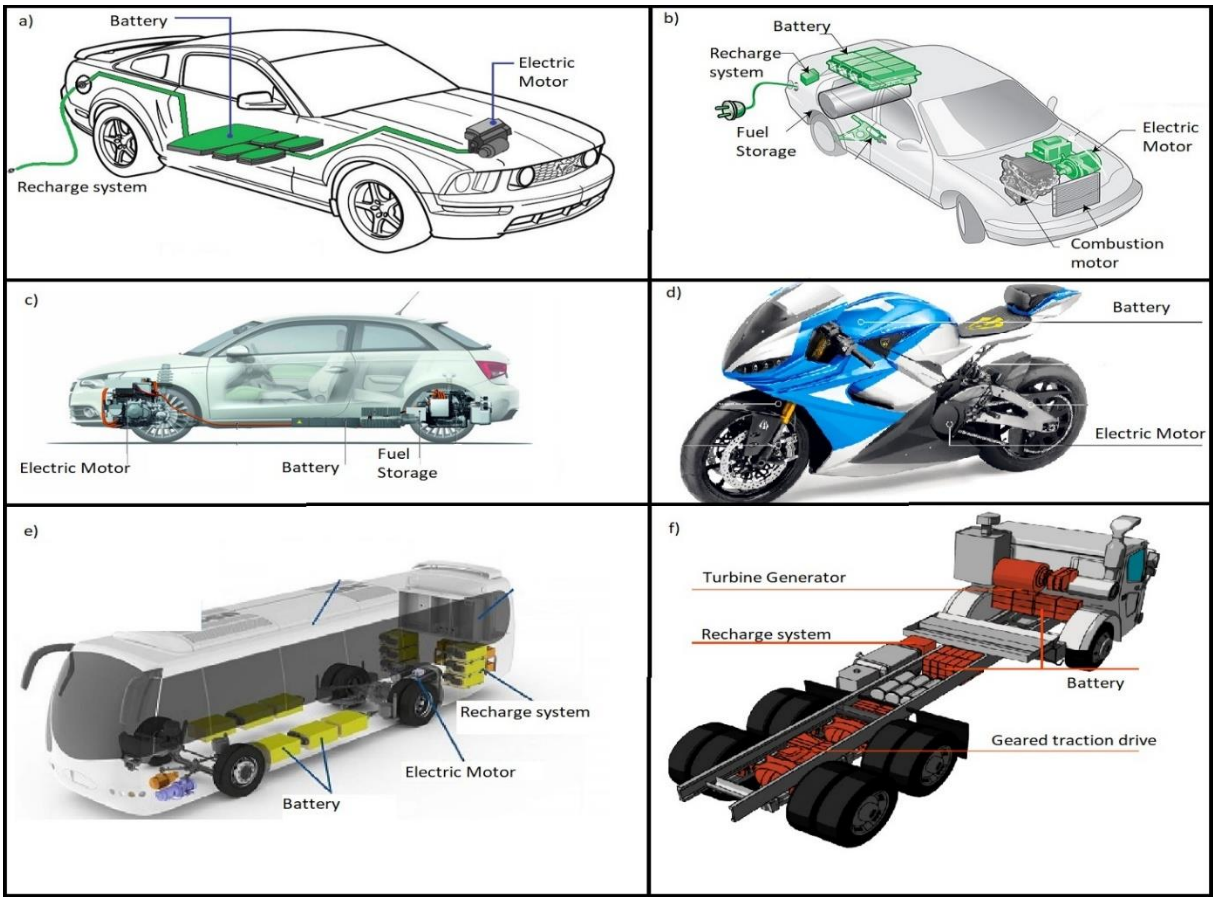
xiii) **Plug-in Hybrid Electric Bus (PHEB):** a bus similar to PHEV.

xiv) **Electric Garbage Truck (EGT):** Electric truck that travels the urban zone collecting the garbage.

xv) **Plug-in Hybrid Garbage Truck (PHGT):** a garbage truck similar to PHEV.

The focus of the present work is to analyze the dynamics of EVs that can connect to the distribution network and will be called hereafter by distribution network connection electric vehicle (DNCEV). Therefore, DNCEV means that the EV can connect to the distribution network to recharge their battery (BEVs, PHEVs, EREVs, ETs, motorcycles, electric quads, BEBs, PHEB, EGT, PHGT). This work excludes V2Gs, as the state of the art of distribution network precludes a more detailed analysis of the behavior of these vehicles. Then, in Fig.1 are shown the examples of the types of DNCEV covered in this work.

Figure 1 – Examples of the types of DNCEV



Source: Author's own elaboration.

In Fig. 1, a) corresponds to BEV; b) to PHEV; c) to EREVs (where a to c can be ETs); d) represents motorcycles (electric squads are similar but with four wheels); e) represents BEBs, which can also be PHEB if they have a combustion motor and f) represents EGT which can also be PHGT if they have a combustion motor.

Some developing countries such as Brazil have created laws and regulations to encourage their acquisition (MORRO-MELLO; PADILHA-FELTRIN; MELO, 2016), and further acquisition of DNCEV is expected for the next few years. However, the DNCEV price, lack of knowledge of technology, lack of infrastructure for maintenance, few CS, low autonomy of batteries, lack of other incentives (such as exclusive corridors or use of bus lanes) are still limiting factors for its purchase (FAPESP RESEARCH, 2017). Nevertheless, although still slow, the insertion of EVs in Brazilian cities should occur in the coming decades. The insertion depends on incentive policies such as free CS, licenses for installing residential charging infrastructure, priority access (access to restricted corridors), parking, free access to high-occupancy vehicles or toll roads, and permission vehicles on the rotations are implemented (MACHADO *et al*., 2020).

The high price for DNCEV in some developing countries will make that their purchase follows a heterogeneous pattern (HEYMANN *et al*., 2017; HEYMANN *et al*., 2019). This pattern can be influenced by the socioeconomic dynamics of the city (ELNOZAHY; SALAMA, 2014). Higher-income regions tend to acquire DNCEV first and affect other areas over time (MORRO-MELLO *et al.,* 2018). Thus, it is expected that there is a heterogeneous spatial distribution of DNCEV in the cities, with clusters in some regions with more DNCEV penetration.

One difficulty purchasing DNCEV is that consumers may have a relatively poor understanding of fuel economy and the advantages of DNCEV operating costs. So, socioeconomic factors also influence the type of DNCEV to be acquired. As seen in (LANE *et al*., 2018), PHEVs have greater adherence to younger, wealthier, more studied, perception of ease of use and disadvantages of the technology and available charging infrastructure, compatible lifestyle, previous experience with a PHEV. The social interaction (hear about trusted colleagues' experience with vehicle technologies) can also be attracted to alternative vehicles. Their use can serve as a means by which to transmit attitudes of greenhouse gas (GHG) reduction or enthusiasm for new technologies, lifestyle choices, including financial management, activity, and fitness, and have a strong sense of community. Among the individuals who prefer a BEV are those who prioritize high fuel economy and environmental performance. The preference for purchasing a model for another of the BEVs considers size, price, space, and performance (REZVANI; JANSSON; BODIN, 2014).

BEVs and PHEVs attract different subsets of Norway: BEV owners are more likely to live in urban centers and own multiple vehicles. In contrast, PHEV owners are geographically dispersed and more likely to live in single-vehicle households

(ZIMM, 2020). Moreover, in developing countries like Brazil, the lack of information between BEV, PHEV, and other DNCEV makes studies necessary to differentiate their acquisition, driving, flow, SOC, and charging patterns.

The spatial estimation of DNCEV buyers is essential to assist in the electrical network planning studies with the increasing load due to the EVs' recharge. In countries with many DNCEV, it is observed that most private DNCEV owners perform recharges at night. In this way, the demand of the distribution network can be increased and cause problems, in the case of simultaneous charging and coinciding with the maximum peak of the system. In the transport system studies, the planning of CS, the driving pattern of DNCEV are essential to the transportation system, operation, and planning.

In general, the influence of DNCEV buyers on their neighbors is not considered but important, as shown in (MORRO-MELLO; PADILHA-FELTRIN; MELO, 2017). The methodologies that model such impact use socioeconomic variables without modeling spatial interaction among inhabitants to obtain EVs. Spatial regressions can estimate the region’s most likely to acquire EVs per subarea considering the interaction among the inhabitants, modeling how initial acquisition in a subarea may influence other inhabitants.

The results from these regressions can be spatial databases inserted in geographic information systems (GIS) to build spatial heat maps with the rate of EV buyers per subarea. These maps allow us to visualize the regions that may have a load growth because of the recharging of EVs. In this way, to show the usefulness of spatial regressions in load forecasting studies, this work presents in the first module the application of spatial regressions in a city, showing the different scenarios of load growth that can be obtained from such regressions.

This work compares each of the stages of acquisition of DNCEV over five years, providing spatial heat maps with the rate of EVs per subarea. This work differs from others found in the literature because, models the spatial interactions among the inhabitants, creating a spatial database with the number of DNCEV acquired and the influence of the neighborhood in the acquisition of EVs. Such a database can be incorporated in any GIS available in the electric sector companies, helping to plan residential load increase; the transport sector, with their preferences; in car dealerships, sales studies; in public companies and planning studies.

1.3 URBAN TRAFFIC MODEL

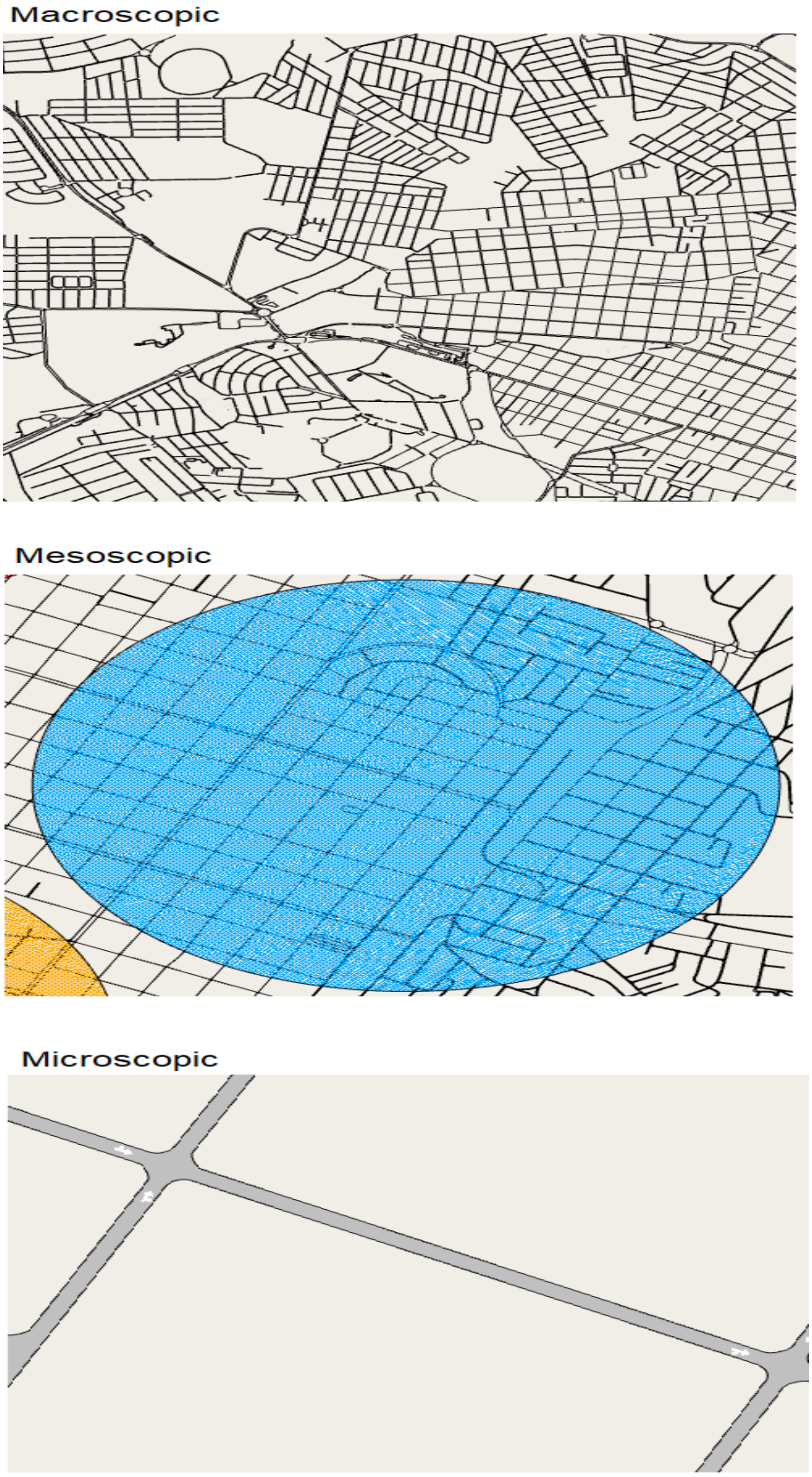
The use of DNCEV in developed countries is already a widespread technology. Therefore, it is possible to find a database with the circulation history of these vehicles, real-time SOC, residential and CS electrical consumption actual data, reduction of gases that intensify local pollution, operation of distribution networks with recharges, among other aspects.

In developing countries like Brazil, the introduction of DNCEV is still slow, and the database with historical data does not exist. Therefore, to assist public and private planners involved in some stage of the introduction, maintenance, infrastructure, and production chain related to DNCEV, scenarios for all agents involved in this process are necessary. After an analysis of the introduction of these vehicles in the urban zone, the behavior along the streets and avenues of the cities (modeling of variables associated with DNCEV) should be performed to assist in the decision-making of the agents involved.

Several analyzes can be performed with the help of transport simulation systems (TSS), more simplified, or with a higher degree of complexity. However, due to the characteristics of DNCEV and their need to connect to the network, it is necessary to acquire information on residential and CS charging, real-time SOC consumption, driving patterns, among others. To obtain the data, it is required to model and simulate characteristics of origins and destinations (O-D) in an urban zone. Also, it is essential to model the influence of other vehicles such as congestion points, stops, public transport, traffic control, CS location, recharge time in CS (MORRO-MELLO *et al*., 2019).

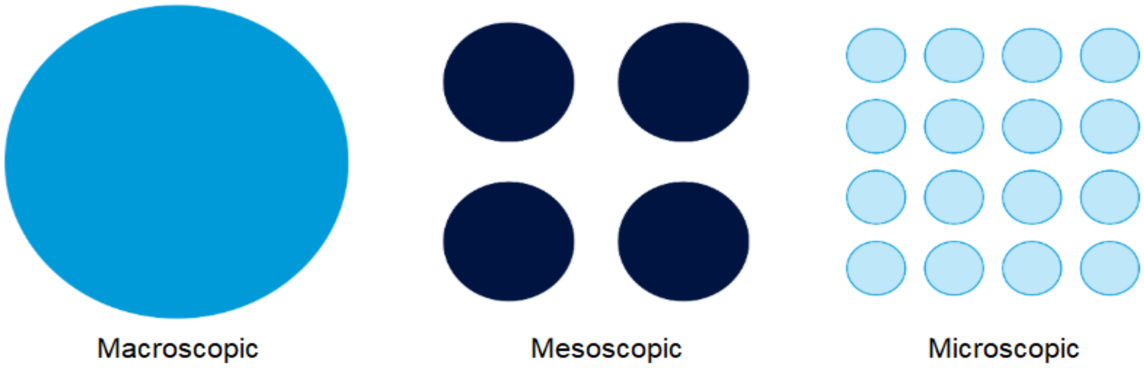
For more simplified analyzes, the use of computational tools for modeling transport systems that allow macroscopic simulations (fewer variables and details, simulating the flow as a whole) is sufficient. As the degree of complexity and the number of variables to be modeled and information to be acquired increases, computational tools that allow mesoscopic simulations (modeling parameters for groups of vehicles) or microscopic simulations (modeling parameters of each vehicle, with more detail) are necessary (PUPPO; TOSIN, 2021). In Fig. 2, an example of the modeling and simulation for a generic city is shown, and in Fig. 3, an example of the vehicle modeling at each simulation level.

Figure 2 – Modeling and simulation levels - City



Source: Author’s own elaboration.

Figure 3 – Modeling and simulation levels - Vehicles



Source: AIMSUN, 2021.

In Fig. 2, at the macroscopic, mesoscopic, and microscopic level, the information modeled and acquired after the simulations is, for the city, for groups divided spatially and for each street and avenue, respectively. In Fig. 3, the vehicles modeled and simulated at a macroscopic level have similar characteristics; at mesoscopic, vehicle groups have identical features, and each vehicle has its attributes at a microscopic level.

Due to the large volume of information required for DNCEV, microscopic simulations (AIMSUN, 2021) should be performed for this vehicle category. These simulations consider the individual characteristics of the DNCEV and are possible to obtain unique data after the simulations. However, for the other internal combustion engine vehicle (ICEV), a mesoscopic simulation with similar characteristics can be performed since individual information for ICEV is not required. Thus, the model becomes hybrid by merging mesoscopic and microscopic simulations depending on the type of vehicle to be simulated.

Few computational tools allow hybrid simulations of the transport system. One of these tools is AIMSUN (AIMSUN, 2021). The AIMSUN tool, a traffic simulator software, has a complete package for studying transport and traffic with simulations that allow:

A. Transport and traffic studies: traffic light optimization, impact reports, traffic demand, public transport demand studies, mobility plan, capacity study, road concessions study, pollutant emissions analysis, among others.
B. Traffic surveys: volume, demand, congestion, traffic conditions.

C. Logistics consulting: dimensioning and optimization of resources, process simulation, supply chain, logistics terminals.
D. People flow, pedestrian simulation.

With several possibilities of input data, data modeling, and programming language, AIMSUN allows the simulation of DNCEV in urban zones and between cities (highways) to obtain information to assist in planning CS and other planning and studies. Among the primary data that can be modeled and obtained with the simulations performed, stand out:

i) Allocation of O-D from DNCEV and ICEV in the urban zone allows the planner to use a database already available for O-D or estimate the acquisition of DNCEV and their destinations over periods.
ii) Driving patterns for DNCEV and ICEV - streets and avenues in urban zones in which vehicles will travel from their O-D.
iii) Use of programming language (python) for modeling variables that are not included in the tool. AIMSUN users can use such as modeling of DNCEV, engine efficiency, modeling of SOC in real-time, regenerative brake, hybrid vehicles with mixed consumption (battery, fossil fuels, ethanol, gas).
iv) Identify locations with better conditions to install CS (places with available physical space, strategic locations).
v) New simulations can be performed with CS spatial allocated in the tool. Simulations provide vehicle information of vehicles entering, recharging, leaving the CS, recharge time, the number of vehicles to enter, waiting time, and information distribution network planners increasing load and planning.
vi) The simulations allow an analysis of the emission of pollutants that contribute to increasing the local pollution that will no longer be generated in the environment and can serve purposes of studies and awareness, advertising and incentives for the use of DNCEV.
vii) Modeling can be carried out at the macroscopic, mesoscopic, microscopic, or hybrid levels.
viii) Modeling of street parameters as exclusive lanes for buses (which can simulate the circulation of DNCEV as a form of incentives for the

circulation of vehicles), traffic light plan, modeling of ICEV stops, speed, among others.

ix) Modeling of pre-programmed bus routes to purchase electric buses, electric garbage trucks, and security services using DNCEV.

x) Model different driving levels: from aggressiveness to smooth, depending on the planner's experience from the urban study zone. Simulations can be performed similar to applications like WAZE, with O-D minimum travel times and/or shortest paths.

Other functionalities in the AIMSUN tool can be used to obtain information from DNCEV or modeled after the needs of planners. All this information and others that can be modeled will be available in a database, which can be used to build spatial maps, in the tool or with the help of GIS tools, with the variables that the planner needs. Finally, an urban traffic model, in addition to the features already described, assists (with its modeling, simulation, and database generated) in obtaining parameters, variables, and decision-making for the various types of infrastructure for charging for DNCEV. Thus, this work uses the AIMSUN tool to model DNCEV and ICEV to find variables that will assist in obtaining parameters for the installation and infrastructure maintenance for DNCEV, the influence of DNCEV on the electricity distribution network, decrease in local pollution, among others.

1.4 INFRASTRUCTURE FOR CHARGING DNCEV

There are different ways to charge the DNCEV. Several factors must be considered to select the type of recharge, such as recharge time, battery life, availability of technology, resources, energy, economic factors, and compatibility with DNCEV. There are three recharge methods. AC recharge, being implemented in public and private facilities, with relatively low investment; DC recharge, requiring investment and super-fast recharge and inductive recharge, occurring through contactless inductors with high complexity and costs. The ways of AC and DC charge are divided into four modes of recharge described below, in Table 1 and Fig. 4.

Mode 1: Single-phase recharging with a maximum of 32A. The recharging device is integrated with the vehicle, with a residual current protection device and a standard plug and socket to make the connection.

Mode 2: Three-phase charging with a maximum of 32A. A recharging device is installed in the vehicle, with a protection and control device integrated with the cable or installed in the wall.

Mode 3: Three-phase charging at CS with a maximum of 63A. The charging device is fixed to the "electro station." The CS has communication, overcurrent protection devices, a disconnection system, payment, and specific outlets for recharging.

Mode 4: DC charge at CS. The charging device is fixed in the CS with protection. System of two plugs and plugs, quick recharge.

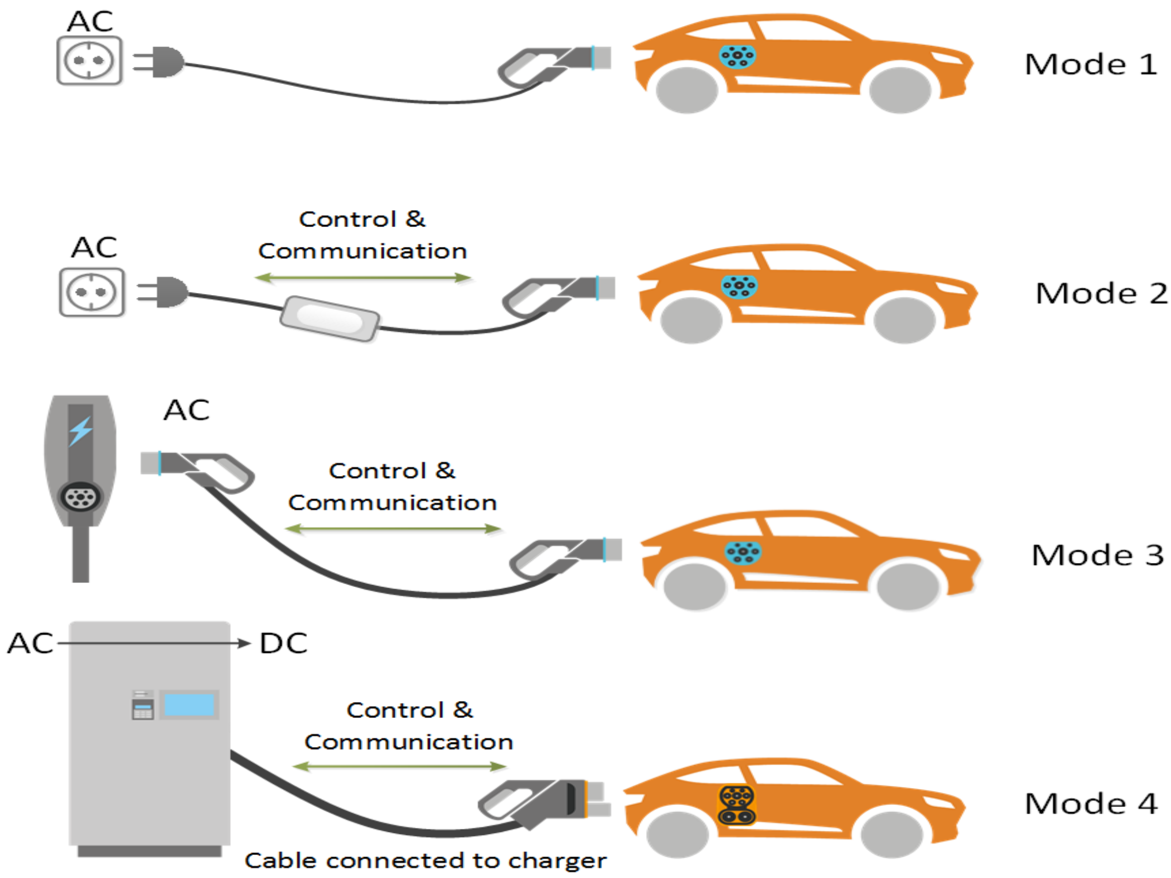
TABLE 1 – CHARACTERISTICS OF THE TYPES OF RECHARGE.

Mode	Recharge time for average range of 100 km	Power source	Electric Power (kW)	Voltage (V)	Maximum current (A)
1	6 – 8 hours	Single-phase	3.3	230	16
1	3 – 4 hours	Single-phase	7.4	230	32
2	2 - 3 hours	Three-phase	10	400	16
2	1 - 2 hours	Three-phase	22	400	32
3	20 - 30 minutes	Three-phase	43	400	63
4	20 - 30 minutes	DC	50	400 - 500	100 - 125
4	10 minutes	DC	120	300 - 500	300 - 350

Source: Adapted from DENTON, 2018.

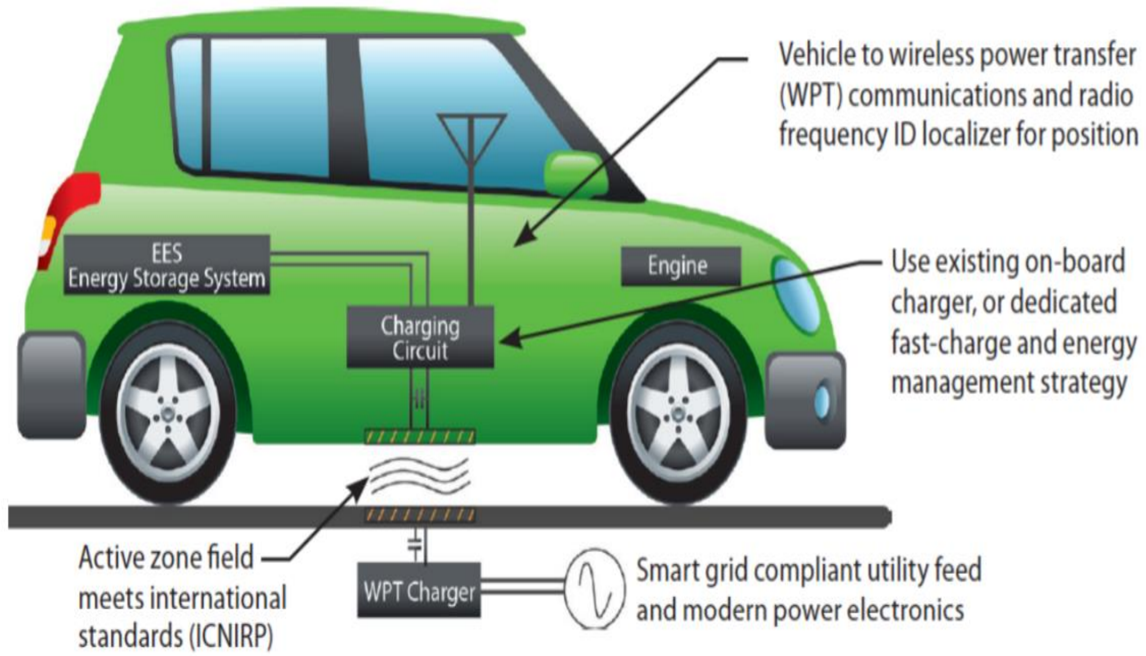
This system works in a massive range of recharge time, conditions, and environments that can be configured to recharge all DNCEV, especially public transport buses, when they stop at the passenger stations. The specifications of these systems depend on construction parameters such as size, area of application, frequency, efficiency, height between DNCEV and WPT, and they can reach 200 kW (DENTON, 2018). Figs. 5 and 6 are shown a stationary WPT for a private DNCEV, BEB, and PHEB, respectively.

Figure 4 – Modes of charging a DNCEV



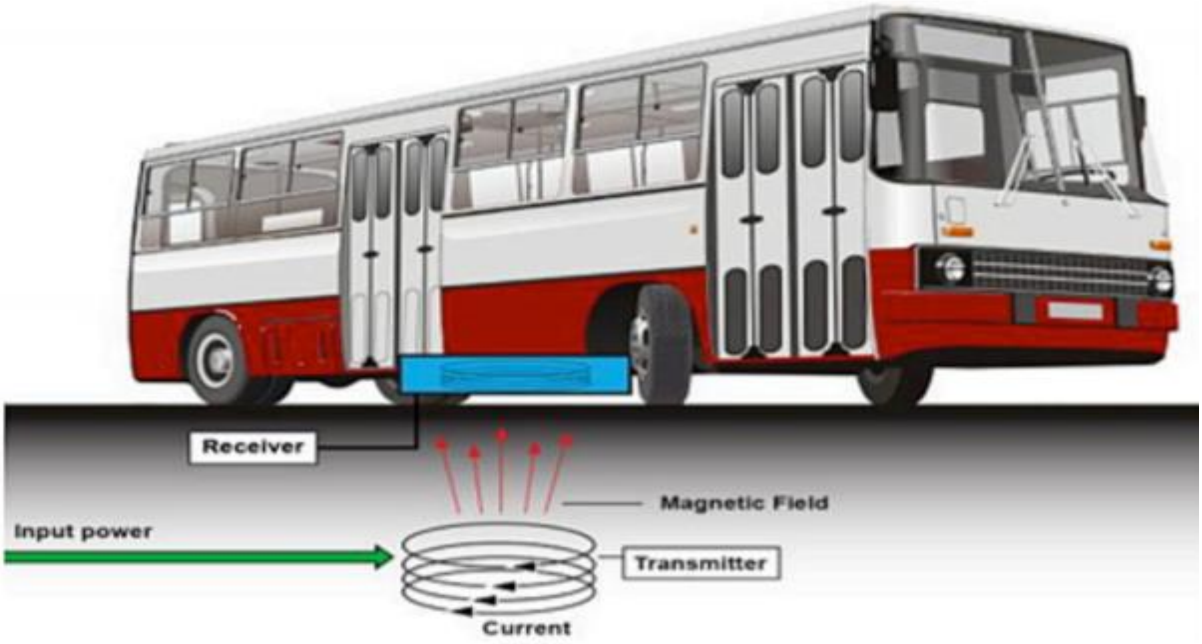
Source: Charging Modes - Deltrix charging solutions, 2021.

Figure 5 – Stationary WPT for a private DNCEV



Source: (BRECHER; ARTHUR, 2014).

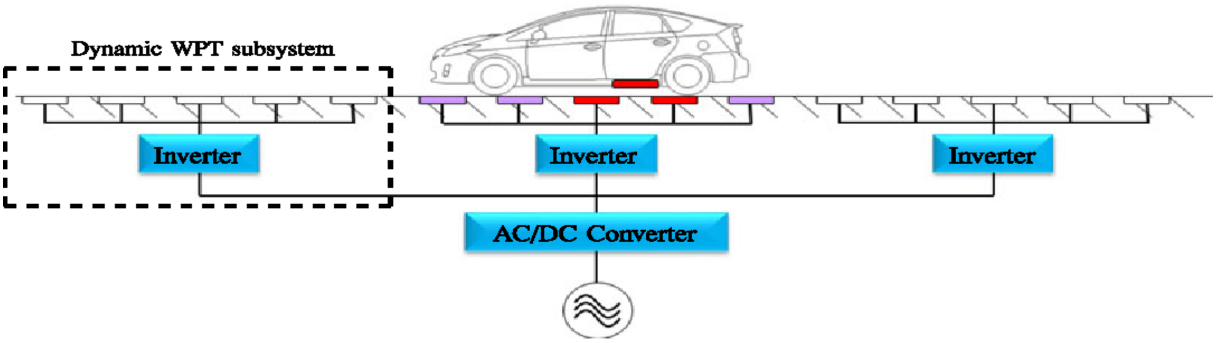
Figure 6 – Stationary WPT for a BEB and PHEB



Source: (BRECHER; ARTHUR, 2014).

Dynamic WPT is a relatively new technology in which DNCEV recharges when traveling on a highway, as seen in Fig. 7. For this type of technology, the main challenges are the coil synchronization, acceptable power levels, DNCEV alignment, speed profiles, multiple DNCEV at the same time (DENTON, 2018). This technology has been applied on some highways to create green corridors to encourage DNCEV. In addition, research (JORGETTO, 2018) has been done to improve the efficiency of recharging with the dynamic WPT.

Figure 7 – Wireless Power Transfer System



Source: (FUJITA; YASUDA; AKAGI, 2017).

Recharges can be carried out in homes, commonly called residential recharging. With less power demand and longer recharging, mode 1 in homes can even be mode 2 in residential shared parking lots and static WPT. Mode 2 can also be present in residential, commercial areas, and parking lots of shopping malls, parks, and the payment for recharge may or may not be necessary. Mode 3 and 4 are present in specific CS requiring payment for recharge. Dynamic WPT needs a green corridor on the highways, which is rare and currently exists mainly for testing and research.

CS should not be located anywhere in an urban zone. Criteria for allocating the CS must be adopted to prevent the CS from being located in an unnecessary location, with little DNCEV traffic, or that the DNCEV that pass through do not need to be recharged, without physical space for allocation, expensive and difficult connection to the electrical network, among others. Many techniques to find the location of CS seek solutions without considering the stochasticity of the problem and/or do not consider the constraints of the various agents involved, which can cause problems to some agents participating in the CS allocation process.

In addition, spatial and technical information should be available to all agents to be incorporated in their GIS tools since the agents involved in this process have used spatial analysis to allocate CS. To help in sustainable city planning, to use a methodology that allows to integrate and attend to the planning requirements of interested agents in the installation process is important, as well as considering some sources of stochasticity. In addition, to the location of the CS, it is also necessary to quantify the SOC of DNCEV when returning to their homes and estimate the energy consumption at the end of the day, based on residential recharge.

Thus, to find the infrastructure for DNCEV, a spatial-temporal methodology was developed. Based on the previous modules, criteria such as SOC, driving pattern, spatial availability for CS allocation, places of significant influence, the concentration of DNCEV are used to allocate CS in the urban zone. Finally, WPT stationary is proposed in bus stops helping in the introduction of BEB and PHEB.

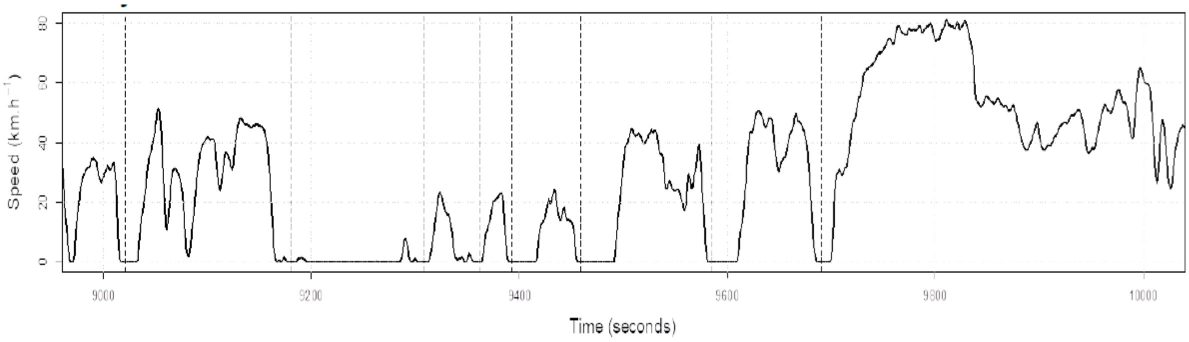
1.5 DECREASE IN LOCAL POLLUTION

GHG reduction in urban zones to decrease local pollution can be achieved through electrification of transportation with DNCEV (APARECIDO *et al.,* 2017; KUMAR; REVANKAR, 2017). Vehicles are primarily responsible for local pollution, causing several environmental, social, and economic problems (ANDRÉ; PASQUIER; CARTERET, 2018; SENGUPTA; COHAN, 2017). The decarbonization of transportation has been used in many cities today (SANTOS; ASENSIO, 2019), associated with an infrastructure and new technologies available that can contribute to increasing the use of DNCEV.

In (MCLAREN; MILER; O'SHAUGHNESSY, 2016), the reduction in carbon dioxide (CO_2) that is no longer generated is on average 135.28 g/km for a pure EV and 81.73 g/km for a hybrid EV. The DNCEV recharging at CS will leave to produce an average of 680.38 g/kWh of CO_2. The sustainable planning for the introduction of DNCEV in urban zones can be carried out with the help of computational tools of TSS and GIS (CIHAT *et al.*, 2019; HUANG *et al.*, 2019). The AIMSUN tool can assist in the modeling of a decrease in local pollution through the GHG emissions model (MORRO-MELLO *et al.*, 2019). Depending on the location of CS, the reduction in pollutant emission values in an urban zone may differ as vehicles may have to travel more to recharge. As part of a GHG reduction policy through the decarbonizing the transportation system (CAROLINA; TEIXEIRA; RICARDO, 2018; MANJUNATH; GROSS, 2017; MUÑOZ-VILLAMIZAR; MONTOYA-TORRES; FAULIN, 2017; HILL *et al*., 2019), information on the reduction of gases (CO_2 and nitrogen oxide - NOx) with of the use of DNCEV are modeled with the London emission model (LEM) presented in the AIMSUN tool (AIMSUN, 2021).

The LEM is an emission model developed by transport for London (AIMSUN, 2021) with observations through average speed models. It uses equations to derive the emissions for an individual vehicle in a set of micro trips that add up to integrate a complete trip. A micro trip is defined as a trip segment where the speed rises from stationary to more than 5 km/h and back to static, as illustrated in Fig. 8.

Figure 8 – LEM micro trips - speed vs. time in an urban drive cycle



Source: (AIMSUN, 2021).

After driving pattern simulations of vehicles, the LEM shows the emissions of CO_2 and NOx in g/km. Therefore, to quantify the reduction in local pollution, the LEM is included in all DNCEV and ICEV. The quantification of DNCEV pollution is the decrease expected with their introduction in urban zones. With the expected reduction shown in spatial maps of the city as shown in an example in Fig. 9, further studies related to the area of health and environment, with the consequences of this decrease in local pollution, can be carried out.

Figure 9 – Example of the spatial map with local pollution caused by vehicles

Source: Pun; Manjourides; Suh, (2017).

This module intends to investigate the sustainability of the introduction of DNCEV in the urban zone, in each street, observing the reduction of local pollution through the behavior of travel, time, congestion, speed, distance that will provide guidelines for urban planners and other companies that need this data for analysis and planning.

1.6 INFRASTRUCTURE AND DNCEV ELECTRIC NETWORK CONNECTION

The installation of CS has happened in many cities as a part of the necessary infrastructure for DNCEV. CS must meet the demand for DNCEV that will be recharged throughout the day and located in strategic places (ERBAS *et al.,* 2018). Due to the short time required to charge a DNCEV during the day, CS has high energy demands and requires a specific kind of installation.

The price of kWh in residential recharges and semi-fast charging stations are lower compared to fuel prices for ICEV considering both costs and efficiency (LUTSEY; CUI; YU, 2021) and scenarios for the coming years, even considering thermoelectric (more expensive energy generation) still makes the scenario favorable for EVs (KEWEN *et al*, 2021). In the case of fast charging stations, the charging price is higher (MURATORI *et al*, 2019). The introduction of photovoltaic panels and energy storage (battery) helps to reduce the price of kWh, making it economically viable to mitigate fixed cost and demand charges. Energy storage alone mitigate demand charges, reducing costs for peaky or low-utilization loads. Photovoltaic panels help mitigate energy charges. Their combination can synergistically deploy to provide cost reductions (MURATORI *et al*, 2019).

Distribution companies must fulfill the growing connection requests for the CS. Due to the low acquisition of DNCEV in most cities, there may be no significant impacts on the network. However, due to the goals and incentives for electric mobility, it is necessary to analyze the connection point better to mitigate future problems (VISWANATHAN *et al.,* 2018). Therefore, the connection of these stations in the distribution network should consider studies of how to ensure adequate energy levels, since CS can cause voltage deviations, unbalanced loads, and abrupt increases in power requests (FLORES; SHAFFER; BROUWER, 2016; ELMA, 2019; ZHANG, 2018). These issues need to be considered by planners seeking to identify the most favorable conditions for the agents involved in the installation process (WARGERS *et al.,* 2018; GLOBAL EV OUTLOOK, 2020; FLAMMINI *et al.,* 2018; SBORDONE *et al.,* 2015).

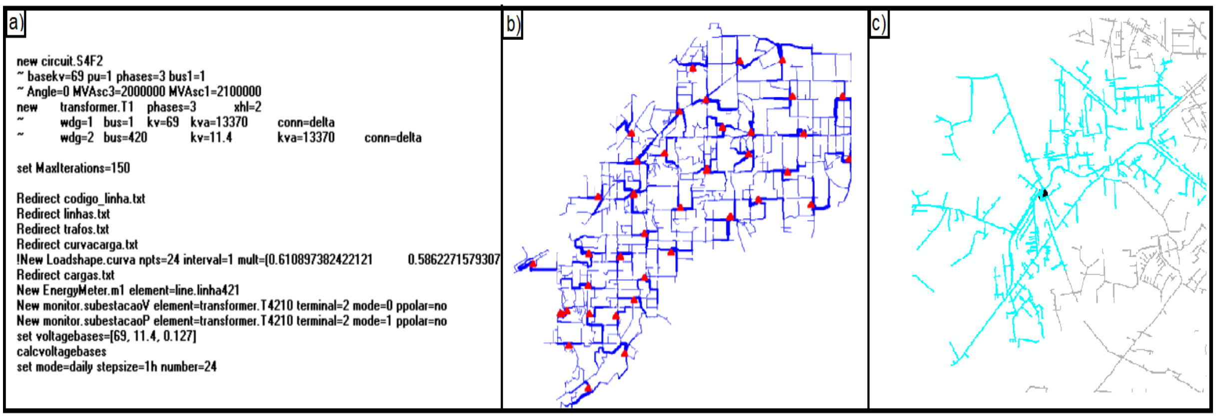
Some studies in specialized literature focus on expanding the distribution network for CS that can increase investments (WANG *et al.,* 2015; HEYMANN *et al.,* 2018). However, these studies are not articulate how stations can meet this new demand without new investments in the electric network. To accomplish this goal, this work argues that with the request (several stations that must be connected), the best way to meet them must be found without causing problems with the network planning, reducing or avoiding investments in new installations and reinforcement in the distribution network. This evaluation must allow distributors to take advantage of the current network elements' unused capacity (supply capability) (CELG-D, 2016). It must also allow them to create a zone for exploring other points within the electrical network instead of connecting CS to the nearest network point. This strategy restricts the number of potential solutions to this power distribution problem. Exploring these zones increases the possibilities for maximizing the network elements’ supply capability.

Distribution companies have technical criteria stipulating the connection of new loads to their less overloaded and/or less distant elements. This strategy is effective in dealing with low-usage new loads. However, for high-usage new loads like CS, a zone to explore other points of the electrical network can be advantageous for distribution companies, allowing them to reduce investments, avoid overloads, and prevent inadequate voltage drops and losses. Also, looking for the unused capacity of the current elements to connect the CS is a strategy for minimizing network reinforcement and expansion investments. Finally, spatial tools (MELO; CARRENO; PADILHA-FELTRIN, 2012) can help choose connection strategies for different locations since CS can be connected at low or medium voltage depending on installed power.

In contrast to recharging in CS, many vehicles are recharged in their homes, mostly at night. The DNCEV owner uses the vehicle throughout the day and at night, arriving at his home, recharges it. With few vehicles connecting at night, there should be no significant impact on the distribution network. As the introduction of DNCEV increases, many vehicles will begin to connect to the distribution network and may overload it. The overload may occur due to the disproportionate increase in recharging simultaneously, and/or many DNCEV owners will make the connection to the network in the peak period in the early evening. Therefore, it is necessary to find trends in the charging profile by subareas of the urban zone with the increase of DNCEV and create strategies to mitigate such problems with incentives for charging. In addition, the regions will have different charging profiles, and depending on the profile, it is possible to create stratified charging strategies per region, to avoid overload.

Tools that model the distribution network characteristics (MONTEIRO *et al.,* 2005) are necessary to obtain voltage and current conditions, plan for a safe connection of services, and deliver reliable energy (HEYMANN *et al*., 2017; XIAO *et al*., 2014). These tools provide a large amount of data about distribution network elements, supply capability, spatial location, and other aspects of the system. The OpenDSS tool (ELECTRIC POWER RESEARCH INSTITUTE, 2018) allows the modeling and simulation of the distribution network with a high level of detail of the components and therefore was used in this work. Also, distribution companies use GIS tools for analyzing, forecasting, and planning the connection of new loads in the distribution system (MELO; CARRENO; PADILHA-FELTRIN, 2012). These GIS tools allow for the coordination of urban planning information with the data obtained via network planning tools; in particular, CS information can be placed in a spatial database for electrical utilities. Fig. 10 shows an example of using OpenDSS to model and simulate the distribution network's power flow, with spatial characteristics model and communication with other GIS tools.

Figure 10 – Distribution network model in OpenDSS



Source: Author's own elaboration.

In Fig. 10, it is shown in a) an example of modeling a distribution network in OpenDSS, in b) an example of a spatial distribution network in OpenDSS, and in c) an example of a spatial distribution network a GIS tool. Thus, the results obtained in OpenDSS analyzes can be used in GIS tools, present in distribution utilities.

Thus, this work proposes a methodology to find the connection points between the CS and the distribution network through cost functions, finding the least expensive connection for the distribution companies, prioritizing the connection of elements with available load (elements that have supply capacity to meet the CS demand) and the introduction of photovoltaic panels. In addition, an analysis of the DNCEV residential recharge is carried out to find the demand for recharge.

1.7 CONTRIBUTIONS TO RESEARCH

Each of the five modules produces a spatial database with the introduction of DNCEV over a planning horizon, with the characteristic of urban traffic, the introduction of infrastructure, decrease in local pollution, and connection of DNCEV and CS in the distribution network. The database produced in each module serves as a basis for the others. Once all five modules for a period of time are finished, and a database with all the results is generated, this database will serve as a starting point for planning a new time horizon. A new time horizon, therefore, considers the results of the previous planning. Therefore, for this work, a time horizon of five years to introduce DNCEV will be carried out from the initial state (year 0) until the fifth year.

The results of each of the five study modules produced for each planning year will be presented in spatial thematic maps with the help of GIS tools. Due to the multidisciplinary of this study, the presentation of these data in spatial maps helps interpret results. Furthermore, it allows communication between the various agents who will introduce DNCEV and their infrastructure, such as research studies, engineering, environment, sustainability, architecture, social policies, public policies.

The methodology proposed in this work was applied to a specific city. The reader will understand throughout the work that due to the amount of data processed and the integration of computational tools, it was not possible to apply the proposed methodology in other databases, for other study areas in the doctorate time. However, it now engages, from the proposed methodology and path to such methodology that will be exposed below, the readers the replication of this work in other cities. This work should not be understood as applicable only to the urban zone used. It is expected that it will be replicated in other cities and that the results will help the various agents that will participate in the process of introducing the DNCEV. To assist in understanding, the reader can also access the papers that were produced until the date of completion of this work and are described in appendix 1.

In this work of introducing DNCEV in urban zones, a purchase intention survey was not carried out. The methodology covered in this work can be applied to any urban study zone that wants to introduce DNCEV and consider several public and private agents that will participate in the introduction process considering the acquisition of DNCEV, traffic model, infrastructure for charging, decrease in local pollution and impact on the distribution network. The urban zone which the methodology was applied is located in a medium-sized Brazilian city. With the Brazilian sociocultural reality, it was observed that a DNCEV purchase intention methodology would not reach its purpose to be applied, since the inhabitants do not have sufficient knowledge of the DNCEV advantages and technology. Therefore, DNCEV buyers will acquire knowledge from an utility marketing policy, government agencies, tax incentives, among others, which are still being built for the urban zone of application as well as for the entire Brazilian scenario. Finally, the main contributions of this work are described below:

i) The proposal uses a spatial model with interactions among the inhabitants to find the temporal rate of acquisition of DNCEV per subarea.

ii) The proposal model simulates urban traffic dynamics with ICEV and DNCEV, using a hybrid simulation (mesoscopic and microscopic), considering stochastic factors, such as the SOC at the beginning of the traffic simulations.

iii) The proposal helps quantify the decrease in local pollution by introducing DNCEV, important information to various sectors involved such as selling, developments, planning horizon, and new engagement policies.

iv) The methodology assists with the process of choosing connections for CS in the distribution network, proposing a local search algorithm based on graph theory, calculating the total cost of connection related to the connection branch. The methodology uses the supply capability of the current network elements to reduce investments, ensures a safe connection, and considers whether the type of connection will be at low or medium voltage. The model can help distribution planners to reduce new investments of expansion.

v) The proposal characterizes the requirements of the planners. As a result, a spatial-temporal database can be processed by any GIS of the public or private agent involved in the introduction and infrastructure process, as seen with the creation of spatial maps of all module results.

vi) Using a GIS tool to link spatial databases from other urban planning areas with distribution network planning. The tool helps decide how and where to connect CS, identifying the places that need more attention in planning power-distribution systems.

2 LITERATURE REVIEW

Many works are found in the literature, with different approaches to DNCEV, such as their acquisition, infrastructure, electric network operation, and planning. On the other hand, there are few works found for traffic flow and GHG reduction with the introduction of DNCEV. Moreover, a few works spatially treat information, presenting a methodology and results that can be used by several agents who will participate in the process of introducing DNCEV. Generally, such works are restricted to one area of knowledge, solving a specific problem for an agent. Below, a summary of some works in the specialized literature for each of the modules will be presented.

2.1 DNCEV ACQUISITION REVIEW

Some works found in the specialized literature deal with the acquisition of DNCEV. However, these works have not considered the spatial interaction among the potential buyers (BERNARDS; MORREN; SLOOTWEG, 2018). This interaction also has been observed for other technologies (BOLLINGER; GILLINGHAM, 2012) and results from the influence that a DNCEV buyer can accomplish in the vicinity. Furthermore, this interaction has been studied and characterized to quantify the potential market (LI *et al.,* 2017; CHEN; JI, 2016).

A methodology to estimate the DNCEV penetration based on a Monte Carlo Simulation (MCS) technique was proposed (MU *et al.,* 2014). The methodology used the yearly adoption rate, the SOC, and the owners driving behavior as model parameters. The results of such estimation were inserted in GIS to analyze the charging impact on a distribution network. In this class of simulations, it is used stochastic parameters that do not have their interdependence characterized.

In (HEYMANN *et al*., 2017), the authors presented a spatial approach to estimate DNCEV charging events and their impact on the electrical network. While this work uses a diffusion theoretic approach that predicts spatial charging pattern discrepancies for midday and overnight charging, the influence of the neighborhood is not considered.

A conditional autoregressive regression model was used to estimate the number of conventional vehicle and DNCEV buyers using census data of Pennsylvania’s region (CHEN; WANG; KOCKELMAN, 2015). The results show an interaction between the residents with their neighbors in decision-making to buy a DNCEV. However, the methodology determines the spatial relationships between the inhabitants in a global form for the whole city without showing the local spatial influence in small areas (THORSON *et al*., 2015).

In the contributions above, the spatial interaction among the residents in local form was not modeled. This interaction may influence DNCEV purchases in small areas, decreasing the distrust to purchase in the first years. To model this interaction, spatial regressions models were used to estimate the number of DNCEV adopters.

DNCEV in several countries are still a new technology and unknown to many consumers. Thus, intention surveys can be developed by specialists in market behavior and the acceptance of new technologies are important to estimate the acquisition of DNCEV. Research can be published under different aspects such as regional, socioeconomic, influence, among others. To assist in the development of technology acceptance surveys, it is possible to refer to the specialized literature to understand how the introduction of DNCEV and intent surveys are carried out.

In (ROEMER; HENSELER, 2022), the authors used a grounded theory approach to explain the drivers and barriers of acceptance of EV on the employee’s level. The authors extracted five main determinants from interviews and the results show that environmental concern determinant triggering the first EV usage. Later, the acquisition occurs after the comprehension of ease of use, perceived risks, and relative advantage increases.

In (JAISWAL; DESHMUKH; THAICHON, 2022), the study applied analytical procedures with cluster analysis, multiple discriminant analysis and Chi-square test to explore and identify distinct sets of potential buyer segments for EVs based on psychographic, behavioral, and socio-economic characterization by employing an integrated research framework of ‘perceived benefits-attitude-intention’. The results shown that younger consumers are a greater degree of proclivity to espouse internet technology and innovative products or EV rather than their older counterparts.

In (ZHANG *et al*, 2021) the work explores the relationships between EV related information and consumers’ perceptions and adoption intentions. Based on survey data from 343 respondents, the results indicated that environmentally friendly information, performance, and attribute information regarding EVs are positively associated with consumers' perceived value. The research highlights the importance of EV-related information and information quality on consumers' perceptions and adoption intentions of EVs, highlighting that clear information about the technology will help in its adoption.

In (VAFAEI-ZADEH *et al.*, 2022), the authors investigate 213 usable data (using structured questionnaires) of EV purchase intention among Generation Y consumers considering the impact of perceived usefulness, attitude, subjective norms, perceived behavioral control, price value, perceived risk, environmental self-image, and infrastructure barrier. The study shows that only perceived risk had a negative impact on intention and give instructions to better explain EV purchase intention among the Generation Y consumers.

In (SONG; CHU; IM, 2022), the authors study the effect of cultural and psychological characteristics on the purchase behavior and satisfaction of EV. The study shows that motivation for EV usage, reasons for purchase, and satisfaction are different depending on the country. US owners showed a higher propensity to innovate and greater knowledge of EVs than Chinese owners for example. Chinese owners cited reputation and signaling social responsibility as being important considerations in their purchase. The results show how culture and stage of motorization are reflected in consumer behavior and satisfaction regarding EVs.

In (GUNAWAN *et al.* 2022), the authors perform intention research with 526 respondents and discuss a theoretical model and risk perception, using the structural equation modeling method. The aim of the study is to provide an overview of the factors that drive interest in adopting EV. The results showed that the model can estimate the influence by performance and effort expectancies, hedonic motivation, price value, as well as functional, financial, and social risks, giving directions in the adoption of EV.

Five factors (financial incentives, charging infrastructure, social reinforcement, environmental concern, and price) that influence the adoption of EV are studied in (ALI; NAUSHAD, 2022) and serve as a basis for data collected study from 366 randomly selected respondents. Structural Equation Modeling and confirmatory

Factor Analysis were used to analyze the data and conclude that pricing has a substantial impact on the adoption of EV.

The specialized literature shows that the environmental concern is a positive factor when raised in the research while the price, lack of infrastructure are concerns of the interviewees that can influence the acquisition.

All these studies and others found in the specialized literature show the variables that should be considered to assess the potential for EV acquisition. These variables can be conveyed to purchase intent surveys and can be modeled through equations and methodologies to create EV acquisition scenarios in urban zones.

Such research can be carried out spatially, considering different aspects in the regions of the urban zone and temporal as the introduction of EV occurs, like financial incentives, charging infrastructure, environmental concern, decrease in EV price, and others.

These EV purchase intention surveys can be incorporated into the methodology presented in this work. The DNCEV acquisition module can be spatially modified to incorporate such surveys. The intention survey can be carried out by sub-areas, considering socioeconomic aspects, EV price, environmental concern, age, among other aspects. With the surveys carried out, each of the variables and aspects conveyed in the questionnaires and their results can be incorporated into GIS tools. Thus, mathematical models can be created for each of the variables to find the purchase rate.

It can also be incorporated into the methodology in a temporal manner. As EV are acquired, after a certain period (five modules of the methodology applied for a period), intention surveys can be made to understand the difference in behavior and acquisition expectation for the next period. Thus, both spatially and temporally, intention surveys can be applied and incorporated into the DNCEV acquisition methodology.

2.2 TRAFFIC MODEL REVIEW

Related to traffic, DNCEV modeling and simulation are still scarce in the specialized literature. Some papers that deal with the traffic of DNCEV are presented.

In (QU *et al*., 2020), a development of a DNCEV following model based on reinforcement learning to dampen traffic oscillations (stop-and-go traffic waves) caused by human drivers and improve electric energy consumption is proposed with the capability of self-learning and self-correction. The results show that the proposed model improves travel efficiency by reducing the negative impact of traffic oscillations, and it can also reduce SOC consumption. However, the work does not evaluate the dynamics of DNCEV spatially and temporally, and the focus is not on various agents that will participate in the introduction and maintenance of them.

In (CHEN; WU; ZHANG, 2020), the impact of traffic network topological characteristics on the charging characteristics of large-scale DNCEV is presented with a model of the complex adaptive system, using a multi-agent technique in a spatial-temporal manner. The traffic networks of various cities in comparison testify that improving the connectivity of the traffic network can effectively reduce the effect on the power network brought by the charging load of large-scale DNCEV. However, in this work, the method and simulation model considering the DNCEV in a macroscopic way, as a large and unique group, disregarding the difference in the DNCEV group like types, location in the urban zone, and different behavior patterns.

In (RODRIGUEZ, 2020), a study is conducted to evaluate the impact of the SOC driving behavior under various traffic scenarios. To simulate the driver behavior, a widely used intelligent driver model is chosen to characterize the different levels of driver aggressiveness. A microscopic traffic simulator, PTV Vissim, is used to simulate various realistic traffic environments. The co-simulation of the PTV Vissim Component Object Model interface in conjunction with MATLAB allows the energy consumption performance on a DNCEV to be determined for various levels of driving aggressiveness. The results of these driving tests demonstrate that the level of driving aggressiveness cannot be fixed and should instead adapt to the traffic environment to maximize the battery life and range of an EV. However, in this work, an approach to charging locations is not described and/or model. These locations influence the SOC, contributing to driving aggressiveness and instant level of charge along the streets.

In (LEI, 2019), an adaptive equivalent consumption minimization strategy considering traffic information is proposed using traffic simulator Vissim to facilitate the effective energy management of DNCEV. First, using a genetic algorithm, factors in determining initial SOC and driving distance are found. Then, dynamic programming is used to determine the optimal SOC trajectory according to the traffic information, and finally, a fuzzy controller is employed to regulate the equivalent factor dynamic. Simulation in the Vissim and experimental results shows that the proposed strategy can lead to less fuel consumption than the traditional equivalent consumption minimization strategy. The authors do not use the SOC information and driving patterns for other applications like resource allocation for DNCEV users. Thus, the focus of the paper assists only in one of the topics of analysis of DNCEV.

In (BI; TANG, 2019), a dynamic DNCEV routing problem model is designed to plan the logistics industry's itinerary. To reflect the real situation, the model considers a time-dependent stochastic traffic condition and captures the discharging/charging pattern to minimize the overall service duration and planning strategy. The results show benefits for optimal policies and the benefits from accurate modeling of battery dynamics. The traffic characteristics adopted in the paper are based on estimates given by traffic companies without characterizing the real-time driving pattern with a traffic simulation that considers the dynamic of DNCEV applied in a real traffic flow.

2.3 INFRASTRUCTURE FOR CHARGING REVIEW

Others works studied the infrastructure for DNCEV in urban zones. In (ZHANG; KANG; KWON, 2020), the authors using a multi-day data sampling method and analysis of scenarios to provide insights on the bounds of potential DNCEV market under different charging opportunities, including CS charging divided in AC and DC charging. The results showed that facility utilization could be improved without affecting travelers' charging demand. Smart grid charging strategy can significantly reduce the total number of operating chargers during the same time in a day, and DNCEV users' charging behaviors have a minor impact on this improvement. The numerical results indicate that an appropriate number of chargers installed in leisure locations should be more profitable and have a higher charger utilization rate since those chargers help cover DNCEV users' trips. The work uses DNCEV real data to analyze the scenarios. Still, for cities that do not yet have DNCEV, such data do not exist, and simulations to find their driving patterns, among other aspects, are necessary to create and analyze such scenarios.

In the same line as the previous one, the authors in (LEE *et al.,* 2020) examine the charging behavior of thousands of DNCEV in California. The study investigates the charging locations (at work or public location) and the level of charging AC slow charging, AC fast charging, or DC fast charging. The charging behavior differs among DNCEV owners based on driving patterns, preferences, and infrastructure access. The authors identify factors associated with the DNCEV owner's choice of charging location and charging level based on socio-demographic, DNCEV characteristics, commute behavior, and workplace charging availability.

In (FANG *et al.,* 2020), the authors studied the impacts of policy incentives and consumer preferences to promote CS construction. To improve economic efficiency, taxation and subsidy policies are employed. Consumers can choose an ICEV or DNCEV in response to the policy incentive. The time-varying needs of CS and fuel stations in each area are characterized by an evolutionary game model considering the competitive connections between the stations. The results prove the advantages of the balanced dynamic subsidy and taxation policies on the promotion of CS. The penetration level of DNCEV and charging prices are the main driving forces. However, in some countries, the price of DNCEV is still very high, and the study of choice ICEV will always have an advantage. Thus, applying this study to such countries may not be advantageous, requiring studies on the introduction of DNCEV based on other criteria.

In (LAM; LEUNG; CHU, 2014), the authors studied DNCEV CS placement considering human aspects in the long term with many social constraints like satisfaction, drivers' convenience, environmental impact, DNCEV accessibility. The authors propose four CS placement methods, showing their solutions and their pros and cons for quality, algorithmic efficiency, problem size, and nature of the algorithm. However, the available physical space for CS installation is not considered and can cause location and installation problems.

In (SACHAN; DEB; SINGH, 2020), the paper comprehensively discusses basic infrastructures for charging DNCEV such as distributed infrastructure (AC charging) and fast charging infrastructure (DC charging). It has been found that distributed infrastructure shows the best results for the charging of DNCEV. The other infrastructure prove costlier and increase power demand. However, the study does not consider that there are different patterns of conduction of DNCEV. For example, ETs, modeled in (MORRO-MELLO *et al.,* 2019), need recharging in a short period of time, requiring fast charging. In addition, an uncoordinated distributed infrastructure can also cause problems.

2.4 GHG REDUCTION REVIEW

There are works in the specialized literature that deal with GHG reduction through the introduction of DNCEV. In (XIONG; JI; MA, 2020), the authors quantify the environmental impacts and costs of remanufacturing a battery cell. The results indicate that the reductions in energy consumption and GHG emissions by battery remanufacturing are 8.55% and 6.62%, respectively. In (MICHAELIDES, 2020), the authors study the regional mix of electricity generation, and the effect of the shift to DNCEV on GHG emissions is determined. The authors concluded that the simultaneous charging of DNCEV would strain the electricity network's capacity and examine the effects of DNCEV on the further utilization of renewable energy sources.

In (CHOI *et al.,* 2020), the work compares the well-to-wheel GHG emissions of different types of DNCEV and ICEV of various energy policies that could affect future emissions. A framework was proposed to evaluate the impacts of energy policy regarding electricity and hydrogen production on the benefits of using the different types of DNCEV. In (WANG *et al.,* 2020), the study presents a GHG emissions and energy consumption accounting approach for on-road transportation, developed to estimate well-to-wheel emission distributions for household ICEV and DNCEV. The study combines real data with the effects of vehicle electrification and well-to-wheel emission. Mean values for daily regional GHG emissions from household transportation were estimated. The results of the policy scenarios present insight into the effectiveness of DNCEV at reducing emissions.

In (BENAJES *et al.,* 2020), the paper assessing the potential of different types of DNCEV when used together with a low-temperature combustion mode. A deep analysis is performed in terms of emissions. The results show that the PHEV has the highest benefits in terms of fuel consumption. With this technology, it is possible to achieve the 50 g/km CO_2 target for the PHEVs while NOx is under the limits. In (KIM; KIM; LEE, 2020), the paper approaches GHG emissions caused by DNCEV by examining the power mix and resulting change of market share. In numerical terms, the estimated GHG reduction is 122,441 tCO_2, which constitutes only 4.7%. Therefore, the authors concluded that it is necessary to clarify the segmentation of DNCEV to optimize efficient infrastructure investment and a stable diffusion of environment-friendly vehicles.

The authors in (DOLUWEERA *et al.,* 2020) examine the energy and GHG emissions impacts of DNCEV on electricity and transport systems, using a hybrid simulation model and develop a new component to model DNCEV fleets. The analysis shows that the adaptation of DNCEV can contribute to the 2030 emissions reduction target of 30% below 2005 levels. In (ALIMUJIANG; JIANG, 2020), the paper shows the co-benefits generated by using three types of DNCEV by combining environmental benefit and cost-effectiveness analyses. The results show that BEBs provide the highest co-benefits. Thus, replacing traditional fuel buses with BEBS can reduce air pollution and CO_2 emissions. In addition, private DNCEV and ETs also provide the co-benefits of reducing CO, NOx, NMHC, and PM10 emissions.

In (VILCHEZ; JOCHEM, 2019), the paper investigates the possible impacts of DNCEV on future energy demand and GHG emissions until 2030 by using a system dynamics model covering nine-car technologies in different countries. GHG emissions from cars in the countries are simulated to reach up to 2.6 gigatons in 2030. The main conclusion from model-based policy analysis is that DNCEV may positively contribute to emissions mitigation in the passenger road transport system.

All works cited and others found in the literature use models, simulations, and perspectives to quantify GHG reduction with the introduction of DNCEV. However, the papers found do not conduct a study to find the reduction in local pollution with the introduction of DNCEV. As renewable sources of energy generation will be necessary to quantify GHG emissions, and this may vary depending on the study regions and different characteristics and perspectives, the introduction of DNCEV, in terms of pollution, has primary consequences in the cities its decrease. Therefore, quantifying local pollution reduction in urban zones, subareas, streets, and avenues is necessary and extremely important. However, the quantification is absent in the works cited and serves to raise the awareness of the local population, improve the quality of life, reduce respiratory diseases, and only ultimately (also important) the prospects for GHG reduction.

2.5 IMPACT ON THE DISTRIBUTION NETWORK REVIEW

To connect DNCEV in the distribution network, many papers are found in the literature that deal with the residential and CS connection. In (ZHANG; YAN; DU, 2015), the authors show that the DNCEV demand has a significant impact on the location of CS in the distribution network, comparing the total electricity required and the charging profile. In (MOHAMED *et al.,* 2016), a study is presented with the impact of the CS on the capacity of distribution feeders. The methodology examines the different factors that affect the impact of the DNCEV charger on the network. The results show overload in the distribution networks under a certain system of charging with high levels as the use of DNCEV grows, impacting the planning and operation.

Other works in the literature deal with factors that affect the way of charging in the distribution network (PARKS; DENHOLM; MARKEL, 2007; CAROLINA; TEIXEIRA; RICARDO, 2018) such as impacts on the voltage levels, different charging variables, time, and frequency of charge. To avoid these important problems in the distribution network, the use of a coordinated charging methodology is recommended. EV charging is done by smart charging at a specific time in a specific period when the load is low. As a result, there is a decrease in the daily cost of electricity, voltage deviations, peak loads in transformers and current lines, congestion in the distribution network, waste of renewable energy resources, energy losses, and incremental investments. Coordinated charging is an efficient and valuable strategy for DNCEV owners and network operators.

Of all five modules, the charging and influence of DNCEV in the distribution network is the most discussed topic in the specialized literature. Thus, the present work proposes a different approach from those found to assist distribution companies in decision-making for CS connection. Using spatial modeling, this work finds the least-cost expansion for the distribution company to connect the CS, prioritizing the current elements of the network, decreasing the cost of new investments. Finally, it finds the increase in residential load with night charging exposes such increase in spatial maps by zone.

Several works are found in the specialized literature related to DNCEV, as demonstrated in this literature review with the introduction, traffic, infrastructure, GHG emission, and distribution network. The difference between this work to the others is integrating all these modules in a spatial-temporal manner. Thus, each result of a module serves as a basis for the others and the result for a certain period of time, serving as a start for the subsequent period. In addition, each of the modules forms a spatial database that is used in other modules to create planning criteria. Finally, all the results are shown on spatial maps of a study zone, with the help of GIS tools, providing the visualization of the results for several agents that will participate in some stage of introducing DNCEV.

3 PROPOSED METHODOLOGY

The methodology proposed in this work is divided into five modules. Each module result will be the input database for the next module. The result of the first five modules for a given period will serve as a basis for the next period. The input data for the proposed methodology are:

a) Urban zone, with streets and avenues, sectors, and socioeconomic information characterized spatially divided into subarea.

b) Number of ICEV and DNCEV in each subarea.

c) O-D of vehicles divided by periods of the day (i.e. residential to commercial and industrial in the morning and the opposite in the end of the afternoon).

d) Electrical network spatial modeled with technical information on network elements, consumption, and current supply capacity.

Such input data will be used during the five modules, being available in a spatial database and used with the help of GIS tools.

3.1 MODULE 1: ACQUISITION OF DNCEV

The acquisition of DNCEV is developed using spatial regression, with a combination of three methods: economic analysis (MORRO-MELLO, 2016), Geographically weighted regression (GWR) (MORRO-MELLO *et al.,* 2018), and hierarchical spatial autoregressive (HSAR) (RODRIGUES *et al.,* 2019).

Spatial regression is a statistical analysis that relates two or more spatial variables and that one of them can be explained by the others. Serve to determine and describe how the variables are related and predict dependent variables' future values. If there is a strong tendency or spatial correlation, the results will be influenced, presenting statistical association in the locations where it did not exist. Different techniques to find the rate of EV buyers per subarea in an urban area are presented to understand the spatial regression better. After, in the case study, each technique is used to find the most viable method that estimates the number of EVs in a subarea.

The economic analysis described in (MORRO-MELLO, 2016) considers cost-benefit analysis to find regions with sufficient income to acquire a DNCEV. In the cost-benefit analysis, the price of a DNCEV, the average income in the subarea, number of residents, individuals, education, among other socioeconomic characteristics, were considered.

A study with the possibility of purchasing a DNCEV by category (LANE *et al.,* 2018) was also used. In this study, it is established that the purchase of a PHEV has a greater acquisition in young groups, wealthy, more studied, with a greater perception of ease of use and greater social interaction (individuals that hear about the experience of trusted colleagues with PHEV technologies, shaping purchase preferences), and prioritizing autonomy.

People attracted to BEVs tend to transmit pro-environmental attitudes or enthusiasm for new technologies, with other lifestyle choices, including financial management, activity, fitness, and a strong sense of community, being individuals who prioritize high fuel economy and environmental performance. Important issues for the purchase of DNCEV: the importance of the policy, such as discounts or tax incentives that minimize the acquisition cost, free CS, free installation of residential charging infrastructure, access priority (access to restricted corridors), parking lots in urban zones, free access to high-occupancy vehicles or toll roads, permission for vehicles on rotations.

Such information can be found in the urban study zone and socioeconomic reports database, with preference patterns of the region's inhabitants. Thus, from this information, the rate of DNCEV per subarea is found ($\widehat{¥}_i$), through an analysis described in (MORRO-MELLO, 2016; MORRO-MELLO; PADILHA-FELTRIN; MELO, 2016).

The GWR model proposed in (MORRO-MELLO *et al.,* 2018) can be used to find the initial acquisition rate of EVs. The model relates the input data to output data by creating groups of explanatory and response variables to obtain the proportion of EVs acquired in a given region. For example, the GWR model uses as input data the socioeconomic data for each subarea, the number of houses with favorable conditions to acquire an EV, average subarea income, and sensitivity measurements.

All this information is classified as explanatory variables. As a response, the model provides the rate of EVs acquired in each region determined by:

$$\hat{Y}_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \epsilon_i \tag{1}$$

In which $\boldsymbol{x_{ik}}$ is the *k* explanatory variable considered in region *i*, $\hat{Y}_i$ is the response variable in region *i*. The explanatory variables in the proposed method are the socioeconomic variables that correlate with the purchase of EVs. The variable $\hat{Y}_i$ represents the estimated proportion of households in region *i* that has the financial condition to acquire EVs. This method adjusts a spatial function *βk* for each *k* explanatory variable using the geographic $\boldsymbol{u_i}$ and $\boldsymbol{v_i}$. The values of *βk* are:

$$\hat{\beta}(i) = (X'W\,X)^{-1}\,\mathrm{X'W}y_i \tag{2}$$

In which *X* is the matrix of the explanatory variables, *W* is the weight matrix that considers the influence of neighboring regions, y_i is the number of houses with economic conditions.

The HSAR model allows characterizing heterogeneous distributions considering the local influence of several variables. The input data for the HSAR model are the socioeconomic variables by subareas of the urban zone and the initial acquisition rate of EVs. This information can be processed by a GIS tool (ESRI, 2017). To characterize the estimated heterogeneous spatial rate of EV in each subarea ($Y_{est(i,j)}$) Eq. (3) is used.

$$Y_{est(i,j)} = \rho W Y_{obs(i,j)} + \beta X_{(i,j)} + \gamma z_{(i,j)} + \Delta\theta_{(i,j)} + \varepsilon_{(i,j)} \tag{3}$$

In which ρ is the coefficient that measures the spatial interaction globally, W is the spatial weights matrix that measures the influence of a determined subarea, $Y_{obs(i,j)}$ is the initial acquisition rate of EVs, $\varepsilon_{(i,j)}$ is the difference between the EV acquisition share within and outside the spatial influence of each subarea, $\theta_{(i,j)}$ and the Δ weights matrix characterize the stochastic nature in the EV acquisition, $X_{(i,j)}$ and $z_{(i,j)}$ characterize the socioeconomic variables in a subarea, β and γ measure the influence of $X_{(i,j)}$ and $z_{(i,j)}$ respectively. The $\theta_{(i,j)}$ values are calculated for different levels. Eq. (4) represent the $\theta_{(i,j)}$ for low level.

$$\theta_{(i,j)} = \lambda M \theta_{initial(i,j)} + \mu_{(i,j)} \tag{4}$$

In which λ is a coefficient that measures the intensity of the spatial interactions, M is the spatial weights matrix, $\theta_{initial(i,j)}$ is a random number between 0 and 1 that characterizes the stochastic nature of EV acquisition, $\mu_{(i,j)}$ is the parameter that accounts for the deviation between the $\theta_{initial(i,j)}$ and $\theta_{(i,j)}$. The parameters $\varepsilon_{(i,j)}$ and $\mu_{(i,j)}$ are calculated through normal probability functions determined by the planner as shown in Eq. (5) and (6), respectively.

$$\varepsilon_{(i,j)} = N(0, \sigma_1) \tag{5}$$

$$\mu_{(i,j)} = N(0, \sigma_2) \tag{6}$$

In which σ_1 and σ_2 can be adjusted by expected or historical values of EV rates. Finally, GIS and statistical software can be used to model the HSAR and find the acquisition rate of EVs in each subarea.

To find DNCEV in each subarea, a combination of three methodologies described above is proposed, named *three-stage DNCEV acquisition*. Eq. (7) proposed in this work, assigns weights to each of the methodologies to find the rate of DNCEV per subarea ($Ac_{(i,j)}$).

$$Ac_{(i,j)} = \left(R \times \widehat{¥}_i\right) + \left(S \times \hat{Y}_i\right) + (T \times Y_{est(i,j)}) \tag{7}$$

Where R, S, and T are weighted with a sum of 1. If the urban zone does not have DNCEV, the DNCEV rate should be found only with economic analysis for the first period.

3.2 MODULE 2: TRAFFIC MODEL

Transportation tools that model the DNCEV characteristics are important to help plan, construct, and maintain their infrastructure. The simulation of the DNCEV, modeling their characteristics and produce information of real-time SOC, driving patterns along the streets, streets most visited, speed, congestion points, among others. This information can be saved in a spatial database for planner users. For the traffic model, some input data are necessary and summarized as follow:

- Transportation network map: georeferenced map with information of urban zone with their main and secondary roads, traffic lights, allowed speed limits, different sectors of the city (residential, industrial, and/or commercial), among other characteristics. The map and information can be found in the transportation department files or georeferenced maps with streets in specialized sites.
- Number of DNCEV obtained in module 1 and/or already allocated in the city.
- Number of ICEV: The number of ICEV that cross the urban zone can be obtained through reports in the transportation department of the analyzed city.
- ICEV and DNCEV O-D: For the simulation of real traffic during the day, modeling ICEV and DNCEV circulation in urban zones provide congestion points, speeds, and travel times. Such information is necessary for the SOC. Transportation departments often take field measurements and divide them into average estimates by hour. O-D characteristics are described in the transport department database used on transport modeling tools at each hour of the day. The O-D information varies from home and/or work to places of leisure, education, health, etc. If the planner does not have complete information, the database of cities with similar characteristics can assist in the decision-making to allocate O-D data.

The map of the urban zone is plotted on a TSS capable of simulating the driving patterns of vehicles over periods of time. ICEV and private DNCEV are allocated to their origins and their multiple destinations determined throughout the day following reports from the urban zone containing such information and returning to their origins at the end of the day. The routes of the BEBs and EGTs are found in the reports and trace previously.

DNCEV's SOC in the city streets is an important piece of information to evaluate CS building. Indicating locations where DNCEV will usually require recharging avoids CS allocation in regions with high SOC in DNCEV batteries. Furthermore, the vehicles always look for the shortest route and/or shortest travel time, and the shortest path algorithm is required for this purpose.

The SOC consumption model in each street is modeled and simulated with a TSS tool such as AIMSUN (AIMSUN, 2021; SUMO; GE; CIUFFO; MENENDEZ, 2014), or VISSIM (GRIGGS *et al.,* 2015). Simulations must be performed for all hours of the day, and a hybrid (microscopic and mesoscopic) traffic simulation must be used. To characterize each DNCEV and SOC consumption behavior at each instant, a microscopic simulation is used.

To characterize O-D for ICEV at each hour and zone, groups of vehicles with similar characteristics of O-D in each zone are placed together in clusters, and the mesoscopic simulation is used. Then, during each hour, a percentage of vehicles in each cluster is assumed to leave and/or arrive at the center of the different zones, such as industrial, educational, health, etc. (this information and the corresponding percentages should be available in the transport department files).

To determine DNCEV's SOC along the city's roads, the model of SOC (GOEKE; SCHNEIDER, 2015) is chosen because it considers several characteristics related to vehicles, cities, and travel times. This model is used to consider the battery discharge due to traveling and its potential recharge (due to the regenerative braking system). The initial SOC can be considered random, representing the stochasticity of the SOC for the first travel, and can be calibrated according to the planner's needs. For the next trips, the SOC considered is the residual of the previous trips. The initial SOC of the DNCEV can also be predetermined if the planners have a pattern of behavior in reports.

Initially, a mechanical power P_M model is presented to consider mass (m), speed (v), gradient, road surface, vehicle dimensions, and engine properties. With this information, P_M is converted to electric power P_E using a homogeneous regression model (kind of linear regression where the intercept is set to zero), suitable for a DNCEV.' P_M the demand of up to 100 kW as explained in (GOEKE; SCHNEIDER, 2015), and the latter is converted to battery power P_B considering the relationship between them.

$$P_M = \left(m * a + 0.5 * Cd * \rho a * Af * v^2 + m * g * sin(\alpha) + Cr * m * g * Cos(\alpha)\right) * v \qquad (8)$$

Where a is the acceleration, Cd is the aerodynamic drag coefficient, ρa is the air density, Af is the frontal area of the DNCEV, g is the gravitational constant, α is the average gradient angle for the city obtained in transportation department files, and Cr is the rolling friction coefficient. $\emptyset_d$ and $\emptyset_r$ are the discharged and recuperated regression coefficients, respectively:

$$\emptyset_d = \frac{P_E^d}{P_M} \qquad \text{for} \qquad 0\ kW \leq P_M \leq 100\ kW \tag{9}$$

$$\emptyset_r = \frac{P_E^r}{P_M} \qquad \text{for} \qquad -100\ \text{kW} \leq P_M < 0\ \text{kW} \tag{10}$$

Here, P_E^d and P_E^r indicate the discharged and recuperated (recovered energy in the braking system) electric energy, respectively. After, the regression coefficients for the discharged φ_d and recuperated φ_r battery efficiency is modeled:

$$\varphi_d = \frac{P_B^d}{P_E} \qquad \text{for} \qquad P_E \geq 0\ \text{kW} \tag{11}$$

$$\varphi_r = \frac{P_B^r}{P_E} \qquad \text{for} \qquad P_E < 0\ \text{kW} \tag{12}$$

Here, P_B^d and P_B^r are the discharged and recuperated SOC, respectively. Then, the following function is used to compute energy consumption ($P_{O-D}(u_D)$):

$$P_{O-D}(u_D) = \left(0.5 * Cd * \rho a * Af * v^2 + m * g * \left(sin(\alpha) + Cr * cos(\alpha)\right)\right) * v \tag{13}$$

Here, u_D is the amount of SOC needed to make a trip. Finally, the battery discharged and recuperated during the DNCEV trip associated with travel time t_{O-D} is:

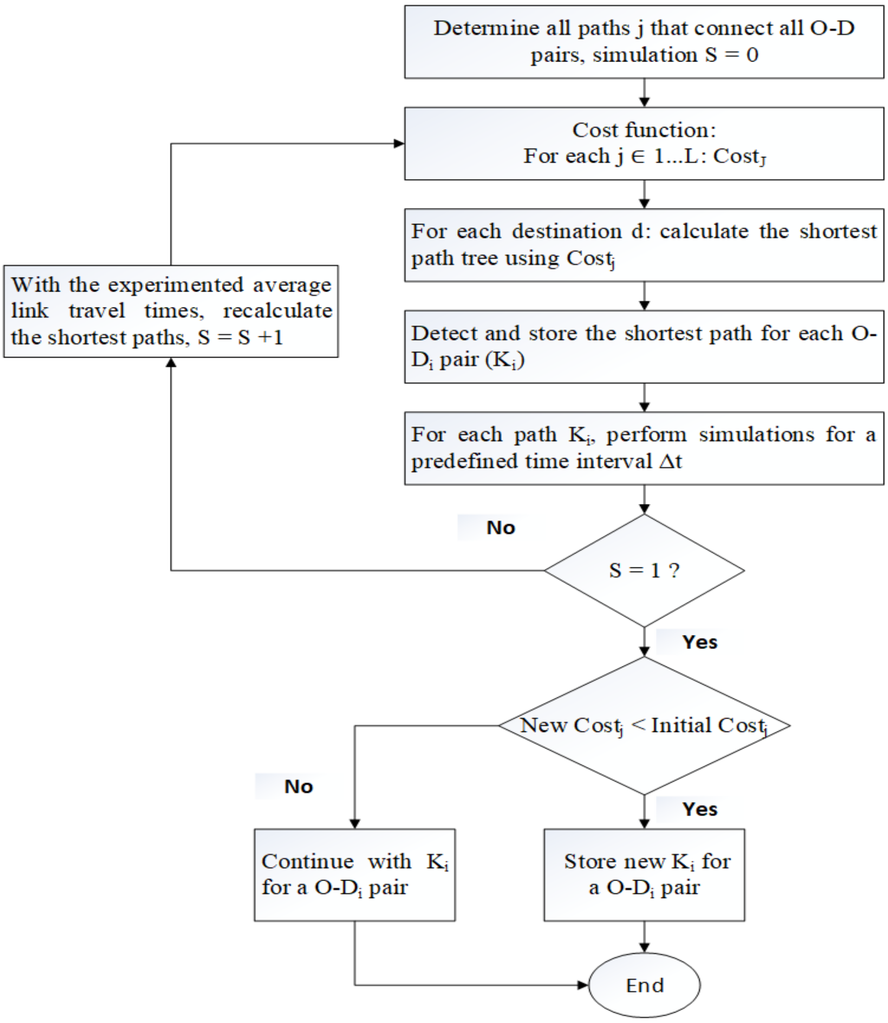
$$\mathrm{b}_{O-D}^d(u_D) = \emptyset_d * \varphi_d * P_{O-D}(u_D) * t_{O-D} \qquad \text{if} \qquad \mathrm{P}_{O-D}^d(u_D) \geq 0\ \text{kW} \tag{14}$$

$$\mathrm{b}_{O-D}^r(u_D) = \emptyset_r * \varphi_r * P_{O-D}(u_D) * t_{O-D} \qquad \text{if} \qquad \mathrm{P}_{O-D}^r(u_D) < 0\ \text{kW} \tag{15}$$

The proposed SOC model considers DNCEV with regenerative braking. Therefore, for DNCEV without a regenerative brake, Eqs. (10), (12), and (15) should be disregarded.

The shortest path algorithm used in the proposed model is based on a cost function for the movement of DNCEV. Like mobile applications that determine the shortest path of an O-D, the algorithm is a variation of Dijkstra's algorithm (AIMSUN, 2021), resulting in the shortest path tree for each O-D pair. ET paths are defined according to the algorithm shown in Fig. 11.

Figure 11 – DNCEV Shortest path algorithm.



Source: Author's own elaboration.

With multiple first paths leading from the O-D structure, the algorithm will first store only the shortest path for each O-D pair. Later, an extra function is executed to update the costs (or equivalently, travel times) considering real-time congestion points and streets' speed limits. If equal costs are detected for an O-D pair when storing the data, the first one already stored remains, as costs are only updated if lower values are found.

Another function was also modeled similar to proposed in (NYOTHIRI *et al.,* 2021), in which DNCEV with low SOC seeks the nearest congested-free CS to perform the recharge and remain for a determined time. The method described in (NYOTHIRI *et al.,* 2021) is adapted and model in the AIMSUN tool based on congestion pricing incentive-punishment rules. The drivers are rewarded for choosing alternative paths to go at CS to mitigate traffic congestion, and a reward system is model to reward drivers for their contributions to reducing congestion. This system can be described as an information technology infrastructure for drivers, helping them to find routes to arrival at CS with lower cost and less charging time, considering free CS. The algorithm for routes is the same as in Fig. 11 and a function is added for managing CS. This function counts the entry, exit and charging times of DNCEV, providing the CS parameters for the DNCEV throughout the simulation.

Simulations should be performed, storing in the traffic simulator the streets visited by DNCEV and their SOC consumption hour by hour. From these hourly records, streets visited by DNCEV are summed up, and the average and coefficient of variation (CV) of their SOCs are calculated for each simulation in every block. To work with a single (summary) value for the SOC, a weighted average is computed, with weights equal to 0.5 for values of SOC with high dispersion (without loss of generality, we assume CVs above 95%, as these values may be sporadic or wrong) and 1.0, otherwise. At the end of these calculations, a spatial database is obtained to create heat maps, where the hottest tonal colors show the most critical locations for the analysis of the CS installation.

3.3 MODULE 3: INFRASTRUCTURE FOR CHARGING DNCEV

To define the places to build CS, the proposed methodology seeks to meet several criteria to find a solution that can meet the needs of the planning agents in the city. First, each agent (public, transport department, CS potential owners, etc.) can provide a spatial database with their conditions and restrictions for CS construction to create heat maps. Then, these maps are superimposed one by one (as layers), pointing at the location of CS where a spatial intersection of suitable locations in all layers is found. The spatial intersection is a Boolean intersection operation, using the logical “AND” applied to all regions that meet the criteria defined by the planner (LATINOPOULOS; KECHAGIA, 2015; ZHANG *et al*., 2020).

The proposal considers as main criteria: highest DNCEV flow and lowest SOC. Such criteria can be found in the layers according to the planner's studies and requirements. In the SOC layer, critical locations can be found by an average hourly SOC of all DNCEV that pass through each street. Critical locations are those with a percentage of the average SOC below a threshold defined by the planner. In the

DNCEV flow layer, critical locations can be defined by the percentage of the total number of DNCEV trips. The places to allocate CS must be selected considering these critical locations, subject to a minimum distance from each other (adjusted by the planner), preventing them from becoming idle in the case of being very close or overloaded when placed too far. This minimum distance between stations is known as the region of influence (RI) in the literature. It varies depending on factors such as the number of simulated DNCEV, vehicles requiring recharging and without finding a free CS (obtained through simulations), city size, and other socio-economic factors (ZHU *et al*., 2016).

The strategy to build CS from the layers is performed from a spatial intersection (using the operation "AND") of the critical locations of SOC consumption and DNCEV flow layers, differentiating the most critical locations from medium critical ones (only SOC or flow location are very critical) and the least critical ones. With this result, a spatial intersection with locations that have physical spaces can be done.

These candidates were found in (MORRO-MELLO, 2018) and updated for this work. The variables used to estimate these locations were: analysis of available physical space in strategic locations such as shopping malls, gas stations, squares, priority traffic routes, supermarkets, commercial and industrial centers. The available physical space used was revised, because for this work, it was considered that the chosen location should allow future expansions, so that the CS is not limited to the initially installed capacity. Candidates are represented as points on a spatial map, corresponding to a specific location on the street where they would be placed.

Therefore, the flow and SOC associated with them are the ones of the specific locations. For the selection of the winning candidates in the most critical locations to build CS, the rated power (the planner needs to define the rated power per station considering economic, technical, or capacity constraints) and a RI (to exclude nearby candidates) needs to be defined. Finally, winning candidates for medium critical locations and the least ones must be chosen. Note that if an intersection of a RI between two distinct critical zones is found, preference is given to the most critical one.

An example of the spatial intersection is shown in Fig. 12, with the hottest tonal colors representing the most critical locations. In this example, the spatial intersection of Maps 1 and 2, which represent flow and SOC, respectively, is performed. As a result, the most (red areas) and medium (orange areas) critical locations are found in Map 3. With the intersection of these results with Map 4, the CS allocation in a most critical location is found in Map 5 (point A), defining the rated power and a RI to exclude the nearby candidates. As shown in Map 5, none of the remaining candidates will be further considered because of this RI.

Note that it is possible to get several locations that have the same conditions to allocate CS. However, due to the large number of simulations performed, although the locations might seem equal, if one checks the detailed records, they always have different values. Thus, it is always possible to select the most critical ones in terms of SOC and flow. Finally, all CS are allocated in urban zones according to the planning requirements. Therefore, the planner can vary the number of CS by varying the radius of the recharging zone and/or initially choosing to build the CS in the most critical locations.

3.4 MODULE 4: DECREASE IN LOCAL POLLUTION

The decrease in the local pollution model and the input data previously described a traditional fuel consumption model to describe GHG emissions is required. Fuel consumption should be modeled computing the decrease in local pollution with the introduction of DNCEV. The LEM presented in the TSS tool (AIMSUN, 2021) is used to compute the GHG emission through Eq. (16) and (17). The LEM has enabled average emissions estimates to be created within the mesoscopic model's functionality.

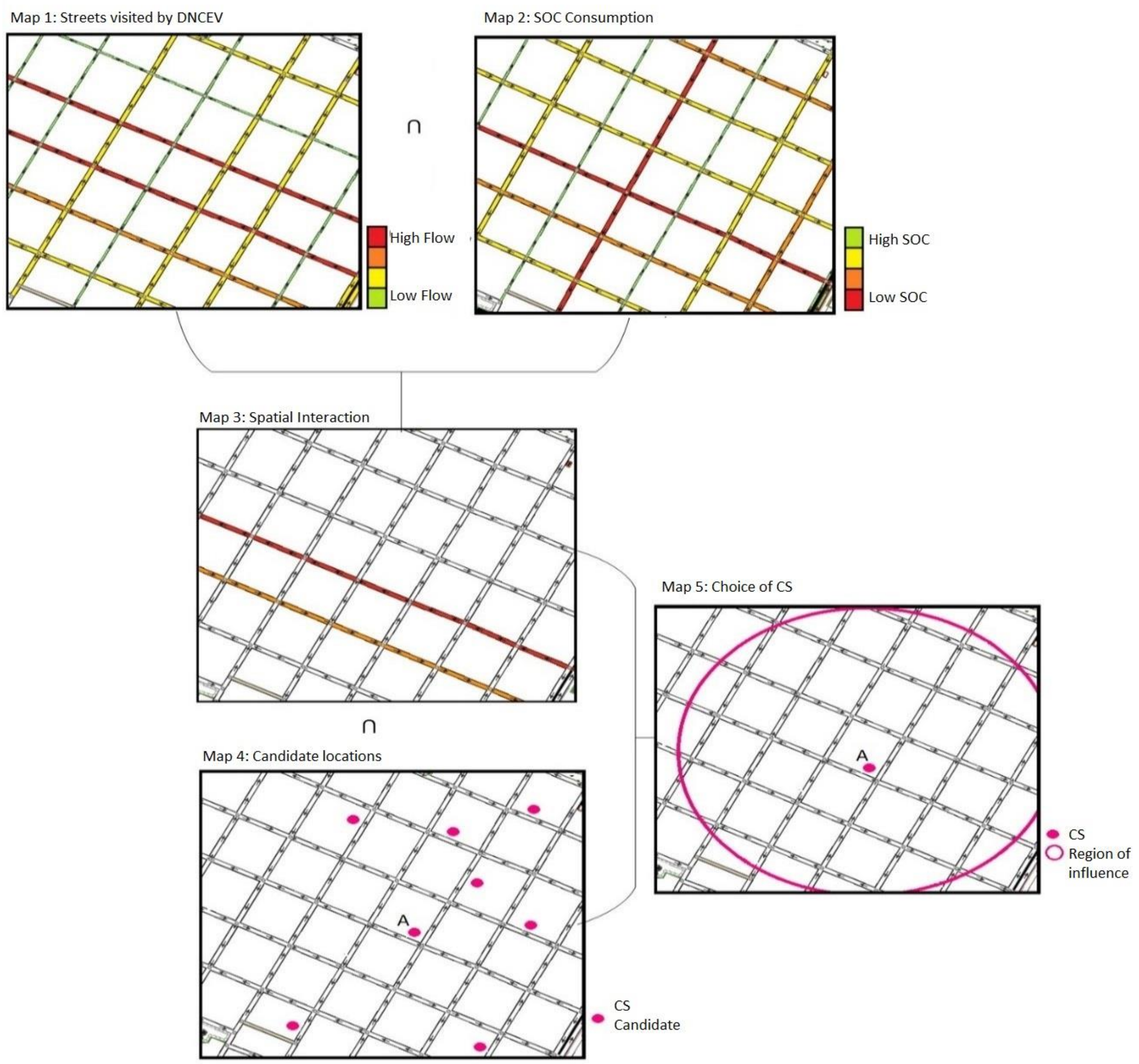
The LEM uses polynomial relationships derived by regression analysis to fit an emission factor for CO_2 and NOx.

$$y = a * x^z + b \qquad if\ x < 10\ km/h \tag{16}$$

$$y = a * x^3 + b * x^2 + x + c \qquad if\ x \geq 10\ km/h \tag{17}$$

Here, y is the emission (g/km); a, b, c, and z are derived constants already defined to each type of vehicle presented in the TSS tool; x is the trip's average speed. If the planner wants to use other parameters of a, b, c, and z for different types of vehicles that are not found in the TSS tool, the planner can introduce new types of vehicles and model their parameters by search in datasheets, technical specifications, and introduce in the tool.

Figure 12 – Example of a spatial intersection.



Source: Author's own elaboration.

The same simulation of module 2 is already performed. At the end of the simulations, a spatial database is generated with the GHG (CO2 and NOX) emissions information that is no longer produced with the introduction of DNCEV. Finally, a comparison can be made with reducing local pollution, finding the zones with more impact in the reduction, creating strategies to decrease pollution in other zones, and finding unknown patterns.

3.5 MODULE 5: IMPACT ON THE DISTRIBUTION NETWORK

In module five, a methodology is proposed to show the impact of DNCEV on residential charging.

3.5.1 Residential impact

To provide the impact in the distribution network with residential charging of DNCEV, a methodology to find the maximum diversified demand is proposed. For this purpose, nightly residential recharge is considered. DNCEV leaves respective homes, according to the results of module 1, with a specific SOC at the beginning of the day. Then, travel through the urban study zone during the day as shown in module 2, whether or not they can recharge in the CS (module 3) and, at the end of the day, return to their homes with a final SOC. This final SOC can be low, depending on the trips throughout the day, initial SOC, or whether the vehicle has recharged in a CS or not.

Depending on the final SOC, and the number of DNCEV in a subarea, it is possible to find the number of vehicles that will be recharged, as described in (UK POWER NETWORKS, 2014). To this end, a method is proposed, through Eq. (18), to find the maximum diversified demand in a given region (IRL) in kW that has a certain number of DNCEV and with average SOC at the end of the day/simulations. The spatial-temporal model of maximum diversified demand, described in Eq. (18), uses the spatial database created in the other modules as input data.

$$\mathrm{IRL(i)} = [1 - \mathrm{RMSOC\ (i)}] \times \mathrm{N(i)} \times \mathrm{P} \times \mathrm{LSF} \tag{18}$$

Here, *i* represents a determined subarea, RMSOC represents the average of the residential SOC (0 to 1), N is the number of DNCEV, P is the average kW per charge, varies by type of DNCEV, and LSF is the diversity factor found in (UK POWER NETWORKS, 2014). The diversity factor is a DNCEV simultaneous charging scale that ranges from 1 to 0.25. The more DNCEV in a given region, the lower the percentage of DNCEV recharging simultaneously.

With the proposed methodology, it is possible to obtain the maximum diversified demand by introducing DNCEV per subarea in a complete urban zone for each study period. As a result, spatial maps are shown with the maximum diversified demand in kW for each period. These spatial maps help distribution companies with energy dispatch and future planning as new investments in critical regions.

3.5.2 CS distribution network connection

The connection process for the CS in the distribution network proposed in module 3 is developed following (MORRO-MELLO *et al*, 2021). It consists of a methodology that explores a list of candidate connection points for CS allocation and allows optimized use of the existing distribution network. The proposal seeks to minimize equipment acquisition and replacement costs to satisfy the CS demand. A power flow is used to guarantee adequate power levels for the possible connection paths. Then, a local search algorithm will be used to find the least costly connection point. The algorithm considers connection costs, operation costs, technical losses, and additional equipment costs and differentiates between the connections for low and medium voltage connections. Such differentiation is used to exploit low voltage transformers' available capacity, allowing CS to be allocated while avoiding unnecessary investments. In other words, if there is not sufficient supply capability in the low voltage transformers, and depending on the CS specifications, new low voltage transformers are allocated, or else a medium voltage connection is used. All relevant information will spatially be modeled in GIS and DSS tools.

A local search algorithm based on graph theory has shown the ability to reduce losses for the distribution company through optimized cost functions. The local search algorithm can be used for load allocation in distribution networks, having low computational time for an extensive set of data. The algorithm is based on graph theory, considering vertices like the CS, feeder, substation, transformers locations, real electric characteristics (datasheet and real load data), and edges representing possible paths between the CS and substation, with real spatial and electric characteristic. Each path between the CS and substation comprises one or more edges spatially arranged, representing the electricity distribution network sections. The cost of a path, based on graph theory, is the sum of the costs of these edges (supply capability) and vertices (distances). Each path between them has costs. The costs are lower with more supply capability the network elements have and the less distance they are. The distribution company must analyze these costs to reduce investments. Graph Theory has already shown to be very suitable for connectivity analysis, as shown in works on landscape connectivity (MINOR; EMILY; DEAN, 2008) or national energy supply infrastructures (DOUGLAS *et al.*, 2011).

In this work, for each candidate solution, total connection costs are calculated. These costs are the sum of charges related to the connection branch, operation, technical losses, and additional equipment purchase. Such fees are calculated according to the connection voltage level. Then, a connection zone is proposed to explore candidate solutions within narrow search spaces.

A power-flow method (GIL-AGUIRRE; PEREZ-LONDOÑO; MORA-FLÓREZ, 2019) is used to model each possible connection in low and medium voltage environments; the simulations are divided into the same feeder barriers. The connections that do not guarantee adequate levels will be discarded. Also, the methodology proposes a different approach to exploit the supply capability that exists in installations in low voltage and medium voltage. Thus, the aim is to reduce the number of new transformers and new lines that must be built to planning the expansion of the network.

The proposed methodology considers the CS found in module 3 spatially distributed in an urban zone. The methodology consists of obtaining only the connections with conditions that ensure adequate power levels to find the least costly connections for distribution companies. Subsequently, a model is proposed to choose among the available connections—namely, the least costly connection for allocation. The CS has high power demands, and differentiation is required to the type of connection, i.e., low or medium voltage. The input databases to perform the methodology are:

i) Potential CS' spatial locations with the required installed capacity (module 3).
ii) The electric network's spatial distribution (substation, feeder, transformer, lines, and connections).
iii) Network information includes the elements' supply capability, the distance between these elements, and technical information about the CS.

All the input data is stored in a spatial database, capable of communicating with GIS and DSS tools. The planners must consolidate input data described in i) to iii) into a spatial database. Information found in other nonspatial databases can be georeferenced and added to the spatial database with GIS tools. Eventually, to process the presented proposal, a spatial database is required for manipulating, crossing information, categorizing, creating rules, mathematical formulations, and simulations with the GIS and DSS tools.

Low Voltage Connections

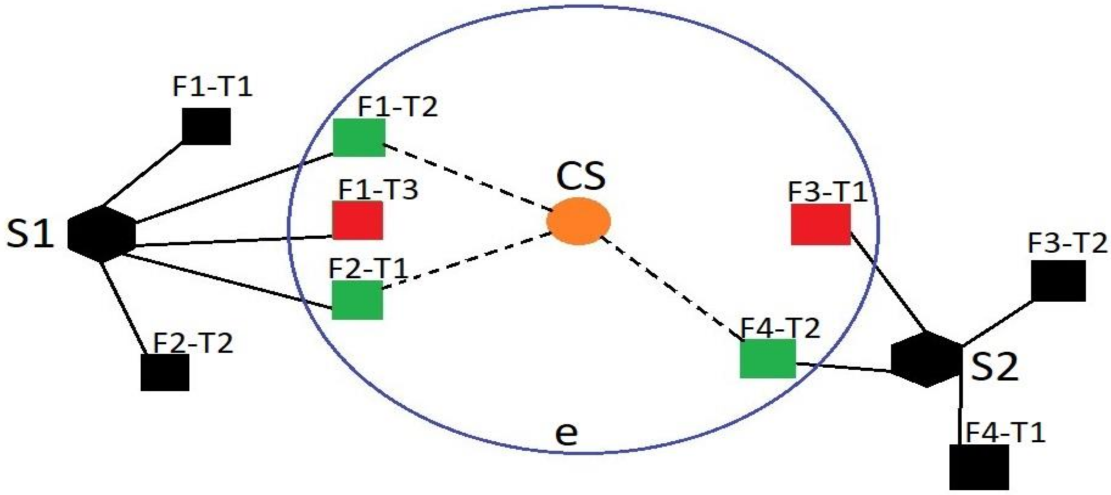
Connections at low voltage are limited by a maximum installed power level that depends on the country or region. Stations connected at low voltage lines must obey these limits. Also, electrical losses grow due to the connection path, and the distribution company provides a maximum limit for the connection path that must be considered to ensure adequate power levels. The unit coefficients method (FIGUEIREDO, 2006) is used to calculate the maximum allowable connection (e) in km in low voltage, as expressed in Eq. (19).

$$e = \frac{\Delta V \times V_L^2}{\left(r \times \cos(\varphi) + x \times sin(\varphi)\right) \times L_{cs}} \tag{19}$$

In this equation, ΔV is the voltage drop allowed in low voltage in PU, *r* and *x* are the resistance and reactance in the connection line in Ω/km, L_{cs} is the station (CS) demand in MVA, and V_L is the line voltage in kV.

Next, in km, a radius for the maximum allowable connection must be determined, with the CS functioning as the center. In this radius of coverage, transformers with sufficient supply capability for the station must be found. The supply capability already available in the transformers allows the existing network capacity to be exploited and unnecessary acquisitions to be avoided. If no transformer is available, new transformers must be acquired for each CS, allocating existing lines (located within the convergence radius), considering the smallest connection path (GONEN, 2014). The costs for this acquisition are computed in the total cost for the distribution company. A power-flow method is used to verify which connections will be within established loss standards, and inadequate connections will be discarded to ensure adequate power levels. Once the existing and new transformers have been determined to function at adequate levels, all possible connections must be subjected to further analysis via the power-flow method, as shown in Fig. 13.

Figure 13 – Possible connections for CS.



Source: Author's own elaboration.

In this example, there are transformers outside the region of connection (in black), inside the area but without supply capability or adequate power levels (red), and inside the region with supply capability (green), which can be allocated for the CS. To identify which connection is to be chosen from the available possibilities, an algorithm is used to connect with the least cost to the distribution company.

Cost function for low voltage

A local search algorithm based on graph theory finds the least costly solution through cost functions by exploring candidate solutions within narrow search spaces. The algorithm searches for the minimum investment necessary for the distribution company. The costs 1 and 2 are obtained in (MELO; ZAMBRANO-ASANZA; PADILHA-FELTRIN, 2017) 3 and 4 in (MORRO-MELLO *et al*., 2021), and as shown in Eq. (20)-(25).

A. Cost of connection ($):

$$Cost_1 = \frac{K_1 \times \ d_{cs,t} \times L_{cs}}{P_{cs,t,f,s} - L_{cs}} \tag{20}$$

In Eq. (20), K_1 is the cost of connection in low voltage in \$/km, $d_{cs,t}$ is the distance between the CS and the transformer (t) in km, and $P_{cs,t,f,s}$ is the supply capability of the elements in MVA. These elements are composed of:

$$P_{cs,t,f,s} = P_t + P_f + P_s \tag{21}$$

P_t, P_f, and P_s are the supply capability of the transformer (t), feeder (f), and substation (s) in MVA, respectively. These supply capabilities correspond to the power of the element minus the power of existing loads.

B. Additional cost of operation (\$):

$$Cost_2 = \frac{K_2 \times d_{cs,s} \times P_{cs,t,f,s}}{P_{cs,t,f,s} - L_{cs}} \tag{22}$$

In Eq. (22), K_2 is the cost of system use in \$/km and $d_{cs,s}$ is the distance between the CS and the substation in km. However, since CS have a high load, technical losses can increase significantly, and their cost must be considered. Therefore, the cost of additional technical losses for the distribution company is calculated, along with other equipment costs required to install CS.

C. Additional Cost of technical losses (\$):

$$Cost_3 = \frac{\left(r_b \times \ d_{cs,t} + r_m \times d_{t,f,s}\right) \times K_2 \times n \times i_m^2 \times c_p \times 10^{-6}}{P_{cs,t,f,s} - L_{cs}} \tag{23}$$

In Eq. (23), r_b and r_m are the low and medium voltage line resistance in Ω/km, $d_{t,f,s}$ is the distance between the transformer and the substation, n is the number of conductor load, i_m is the average current in A, and c_p is the equivalent coefficient of loss.

D. Cost of additional equipment (\$):

$$Cost_4 = C_{e1} \tag{24}$$

In Eq. (24), C_{e1} represents the investment cost of new transformers and power meters in \$. Finally, in Eq. (25), the total cost in \$ for the distribution company with the introduction of a CS in low voltage is:

$$Cost_{lv} = Cost_1 + Cost_2 + Cost_3 + Cost_4 \tag{25}$$

Medium Voltage Connections

The CS with power requirements more significant than those allowed at low voltage must be connected at medium voltage. The connection of medium voltage installations to meet such loads is determined by the study region's distribution company, which sets connection limits. A power-flow method is used for medium voltage connections to ensure adequate power levels. All the possible connections, calculated after the power-flow method has been used, must be factored into the analysis. Four costs are modeled similarly to the costs for low voltage connections.

E. Cost of connection ($):

$$Cost_5 = \frac{K_3 \times d_{cs,li} \times L_{cs}}{P_{cs,f,s} - L_{cs}} \tag{26}$$

In Eq. (26), K_3 is the cost of connections in medium voltage in $/km, $d_{cs,li}$ is the distance in km between the CS and the medium voltage line targeted for connections, and $P_{cs,f,s}$ is the supply capability of the elements in MVA and is composed of:

$$P_{cs,f,s} = P_f + P_s \tag{27}$$

F. Additional Cost of operation ($):

$$Cost_6 = \frac{K_2 \times d_{cs,s} \times P_{cs,f,s}}{P_{cs,f,s} - L_{cs}} \tag{28}$$

G. Additional cost of technical losses ($):

$$Cost_7 = \frac{r_m \times d_{cs,f,s} \times K_2 \times n \times i_m^2 \times c_p \times 10^{-6}}{P_{cs,f,s} - L_{cs}} \tag{29}$$

H. Cost of additional equipment ($):

$$Cost_8 = C_{e2} \tag{30}$$

In Eq. (30), C_e represents investments in new transformers and power meters in \$. Finally, the total cost in \$ for the distribution company with the introduction of a CS in medium voltage is:

$$Cost_{mv} = Cost_5 + Cost_6 + Cost_7 + Cost_8 \tag{31}$$

As input data, a list must be created for all the CS possible connections that have been identified as available. Then, a local search algorithm is applied to allocate the potential CS locations in the electrical network on that list. The algorithm chooses the least costly connection, considering that CS has higher power demands (more rated power) at the medium voltage and are located in regions with a greater need for recharging (zones with more traffic of EV and with low SOC). Therefore, a prioritized list of CS is used. In this list, there is a preference to allocate CS with larger rated power. Furthermore, the allocation of all medium voltage stations comes first, followed by low voltage stations.

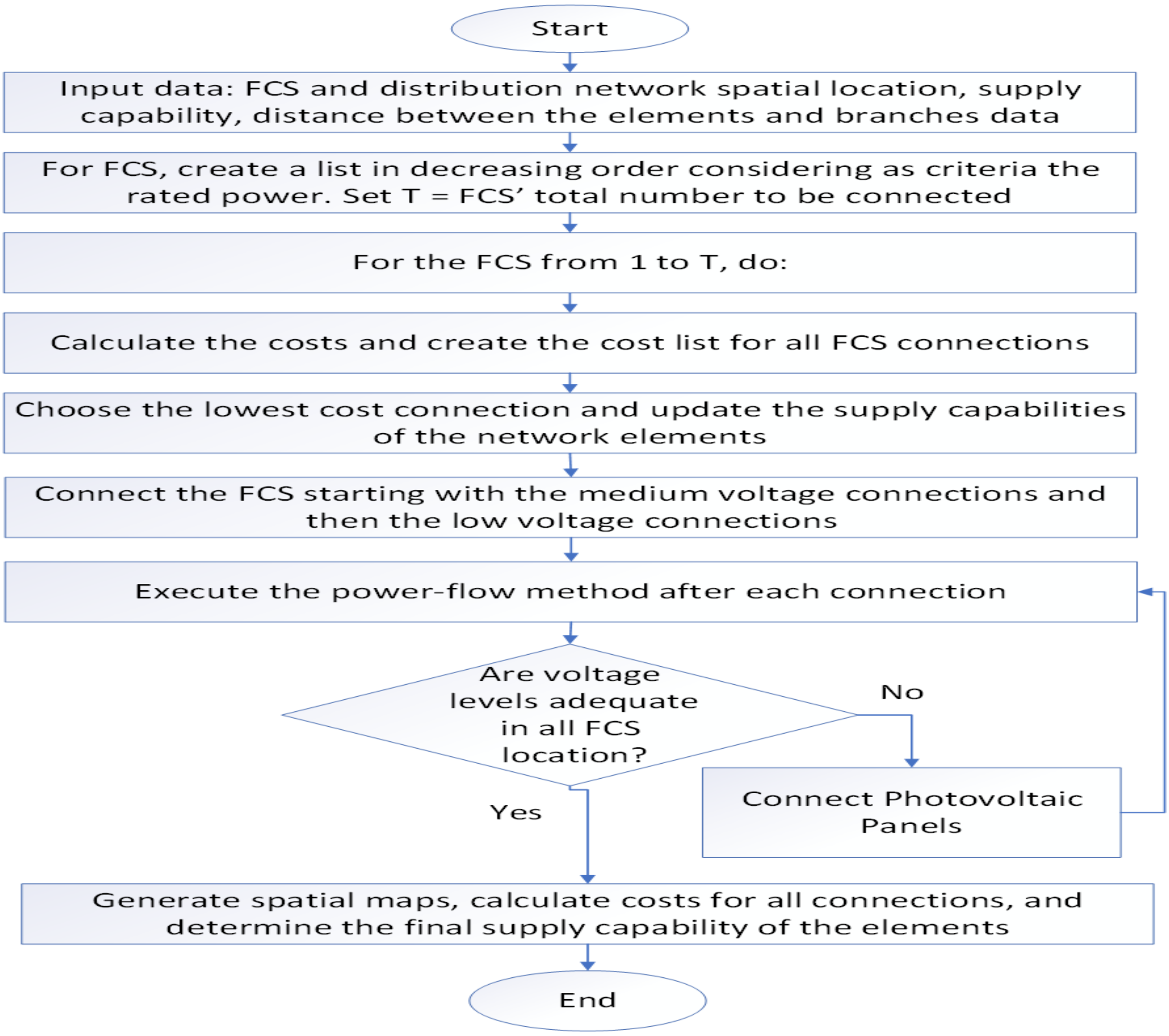
The algorithm initiates using the priority list to connect first the CS that have more rated power on the distribution network. The cost function is performed for each connection, and the lowest cost is selected as a winner, with the values of supply capability then being updated accordingly. A power-flow method after all connection is used to ensure adequate power levels. The power-flow method provides acceptable levels after each connection. Photovoltaic Panels are introduced in the case of voltage inadequate levels. The number of photovoltaic panels allocated is until the levels are within the proper levels. The algorithm ends after all CS are allocated in the electrical network.

Finally, the cost for CS allocations are found, and spatial thematic maps used in a GIS with low and medium voltage connections are generated. Fig. 14 shows an algorithm flowchart that can be implemented in a programming language with T representing CS's total number to be connected. This language should communicate with spatial analysis tools and be selected by the planner accordingly. The proposed methodology's output can help distribution companies analyze and plan electricity distribution systems.

3.6 ALGORITHM FOR ALL MODULES

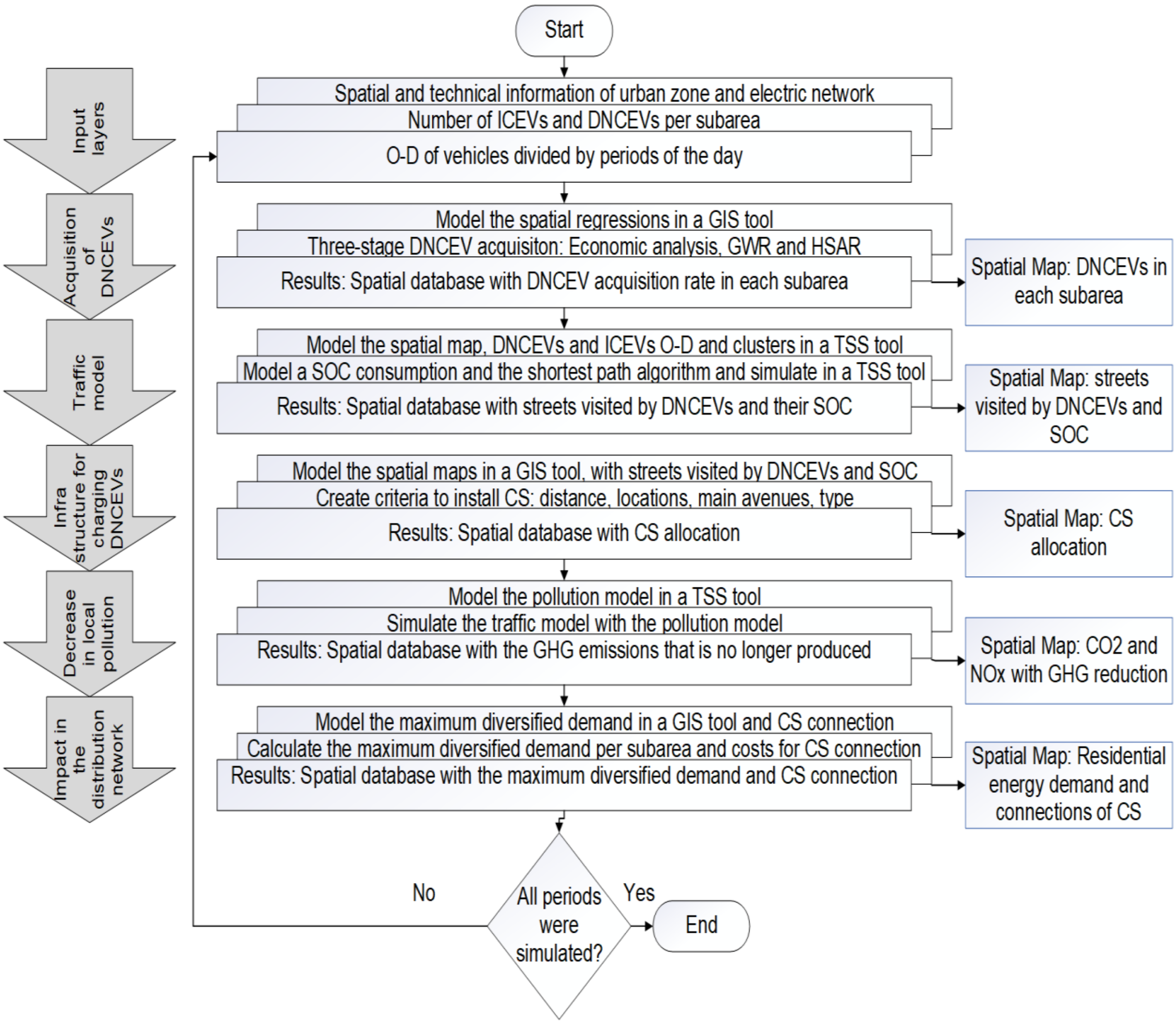
All methodologies described in the five modules; acquisition of DNCEV, traffic model, infrastructure for charging DNCEV, decreased local pollution, and impact in the distribution network; need to form a link. The first input data described in 3.1 is used in a GIS tool. The first input data and the results of module 1 are saved in a spatial database. This database is introduced in a TSS tool for module 2. The results of module 2 join the previous database for module 3 in a GIS tool in which such results are added to the previous database. For module 4, it is used the results of all previous modules in a TSS tool again. With the database of previous modules saved, module 5 is executed, and the results are saved. The database of all five modules serves as a basis for the next period of study. A flowchart with the methodology steps is presented in Fig. 15.

Figure 14 – Flowchart with the allocation algorithm



Source: Author's own elaboration

Figure 15 – Flowchart with the methodology steps.



Source: Author's own elaboration

The proposed methodology is applied in a medium-sized Brazilian city with 231,953 inhabitants and 562 km^2 (16.5 km^2 - urban zone). First, the information of the urban zone is obtained in the urban mobility department files and urban planning files (MARCHIORO, 2014). In addition, the spatial files of the urban zone are obtained from the city plan (MAPAS E INFORMAÇÕES GEOGRÁFICAS, 2021) (Fig. 16), spatial file with streets from the OpenStreetMap (OPEN STREET MAP, 2018) (Fig. 17), and spatial files with the electric network from agreements made between the local distribution company and the present research laboratory (fig 18 and 19). Fig. 18 shows the spatial distribution of the substations S1 with six feeders, S2 with nine feeders, S3 with nine feeders, and S4 with six feeders, and in Fig. 19, all transformers are shown.

The files of the urban zone contain subareas and all socio-economic information for each subarea, including the number of ICEV (approximately 100,000) and their spatial distribution. The files of the electric network contain all spatially located network elements and their electrical characteristics such as voltage, power, supply capability, among others.

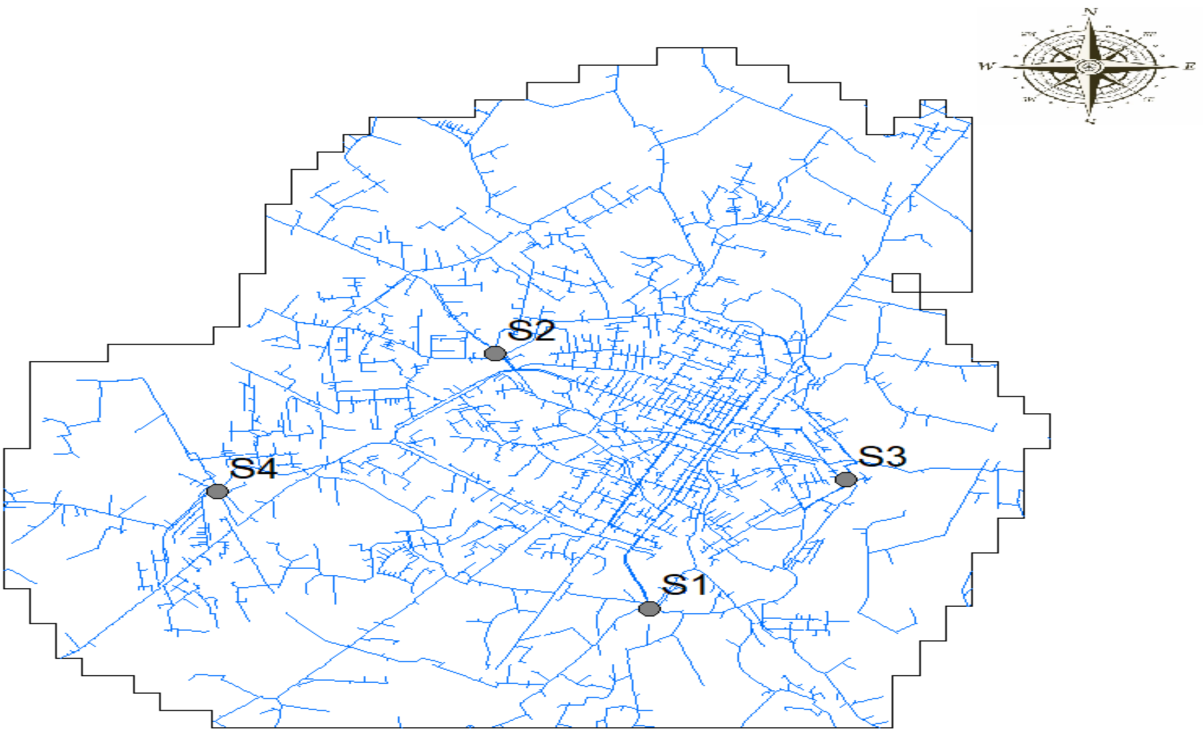
Figure 16 – Subareas of the urban zone.

Source: Author’s own elaboration

Figure 17 – Streets of the urban zone.

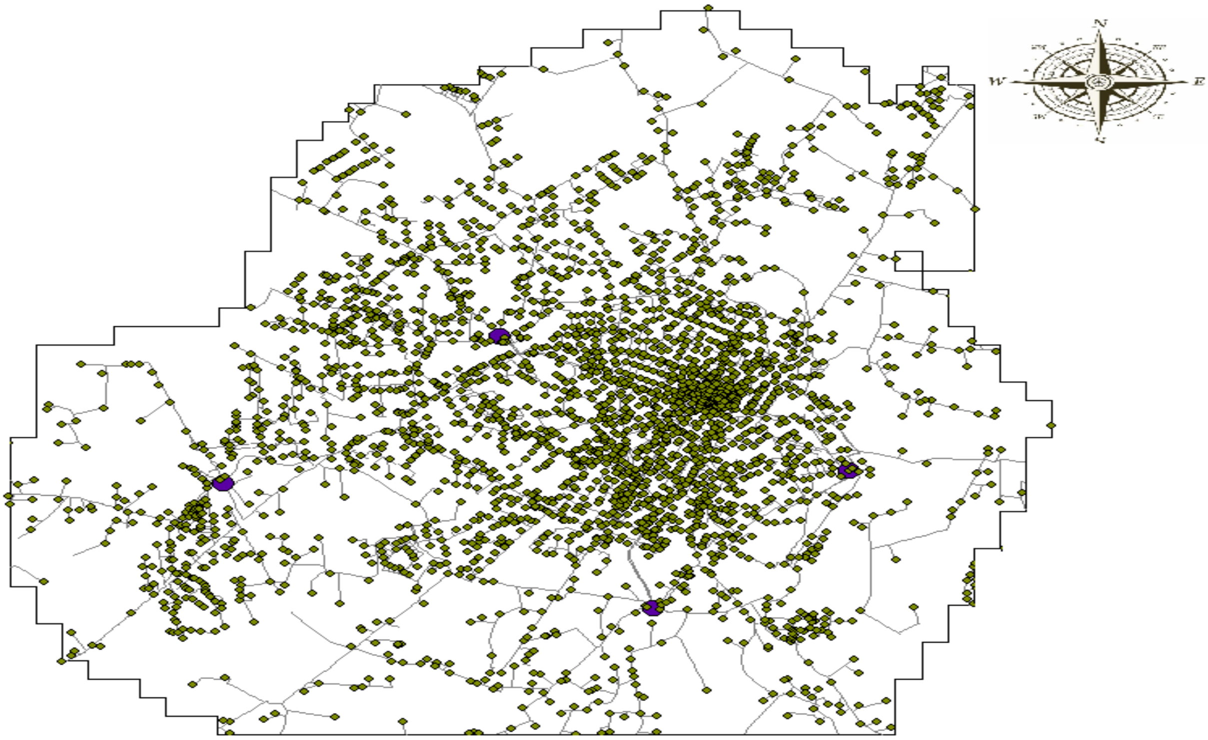
Source: Author’s own elaboration

Figure 18 – Spatial lines and substation of the urban zone.



Source: Author’s own elaboration

Figure 19 – Spatial transformers of the urban zone.



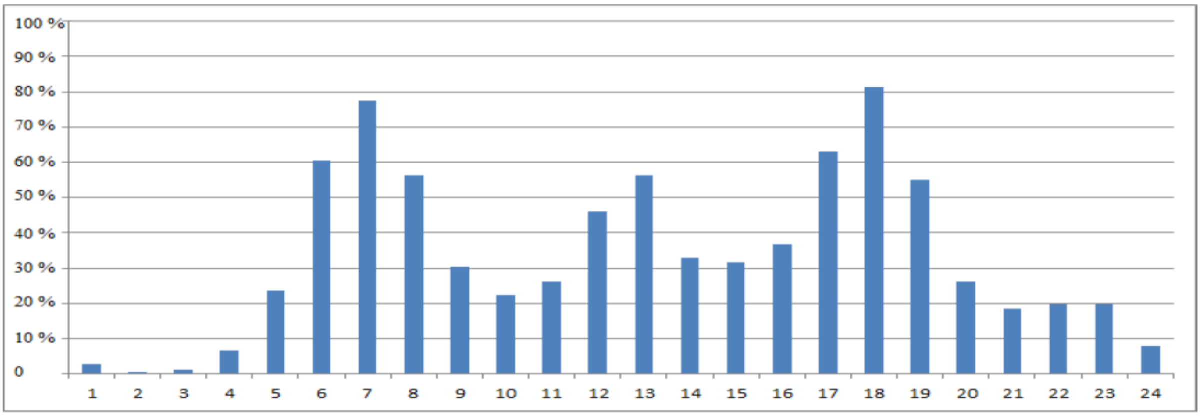
Source: Author’s own elaboration

Due to the amount of information and data in the file with the streets and avenues of the urban zone, an improvement is necessary. For this, the planner must manually improve the existing imperfections. First, the spatial map is plotted on the TSS tool. In this study, the AIMSUN (AIMSUN, 2021) is used, and later imperfections such as traffic lights, a maximum speed of roads, possible errors in streets, errors in intersections, identification of sectors (residential, commercial, industrial, educational, leisure) and other corrections are made. The first DNCEV (420) in the urban zone is obtained (MORRO-MELLO *et al*., 2019). Next, the percentages of vehicles traveling at each hour of the day are obtained from (MORRO-MELLO, 2018) and described in Fig. 20.

The O-D is created for all periods of the day (XIAOCHEN *et al.,* 2021), divided from hourly to a full weekday (24h). The O-D for all vehicles follows (PAIVA, 2010). In the morning, vehicles move from residential sectors to commercial and industrial sectors and go the other way at the end of the day. These two peaks in the early morning and at dusk are well defined. Other periods are modeled according to (ZHANG *et al.,* 2021; MOHAMMADREZA *et al.,* 2021).

The study starts in year 0 and has a 5-year horizon. Thus, the methodology is carried out annually, and the results are generated for each year for each module. The methodology is carried out for all modules in a given period. For the next period, all results from the previous period are used as input data. However, for presentation, discussions, and comparisons, all periods for each module will be presented below.

Figure 20 – Percentage of vehicles traveling the city at each hour.

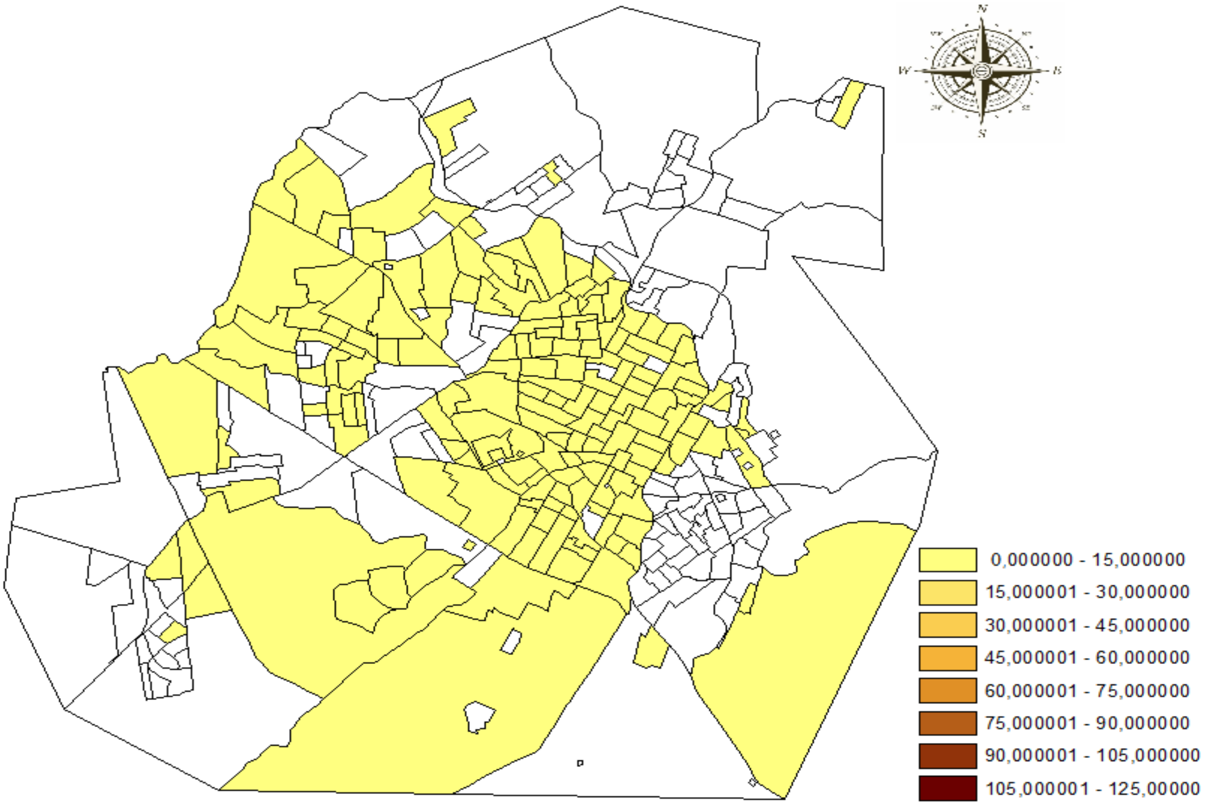


Source: Mello, 2018.

4.1 RESULTS OF INTRODUCTION OF DNCEV

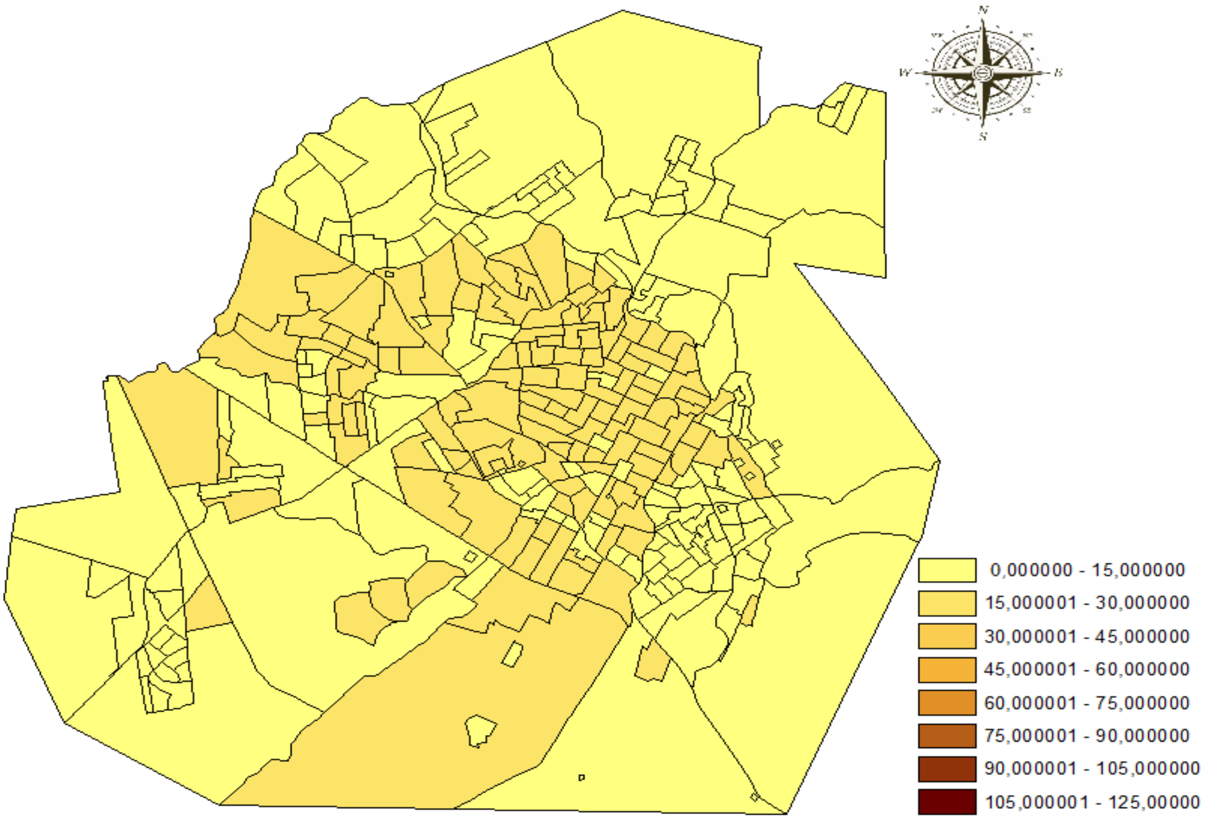
The acquisition of DNCEV through spatial regression in each subarea is found for each period using the ArcGIS tool (ESRI, 2017). For example, in year 0, there are only 420 DNCEV (ETs) distributed in the city, and their spatial distribution in an urban zone is insufficient to find spatial correlation patterns. So, in year 0, only the cost-benefit analysis is used. For that, socioeconomic characteristics such as the average income in the subarea, number of residents, individuals, education, the subareas, and the number of DNCEV expected in the year 0 are found and shown in Fig. 21. After, for years 1 to 5, the three-stage DNCEV acquisition described in Eq. (7) is used to find the number of DNCEV in each subarea, combining the cost-benefit, GWR, and HSAR methodology. The weights w, y, and z were calibrated, after exhaustive tests, to equal values in 1/3 each. Finally, each methodology was calculated, and through Eq. (7), it was possible to obtain the number of DNCEV in each year, as shown in Figs. 22 to 26.

Figure 21 – Spatial distribution of DNCEV in year 0.



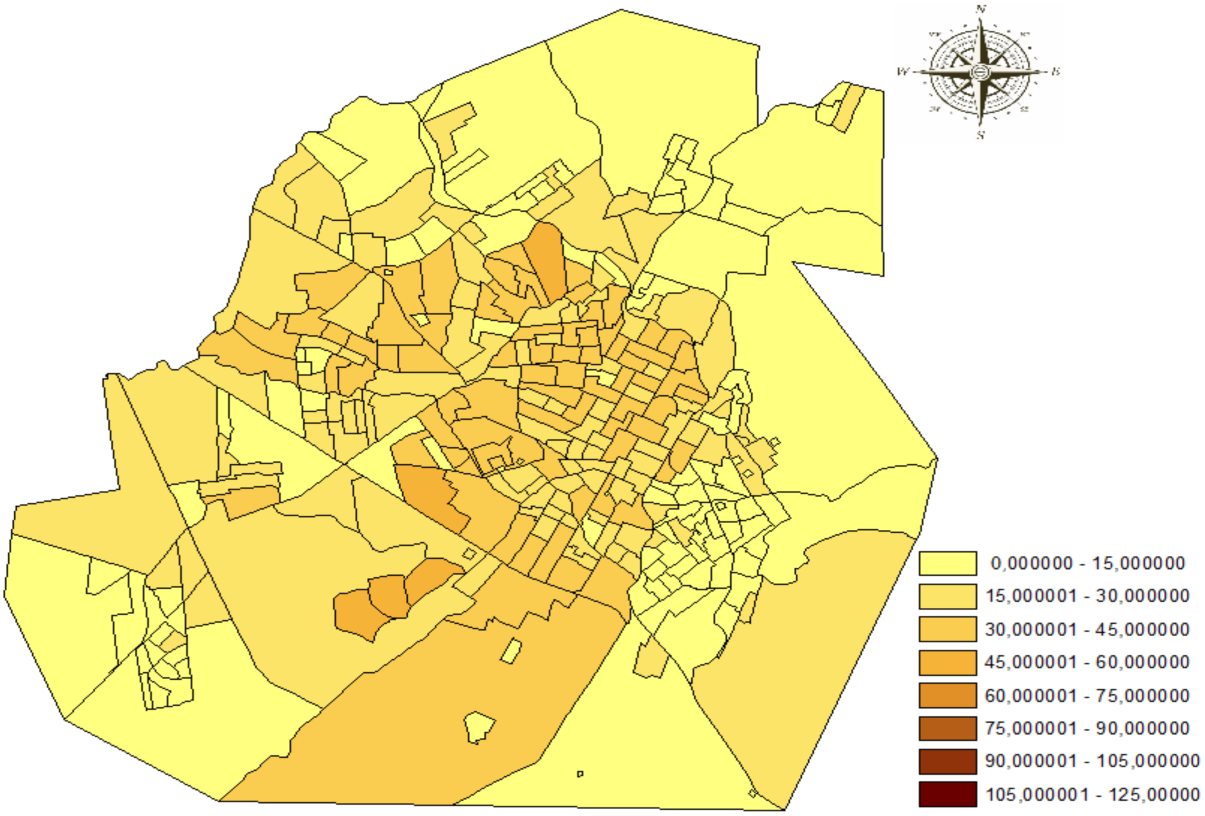
Source: Author’s own elaboration

Figure 22 – Spatial distribution of DNCEV in year 1.



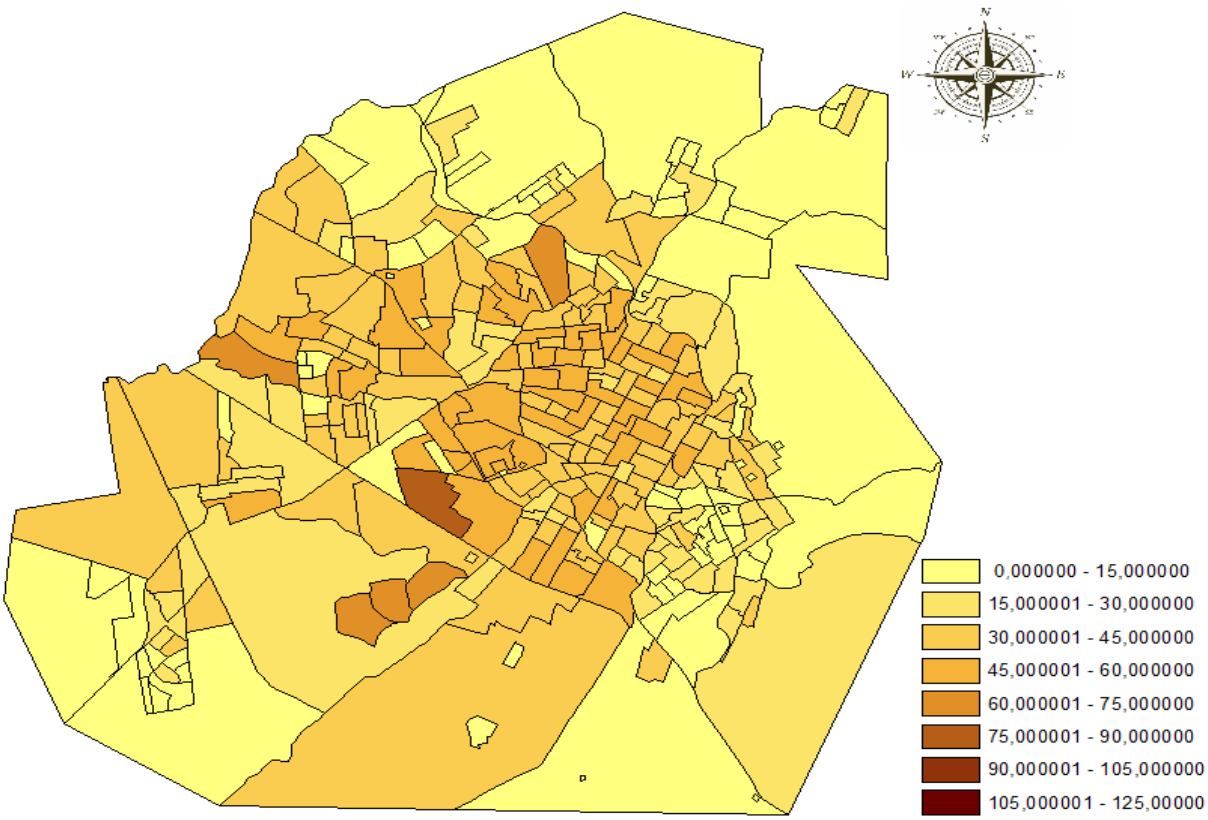
Source: Author’s own elaboration

Figure 23 – Spatial distribution of DNCEV in year 2.



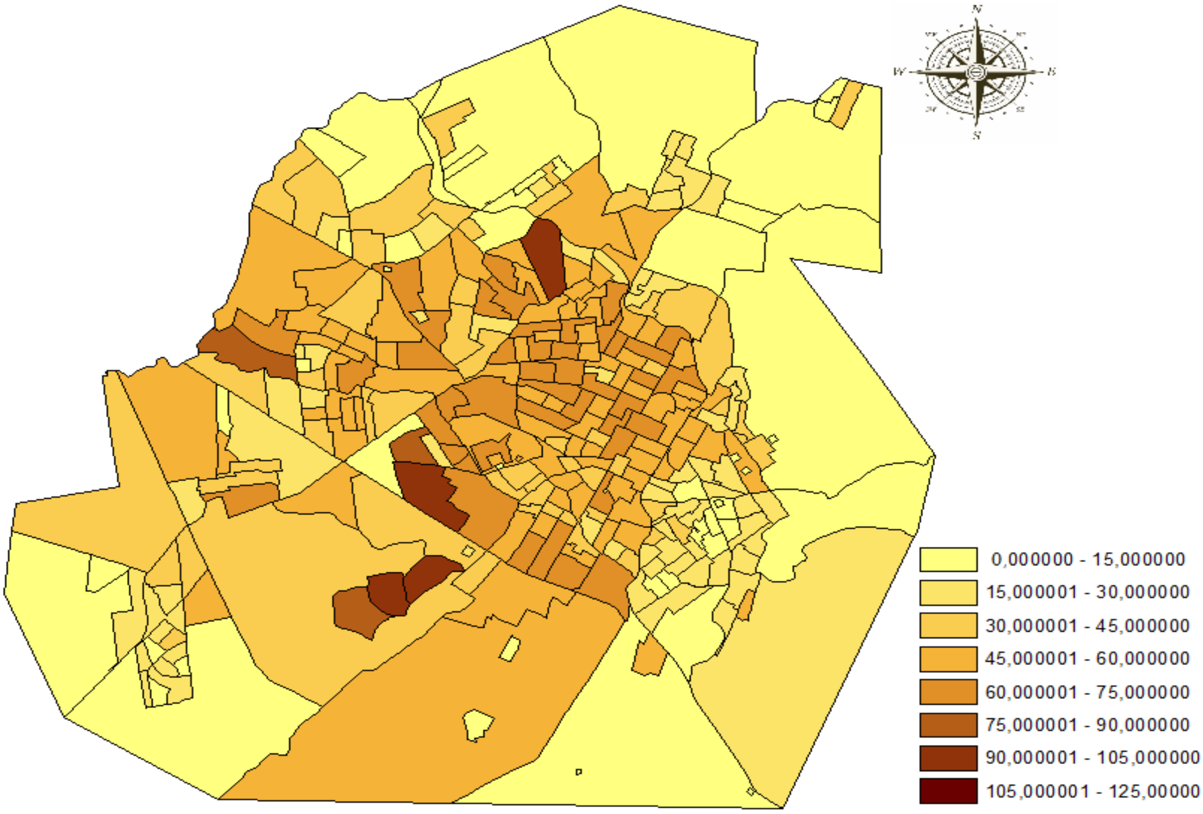
Source: Author’s own elaboration

Figure 24 – Spatial distribution of DNCEV in year 3.



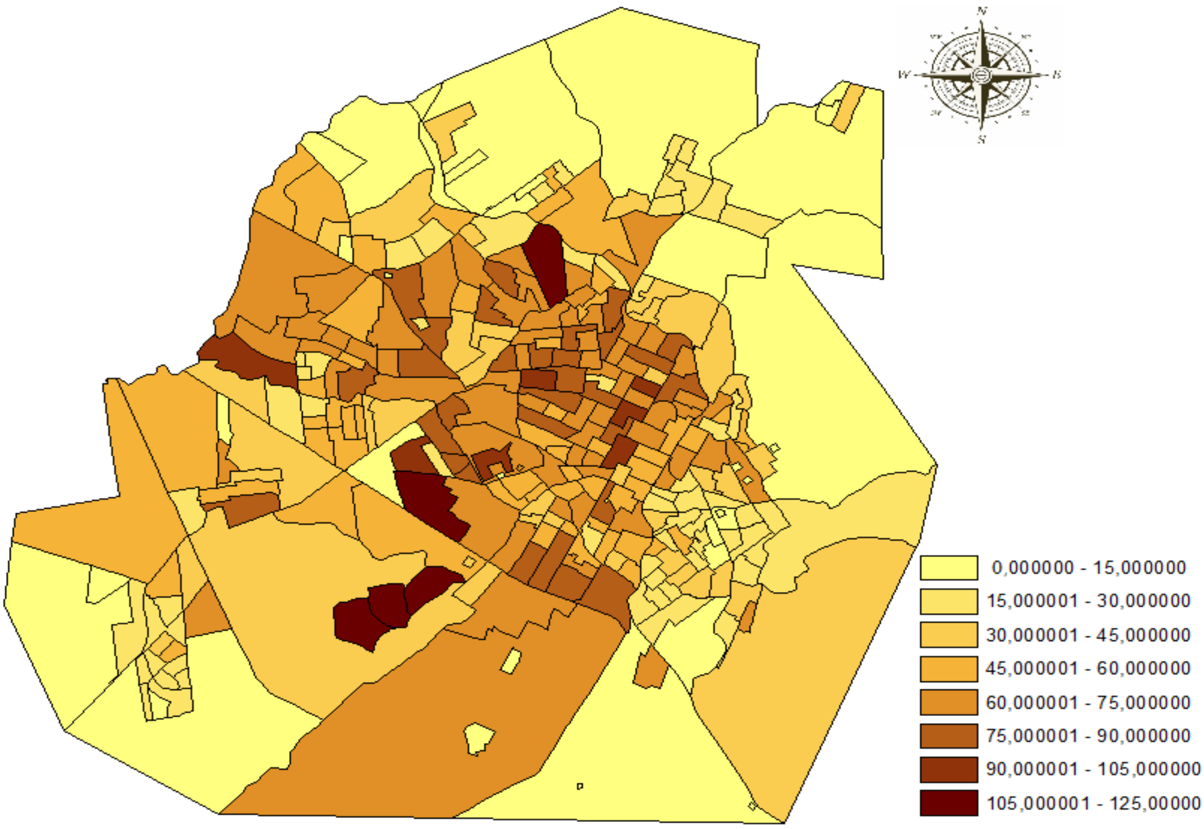
Source: Author’s own elaboration

Figure 25 – Spatial distribution of DNCEV in year 4.



Source: Author’s own elaboration

Figure 26 – Spatial distribution of DNCEV in year 5.



Source: Author’s own elaboration

The total amount of vehicles at the end of year 0 was 1,333 (913 of the cost-benefit methodology plus 420 initially allocated). In the year one to five, the amount of DNCEV is 4,011; 6,689; 9,367; 12,045 and 14,723 respectively. In year 0, with only the cost-benefit methodology, it is possible to observe that the acquisition of DNCEV follows a linear pattern. Subareas that are able to acquire DNCEV are shown in light yellow, and a number of DNCEV are acquired initially. With the introduction of GWR and HSAR correlation models in years 1 and 2, the combination of three methodologies provided that DNCEV was acquired in all subareas but still in a moderate way. In years 3 and 4, it is already possible to note that the homogeneous (GWR) and heterogeneous (HSAR) correlations make DNCEV stand out in some subareas, as in the regions.

Finally, in year 5, the subareas with the highest presence of DNCEV are visualized, the subareas around them have a high presence of DNCEV. Thus, the subareas around those that have a high concentration usually also have high concentrations. Conversely, the concentration is lower in peripheral zones due to the smaller number of vehicles, lower income, and fewer correlation patterns influence.

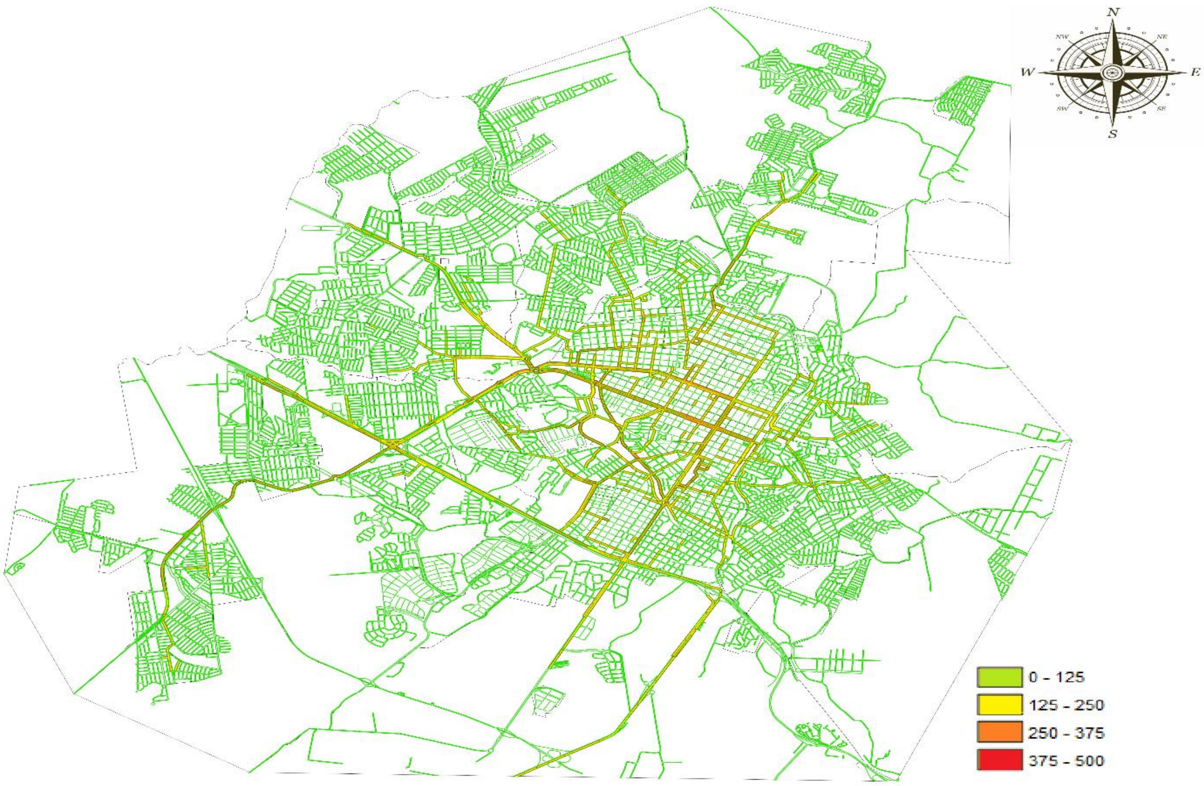
4.2 RESULTS OF TRAFFIC SIMULATION

For the traffic simulation, all the input data are the spatial model in the TSS AIMSUN tool. The O-D is obtained from department files for peak times divided by hours, and for other hours of the day, the use of the percentage of circulation of vehicles in similar cities is used. Clusters perform the O-D allocation. Each cluster of the subarea has one cluster and is both O-D. The percentage of vehicles circulating follows the patterns of Fig. 20. The acquisition of DNCEV replaces the allocated ICEV each year. ETs follow the driving patterns described in (MORRO-MELLO *et al.,* 2019). The routes of the BEBs and EGTs are found in the reports (MARCHIORO, 2014) of the urban zone and trace previously. The maximum speed varies with traffic lights, congestion points and is determined by the allowed speed.

The SOC is modeled in a Python Programming Language and can integrate with the variables in the AIMSUN tool. The microscopic simulation is used to characterize each DNCEV and SOC consumption behavior at each simulation instant. The mesoscopic simulation is used to characterize the group of ICEV. The group of ICEV is important to find congestion points at peak times. Congestion points influence traffic demand and travel times, influencing SOC consumption. The SOC initially follows a normal random distribution (25% to 100%) to characterize the randomness of the SOC. The DNCEV specifications used to calculate the SOC on the city's roads are found in DNCEV specifications manuals (CHEVROLET PRODUCT INFORMATION, 2020; RENAULT TECHNICAL SPECIFICATIONS, 2021; BMW TECHNICAL SPECIFICATIONS, 2018).

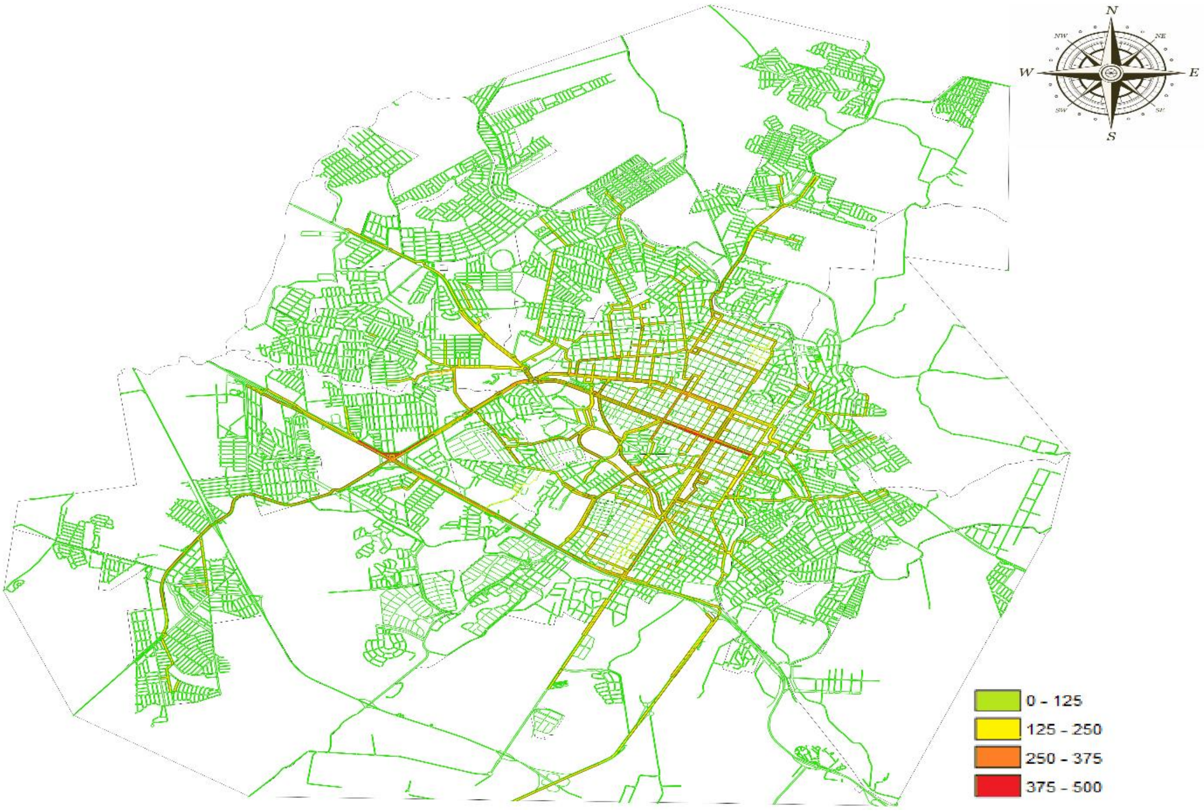
The shortest path algorithm used has two cost functions: shortest path and shortest travel time. Also, a function is modeled in Python that if the DNCEV has low SOC (below 25%), it looks recharge in a CS. This function is only activated at the beginning of year 1, after a CS allocation. Simulations were performed, storing in the traffic simulator the streets visited by DNCEV and their SOC consumption hour by hour. In Figs. 27 to 32, the streets visited by DNCEV are summed up and shown. The average and CV of their SOCs are calculated for each simulation in every block. A summary value for the SOC, weighted average, is shown in Figs. 33 to 38. The hottest tonal colors show the most critical locations for the analysis of the CS installation.

Figure 27 – Streets visited by DNCEV in year 0.



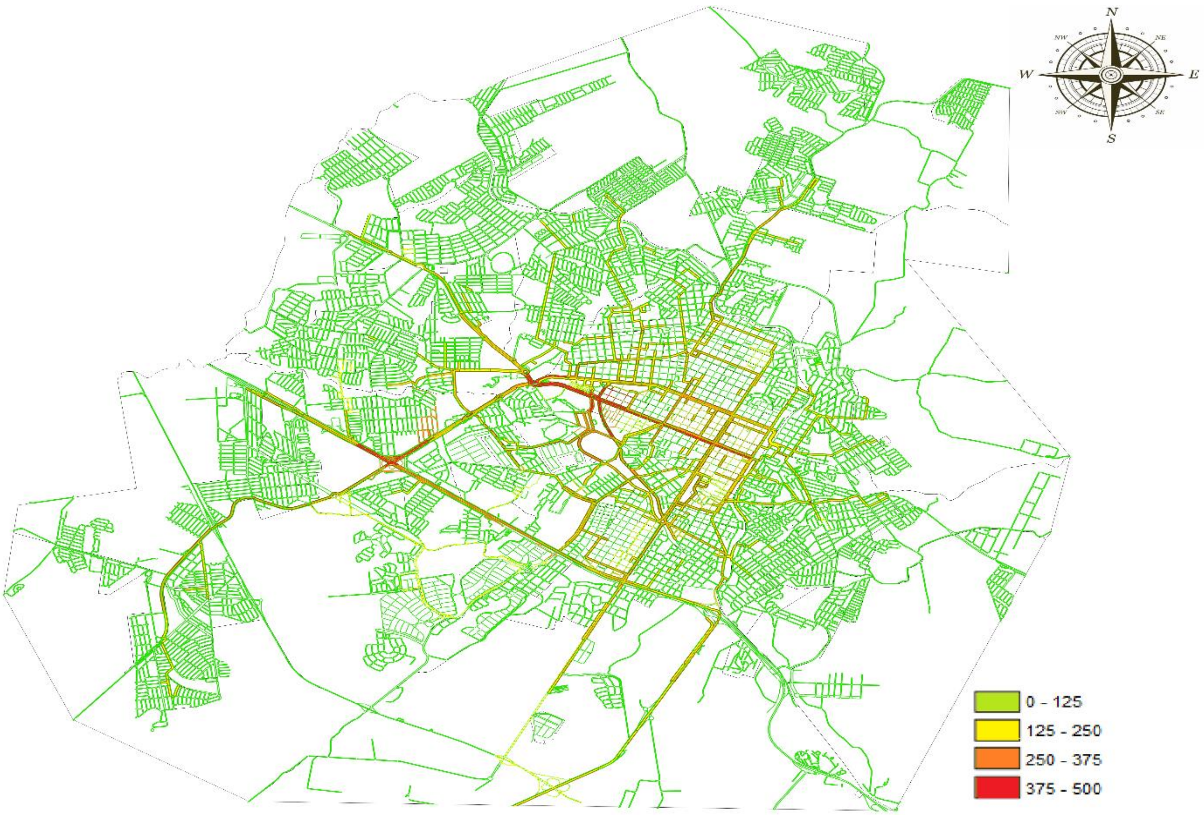
Source: Author's own elaboration

Figure 28 – Streets visited by DNCEV in year 1.



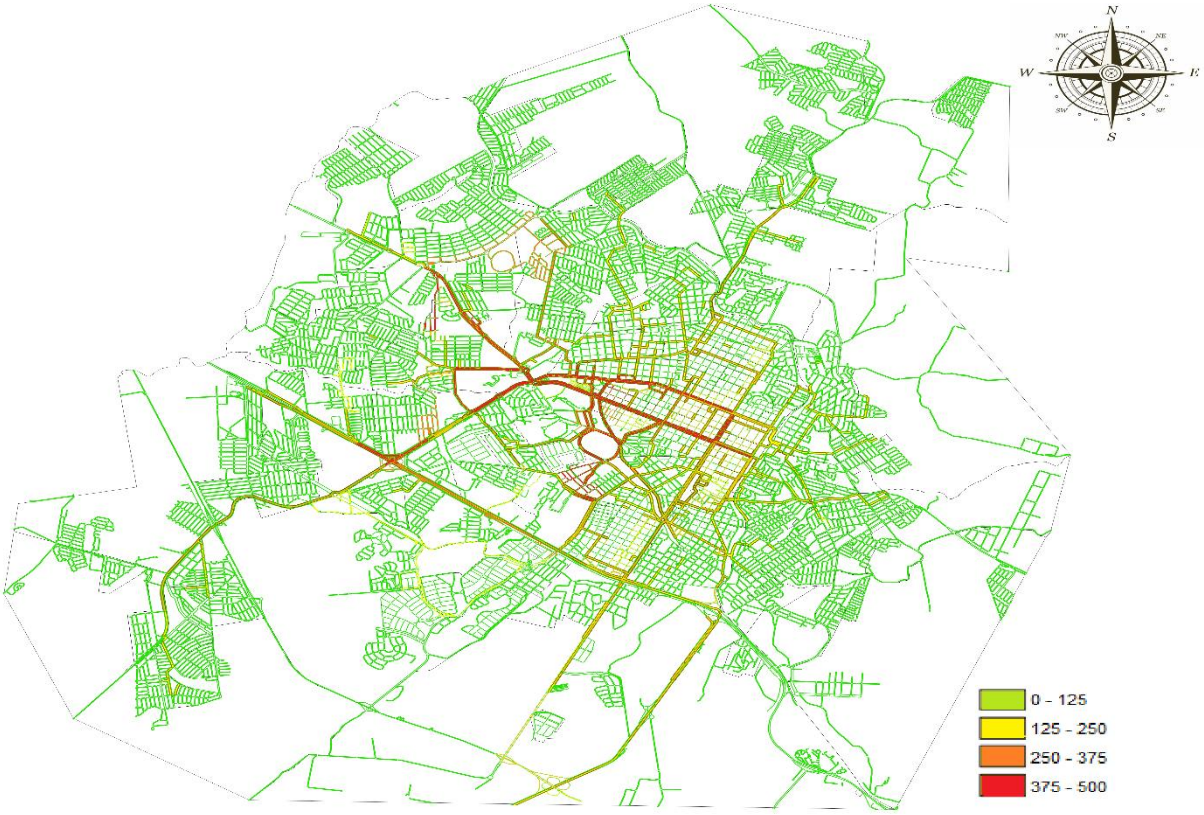
Source: Author’s own elaboration

Figure 29 – Streets visited by DNCEV in year 2.



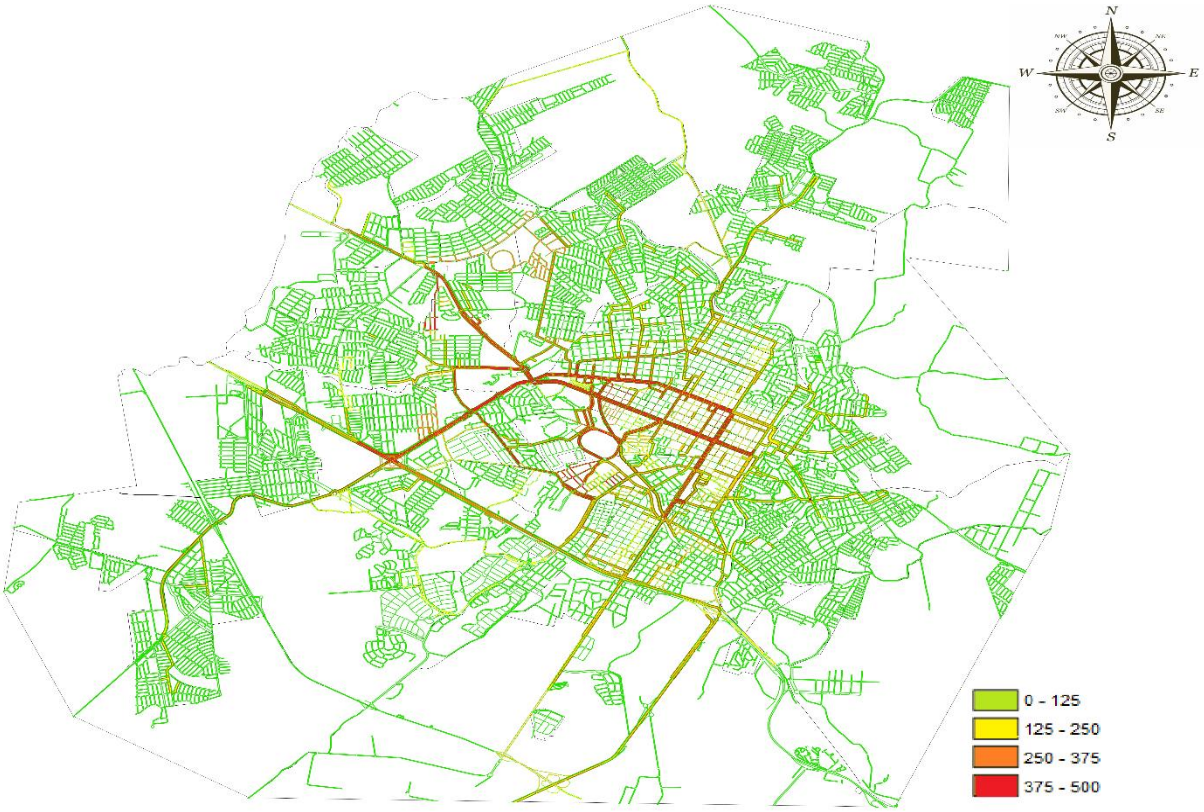
Source: Author’s own elaboration

Figure 30 – Streets visited by DNCEV in year 3.



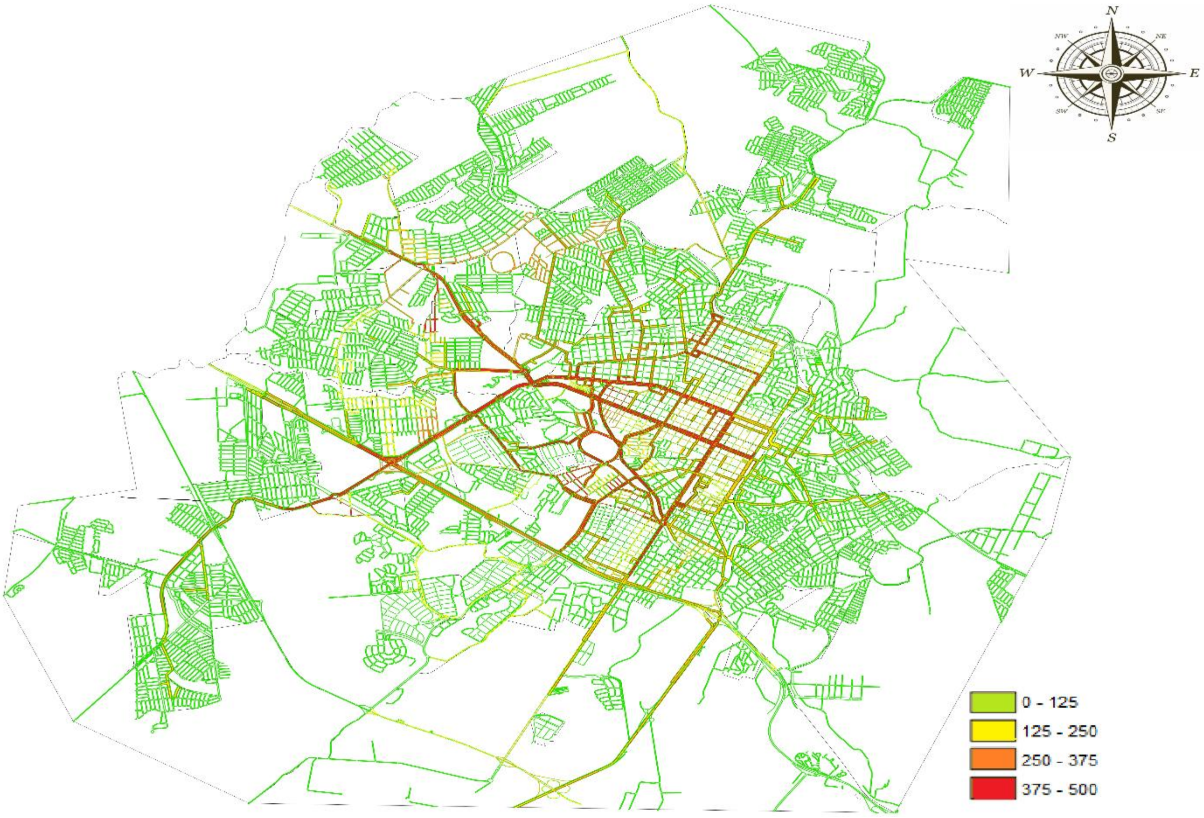
Source: Author's own elaboration

Figure 31 – Streets visited by DNCEV in year 4.



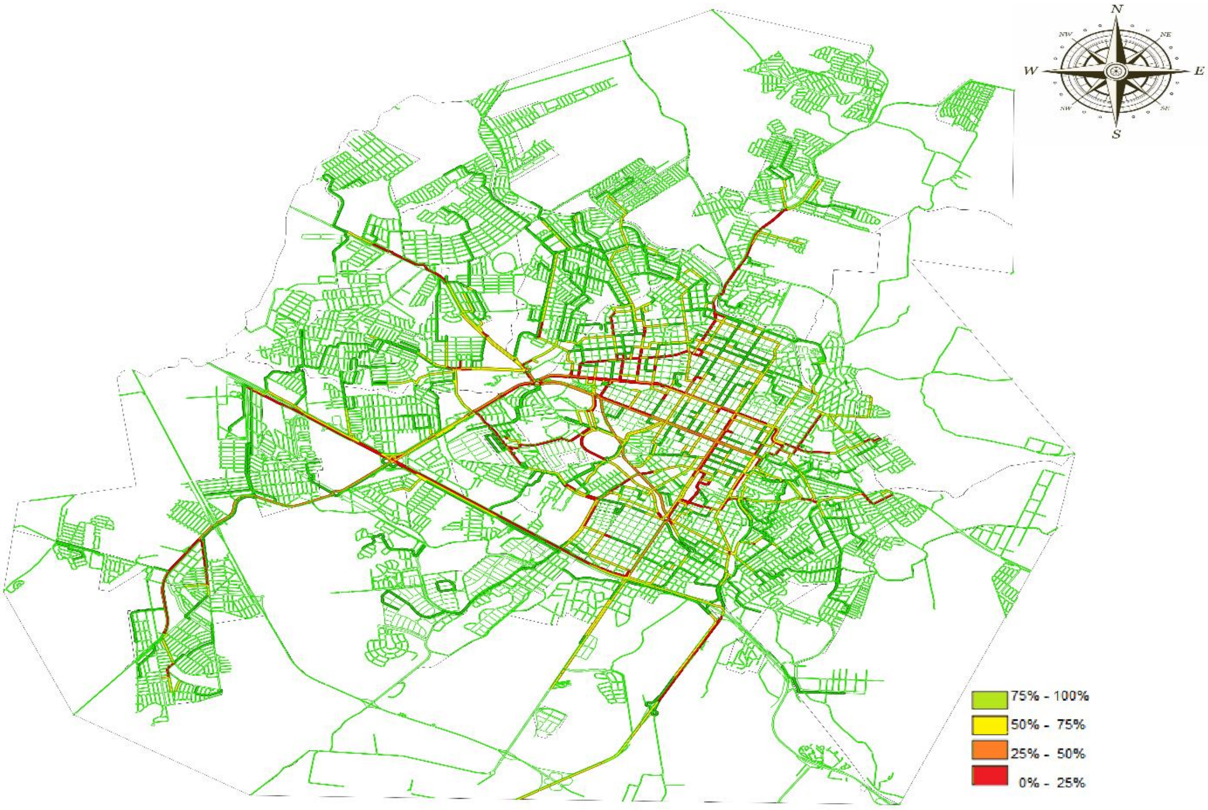
Source: Author's own elaboration

Figure 32 – Streets visited by DNCEV in year 5.



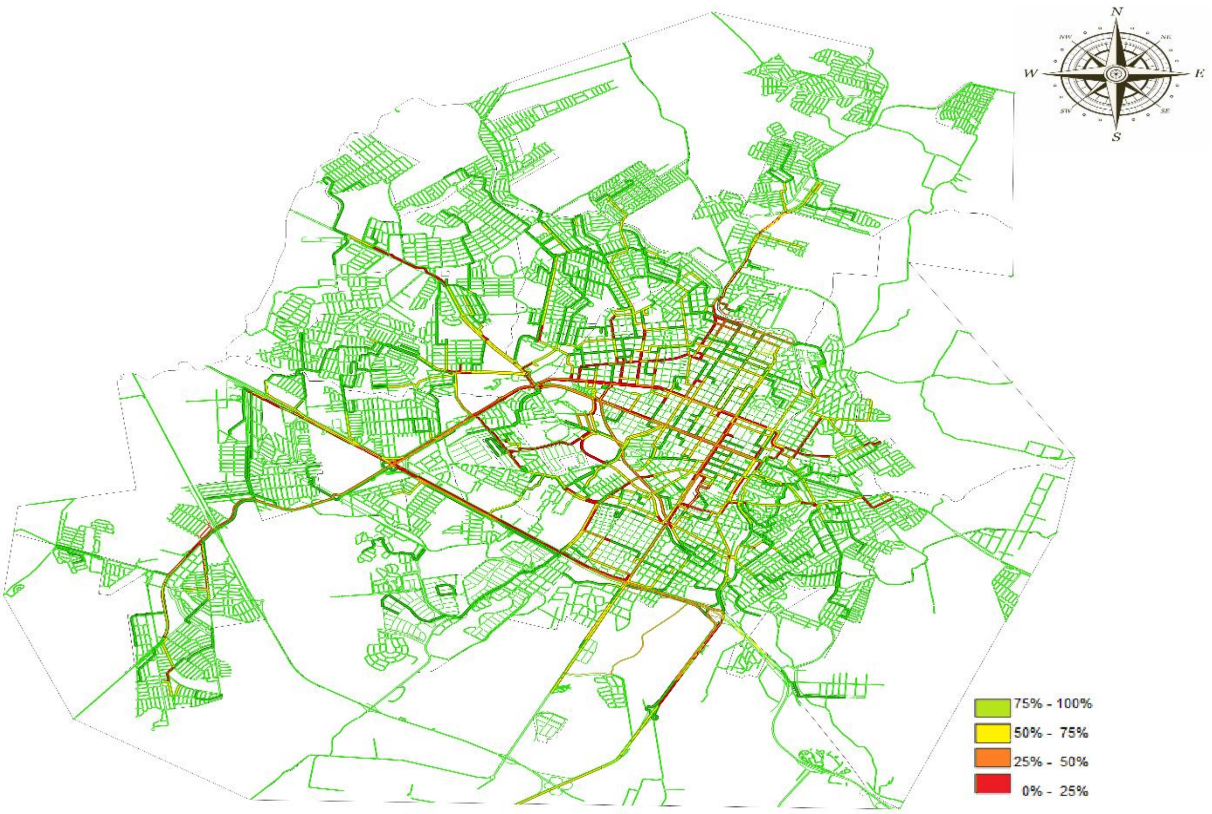
Source: Author's own elaboration

Figure 33 – SOC in year 0.



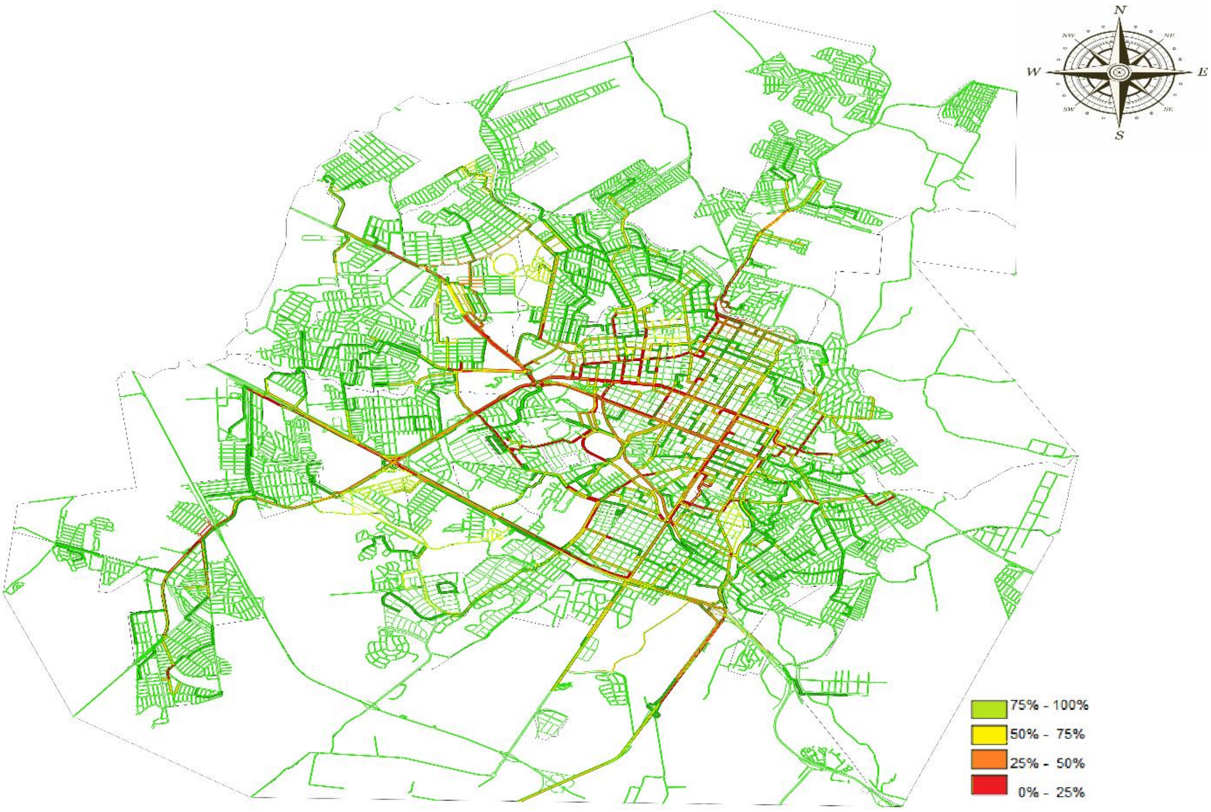
Source: Author's own elaboration

Figure 34 – SOC in year 1.



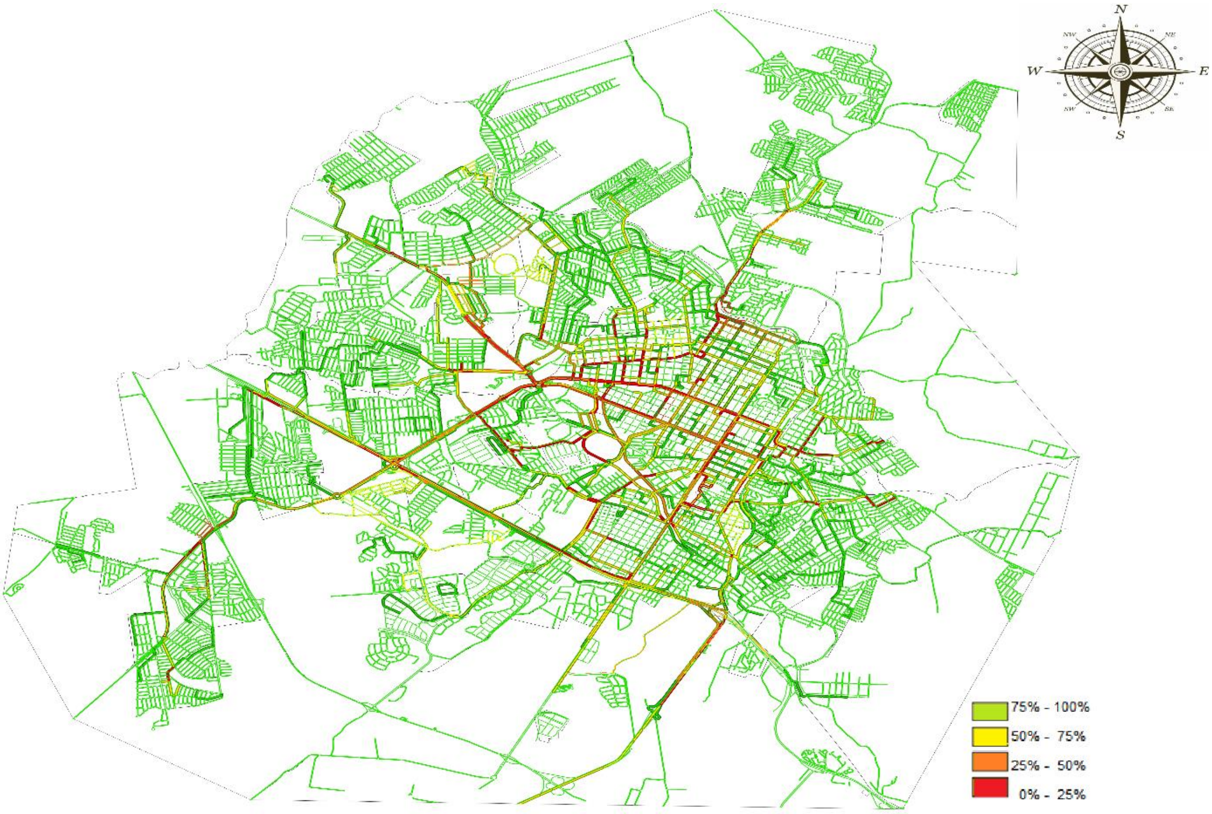
Source: Author’s own elaboration

Figure 35 – SOC in year 2.



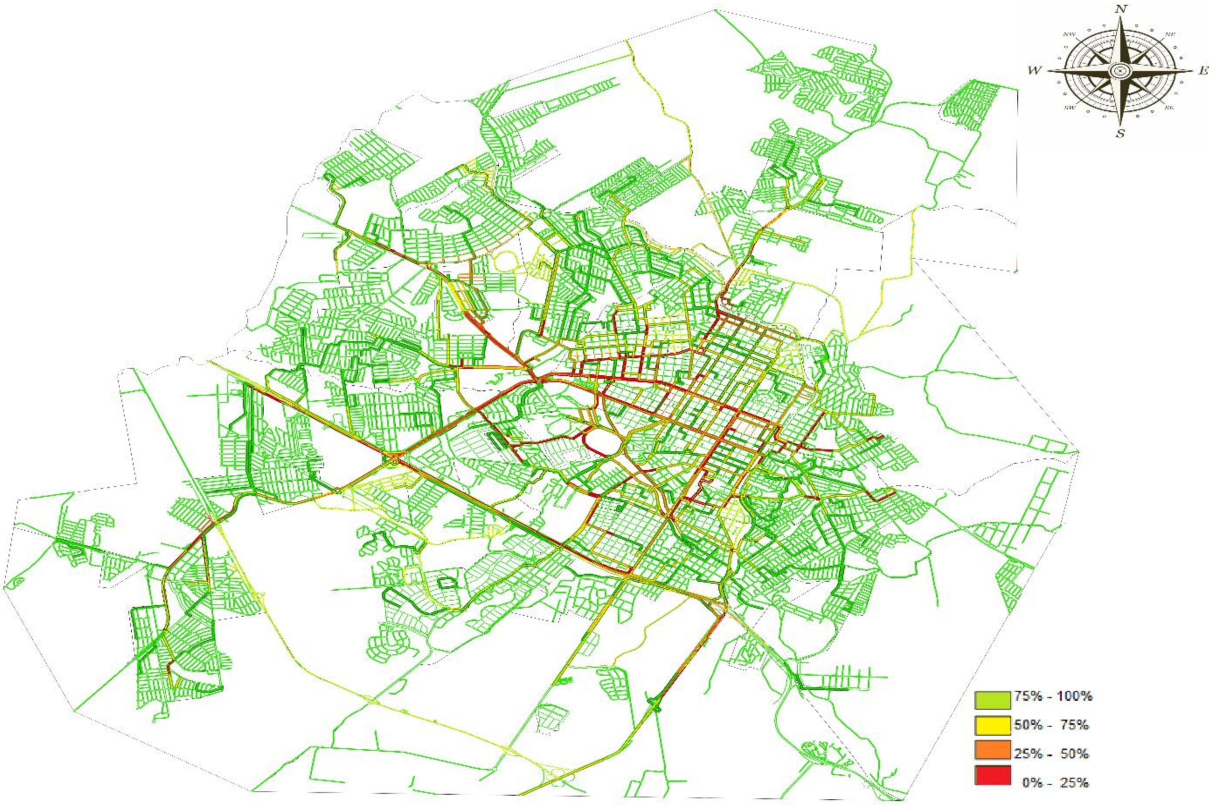
Source: Author’s own elaboration

Figure 36 – SOC in year 3.



Source: Author's own elaboration

Figure 37 – SOC in year 4.



Source: Author's own elaboration

Figure 38 – SOC in year 5.

Source: Author's own elaboration

Each simulation of module 2 in the AIMSUN tool (next 20 version) took four hours and forty minutes on an Intel® Core ™ i7 8750H computer, 2.2 GHz, 16 GB RAM. It is possible to observe through Figs. 27 to 32 represent streets visited by DNCEV that the highest flow of vehicles is, in years 0 and 1, mainly in the main avenues of the urban zone that connect the peripheral areas to the center. As of years 2 and 3, regions in the central zone already reach a high volume of vehicles and main avenues. In years 4 and 5, the central region presents a high concentration of DNCEV, decreasing this concentration as it moves away from the center. The peripheral regions do not suffer significant changes, except in their avenues, since the flow of vehicles is dispersed in the secondary streets.

The average SOC levels along the streets vary more, and not always a region with a large flow of DNCEV has low SOC levels. In the main avenues, it is possible to observe that the average SOC of the DNCEV is, in general, lower than in secondary streets. It is also noted that the patterns of the percentage of SOC do not vary much over the years. That is, streets with a certain percentage in one year vary little for the other years. There are variations in the average, but to produce the maps, such variations are imperceptible. Finally, with the database produced, the allocation of CS in the urban zone is carried out for each period.

4.3 RESULTS OF INFRASTRUCTURE FOR CHARGING DNCEV

The maps of streets visited by DNCEV and SOC are superimposed. To define critical streets that need CS, some criteria are used and summarized in Table 2. After exhaustive simulations, such criteria were defined to find the definitions of CS that would meet the DNCEV throughout the day without leaving them overloaded or too much idle. The number of chargers and charger levels are defined according to the need of DNCEV. The RI, CS radius of coverage was necessary to have a distance between allocations. Such distance was defined after exhaustive tests, finding a common radius for each type of CS defined. Suppose the RI of two or more candidates overlap. In that case, some of them should be discarded according to the database that allows access to the data with decimal numbers. The spatial locations of CS are defined, creating a layer with locations with sufficient space for the allocation in the urban zone. Then, all the 25 m² (MORRO-MELLO *et al.,* 2019) locations are pointed in the layer, and other superimposed were done. Finally, the CS is spatially distribution in the urban zone for each study year and show in Figs. 39 to 44. In Appendix 1, the same Figs. 39 to 44 (Figs. 81 to 86) with their RI are presented. Table 3 shows the number of CS for each year by type of CS.

TABLE 2 – CS CHARACTERISTIC.

Type of CS	**SOC (%)**	**DNCEV in the streets**	**AC Level 2 CS (22kW)**	**AC Level 3 CS (43kW)**	**RI (m) - year 0 and 1**	**RI (m) - year 2 and 3**	**RI (m) - year 4 and 5**
Blue CS	25% to 50%	250 to 375	1	0	800	600	400
Gray CS	25% to 50%	375 to 500	1	1	1,000	800	600
Gray CS	< 25%	250 to 375	1	1	1,000	800	600
Black CS	< 25%	375 to 500	2	2	1,200	1,000	800

Source: Author’s own elaboration

Figure 39 – CS in year 0.

Source: Author's own elaboration

Figure 40 – CS in year 1.

Source: Author's own elaboration

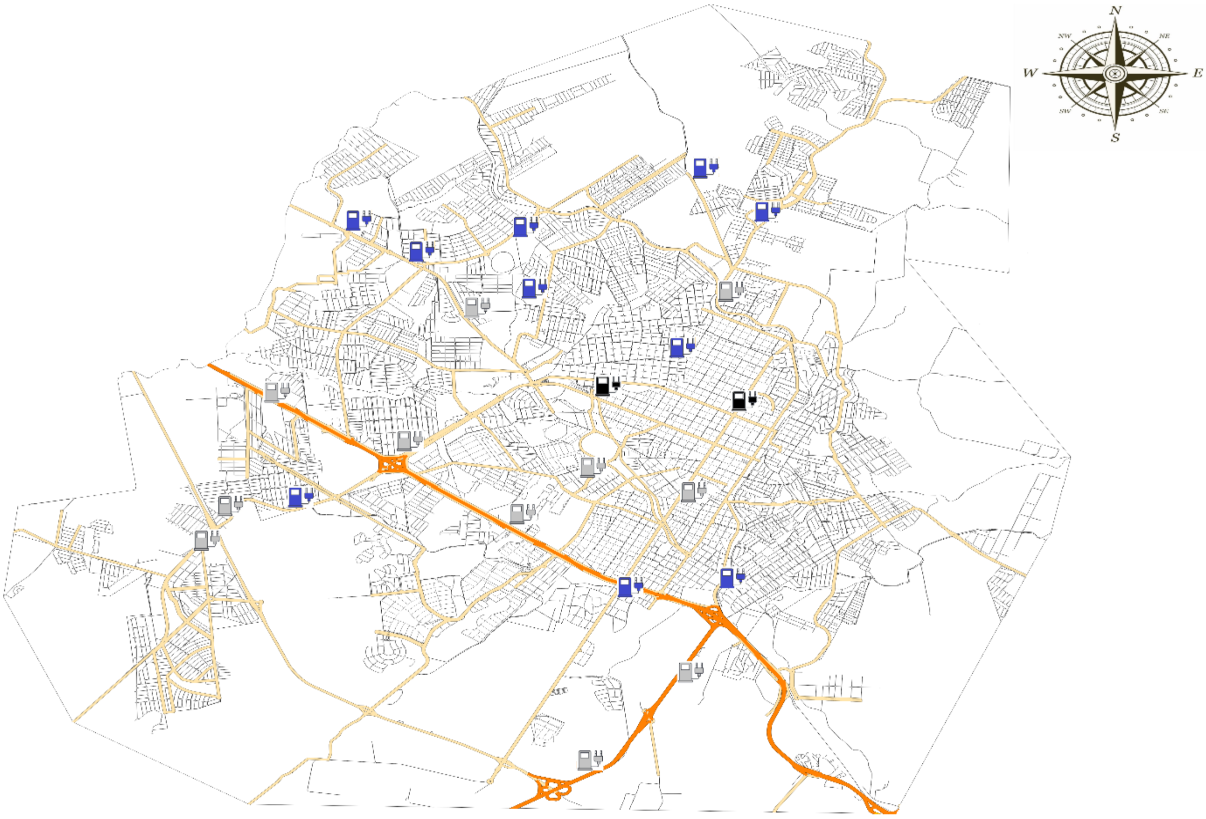
Figure 41 – CS in year 2.

Source: Author's own elaboration

Figure 42 – CS in year 3.

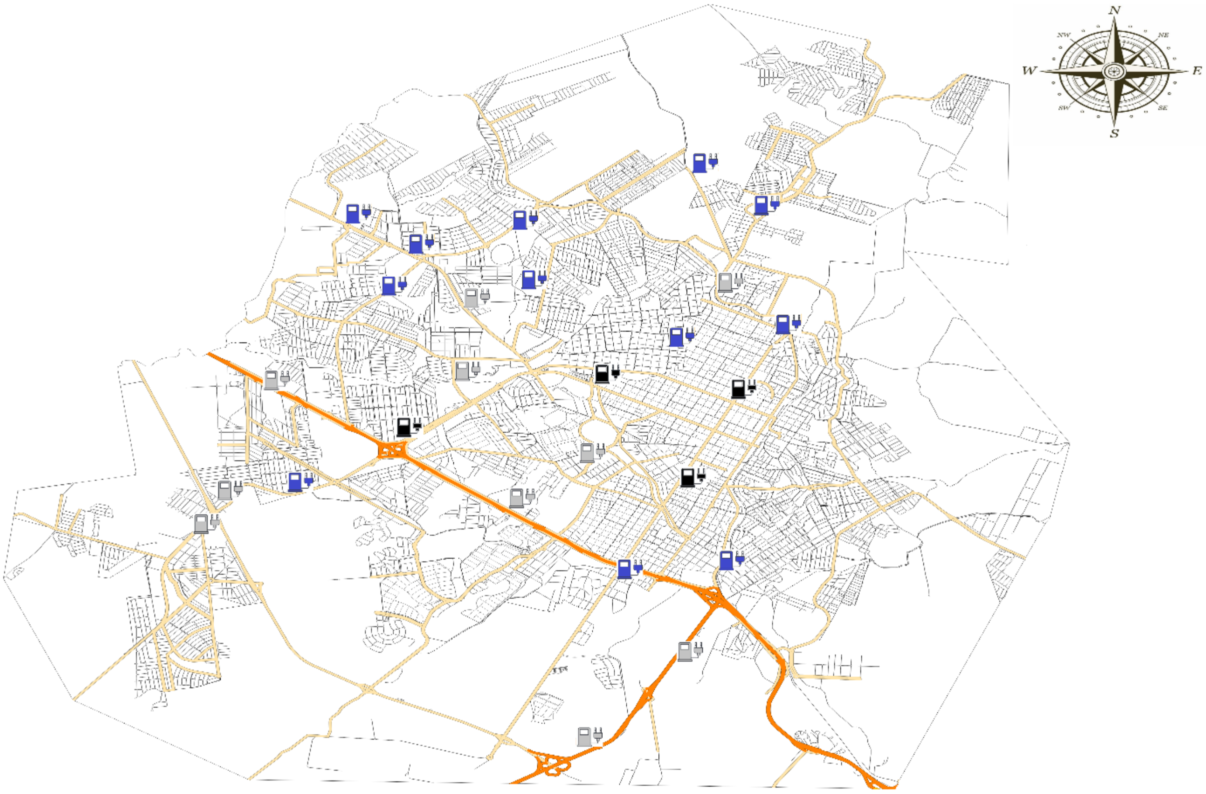
Source: Author's own elaboration

Figure 43 – CS in year 4.



Source: Author's own elaboration

Figure 44 – CS in year 5



Source: Author's own elaboration.

TABLE 3 – TYPE OF CS.

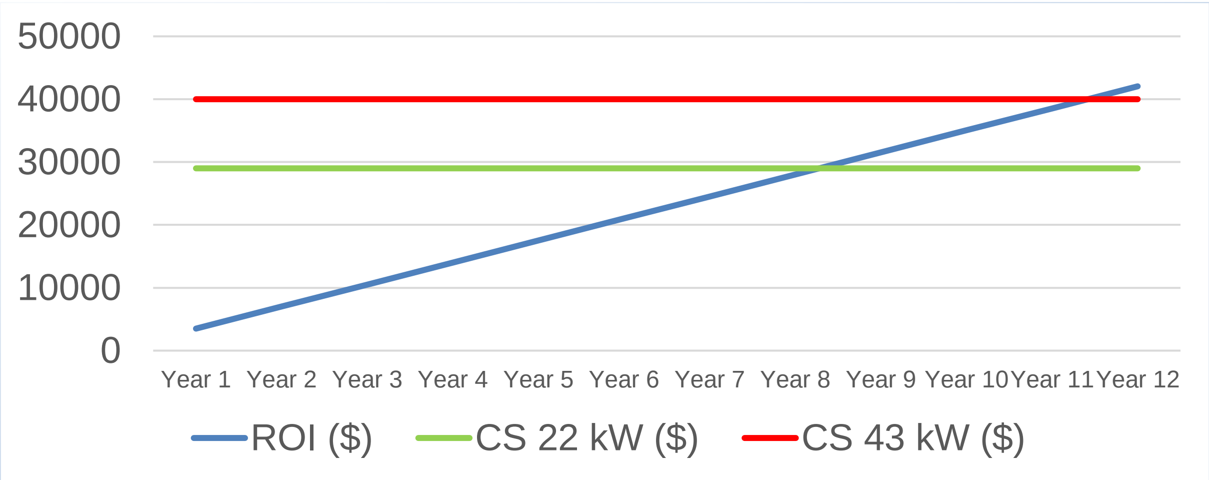
Type of CS	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
Blue CS	1	3	4	5	10	12
Gray CS	6	7	9	8	11	10
Black CS	0	0	1	2	2	4
Total	7	10	14	15	23	26

Source: Author's own elaboration

Note that a CS can change of type in the next years to adapt to its demand. An example of this can be seen from years 2 to 3, in which a gray CS became black. So, there is a gray CS less from years 2 to 3. Therefore, it is possible to observe that such changes were necessary so that, after exhaustive tests in the AIMSUN tool, the model finds an RI that can satisfy the demand for recharge.

Through figures of years 0 and 1, notice the presence of CS only in central regions and in avenues that connect the center to the periphery. Critical regions that require black CS appear for the first time in year 2. From year 2 to 3, there is little change in the CS scenario. In years 4 and 5, the presence of CS in locations distant from the central zone is noted. The presence of CS in some zones denotes the high presence of DNCEV in these regions. Fig. 45 shows the return on investment (ROI) to install an AC Level 2 CS (22kW) and an AC Level 3 CS (43kW) considering the number of DNCEV recharging per day (average hours daily operation - obtained from simulations) and the kWh price ($) to help CS owners in their investments.

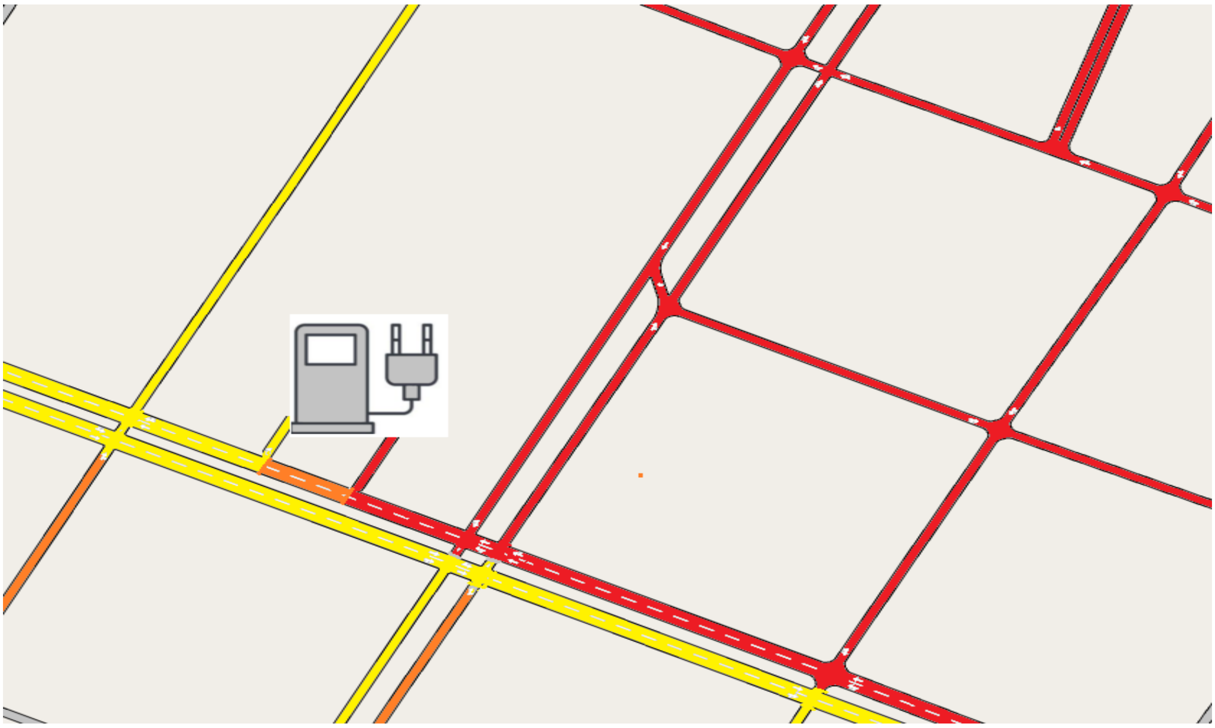
Figure 45 – ROI of CS



Source: Author's own elaboration.

For 22 kW CS, the ROI is just over eight years and for 43 kW is just over eleven years. The scenarios presented from years 0 to 5 can help urban planners, with the construction and expansion of the demand for CS by period, adapting the demand required by DNCEV. After an example of a gray CS in year 2, with the average SOC of all DNCEV that enter (right) and leave (left), the CS after recharging is shown in Fig. 46. In this figure, it is possible to observe that DNCEV that will enter in the CS have low SOC (below 25% on average), and when leaving CS, the SOC has an average of 50 to 75%. Thus, it is shown that the allocated CS helps to recharge the DNCEV that needs it most. Not all DNCEV that pass through the CS will be recharged, and therefore, upon finding the average SOC after recharging, the average will increase, but it will not be close to 100%. The function of counting entry, exit and charging of the CS DNCEV is made available to the other DNCEV so that they can account for the feasibility of entering this CS, considering the distance and cost until arrival at the CS (Fig. 11) and if there is congested-free CS to perform the recharge (NYOTHIRI *et al*., 2021). Thus, CS is managed throughout the simulation, with coordinated charging.

Figure 46 – Example of average DNCEV SOC enters and leaves the CS.



Source: Author's own elaboration.

With the revision of the list of candidates with available physical space to allocate CS in the urban zone (MORRO-MELLO, 2018), there was a considerable decrease in the available candidates. Thus, simulations were made to allocate CS at different points. Other solutions were found, with the allocation of CS elsewhere. The CS allocated with these solutions were simulated in AIMSUN. It was observed that in these other solutions, the central CS were overloaded during peak hours and, therefore, DNCEV had to move to distant CS.

The possibility of decreasing the radius of influence to allocate more CS was considered. However, there are not enough locations with availability for the allocation that meet the demand for recharge. Therefore, the CS allocation results shown in the Figs. from 39 to 44 shows the CS locations that have available physical space, in strategic locations, able to meet the daily demand for recharge, meet criteria for low SOC and high DNCEV flow. Other studied and simulated solutions presented insufficient conditions for one or more modeled variables and, therefore, for this urban zone, it was not possible to consider other solutions. So, the solution presented for years 0 to 5 was obtained after other solutions were considered, being the one that fulfilled the requirements of the modeled variables and enabling expansion over the years. For the replication of work in other urban zones, the CS allocation process can consider other aspects, as well as having more available physical space, and thus generate more feasible scenarios.

4.4 RESULTS OF DECREASE IN LOCAL POLLUTION

For the decrease in local pollution, a LEM (TRAFFIC TECHNOLOGY INTERNATIONAL, 2019) was modeled, computing the decrease in local pollution with the introduction of DNCEV over the years. LEM presented in the AIMSUN is modeled to aggregate the different types of DNCEV. PHEVs are modeled according to their specifications (THE NEW COROLLA MODEL RANGE, 2019) that, at some speed, start the combustion engine and produce GHG.

The mesoscopic simulations in the AIMSUN tool are done, and the LEM has enabled average emissions estimates. With the information of local pollution amount that was no longer generated with the introduction of DNCEV, maps were generated with a daily CO_2 and NOx consumption in g/km for each year and are shown in Figs 47 to 58.

Figure 47 – Spatial local pollution in year 0 – CO_2.

Source: Author's own elaboration.

Figure 48 – Spatial local pollution in year 1 – CO_2.

Source: Author's own elaboration.

Figure 49 – Spatial local pollution in year 2 – CO_2.

Source: Author’s own elaboration.

Figure 50 – Spatial local pollution in year 3 – CO_2.

Source: Author’s own elaboration.

Figure 51 – Spatial local pollution in year 4 – CO_2.

Source: Author's own elaboration.

Figure 52 – Spatial local pollution in year 5 – CO_2.

Source: Author's own elaboration.

Figure 53 – Spatial local pollution in year 0 – NOx.

Source: Author's own elaboration.

Figure 54 – Spatial local pollution in year 1 – NOx.

Source: Author's own elaboration.

Figure 55 – Spatial local pollution in year 2 – NOx.

Source: Author's own elaboration**.**

Figure 56 – Spatial local pollution in year 3 – NOx.

Source: Author's own elaboration**.**

Figure 57 – Spatial local pollution in year 4 – NOx.

Source: Author’s own elaboration**.**

Figure 58 – Spatial local pollution in year 5 – NOx.

Source: Author’s own elaboration**.**

The decrease in CO_2 over the years in the streets was not significant. However, with the replacement of about 15% of the total number of ICEV at the end of the period, the decrease in CO2 in some specific streets and avenues can be seen. Accessing the database, a small reduction can be seen in some main avenues of the urban zone. Unfortunately, DNCEV moves around sparsely, making it impossible to observe the differences in the maps presented.

As for NOx, it is possible to observe more clearly that there was a significant reduction in NOx over the years in some avenues that connect the center and the periphery. The substitution of conventional buses with a high NOx emission rate for BEBs has resulted in a considerable decrease on such routes and is therefore visible on the maps presented. The decrease in GHG emissions from the years for the urban zone for CO_2 and NOx are presented in Table 4. With the database, a comparison can be made with reducing local pollution, finding the zones with more impact in the reduction, creating strategies to decrease the pollution, and finding unknown patterns.

TABLE 4 – GHG REDUCTION OVER THE YEARS.

GHG	**Year 0**	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Year 5**
CO_2 (kg)	559,669	554,910	550,379	548,510	545,553	542,064
NO_x (kg)	1,433	1,405	1,378	1,349	1,310	1,299

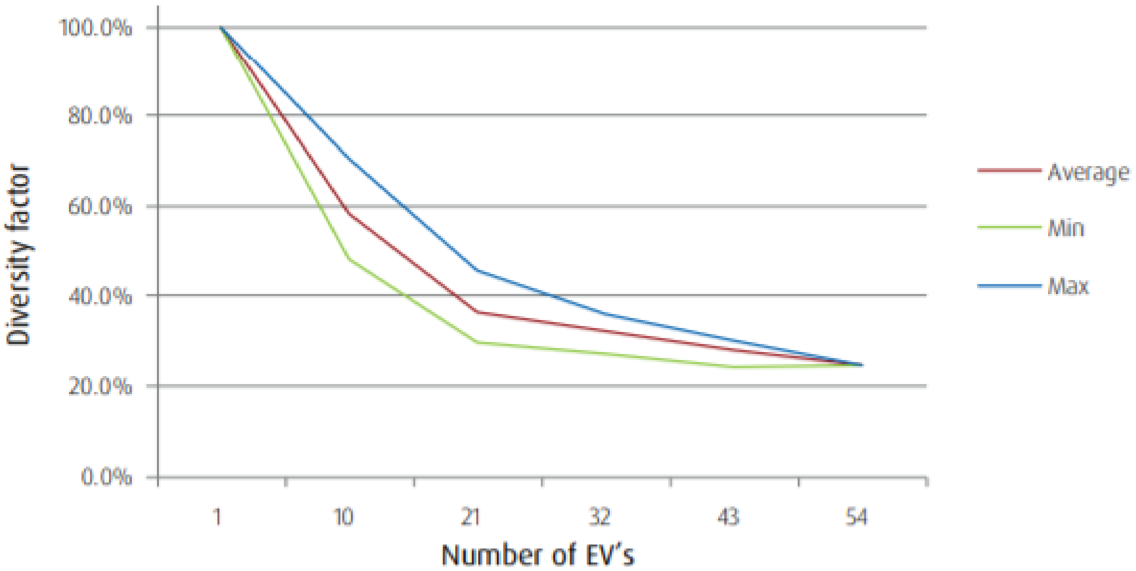
Source: Author’s own elaboration

4.5 RESULTS OF RESIDENTIAL IMPACT

The maximum diversified demand is calculated for each subarea of the urban zone for each year to provide the impact in the distribution network with residential charging of DNCEV.

Accessing the database, it is possible to find the number of DNCEV and the average residual SOC in each subarea for each period. The average kW per charge is 3.3, according to (MORRO-MELLO *et al.,* 2018). Furthermore, each subarea's diversity charging factor is found for each year, according to Fig. 59.

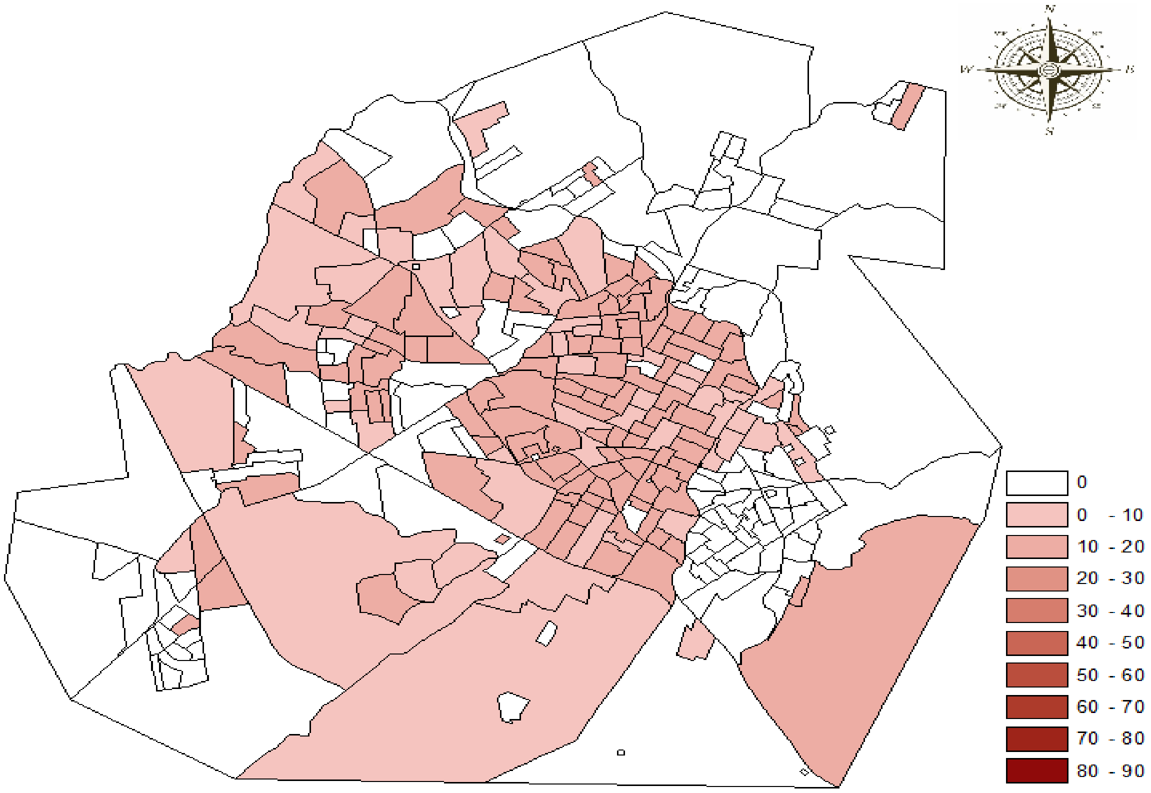
Figure 59 – Diversity factor for residential Charging Factor.



Source: UK Power Networks, 2014.

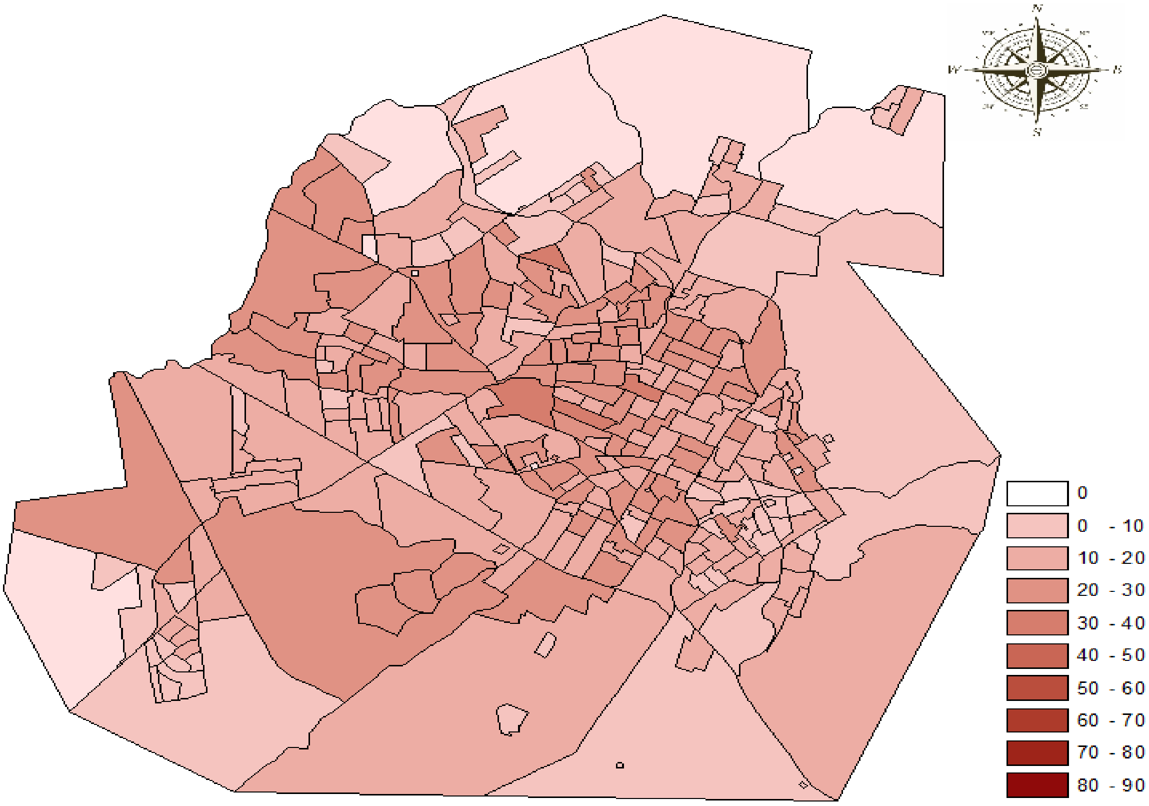
With the variables described, the maximum diversified demand with the introduction of DNCEV per subarea in a complete urban zone for each year is calculated. As a result, spatial maps with the maximum diversified demand in kW for each year are presented in Figs. 60 to 65.

Figure 60 – Maximum diversified demand in kW - year 0.



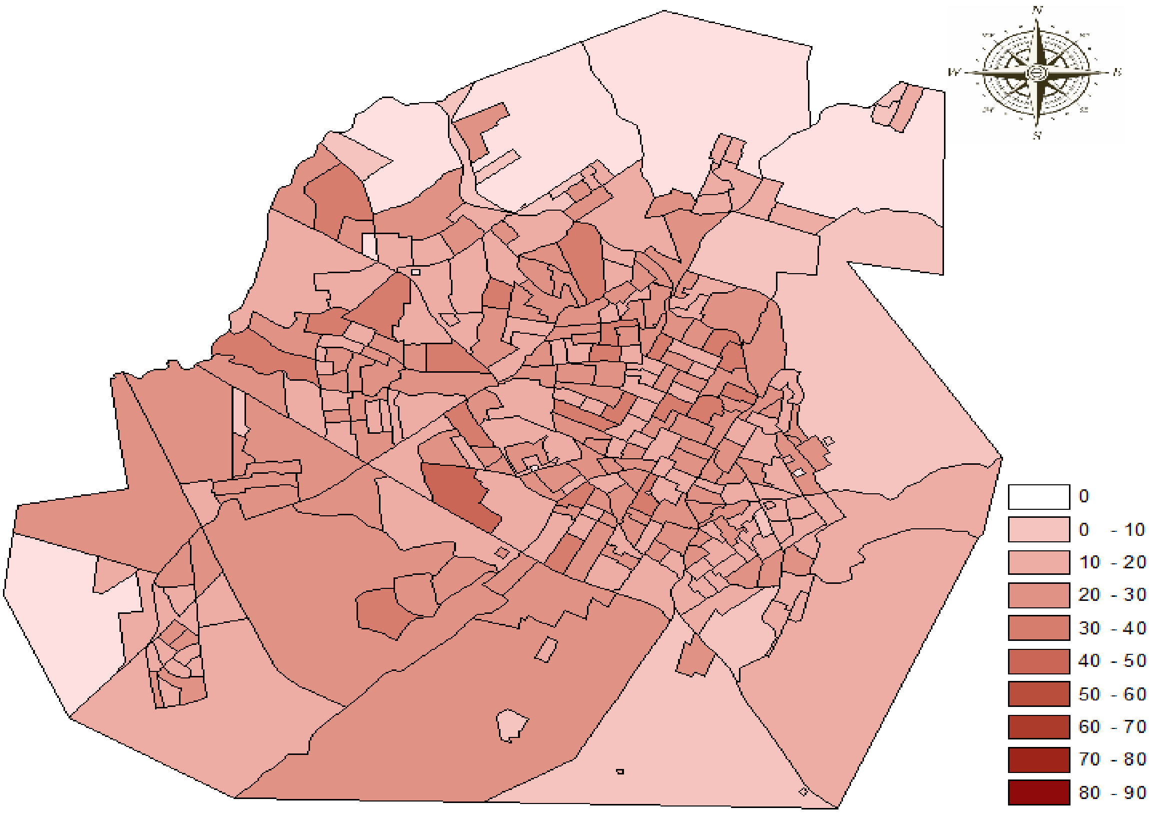
Source: Author's own elaboration

Figure 61 – Maximum diversified demand in kW - year 1.



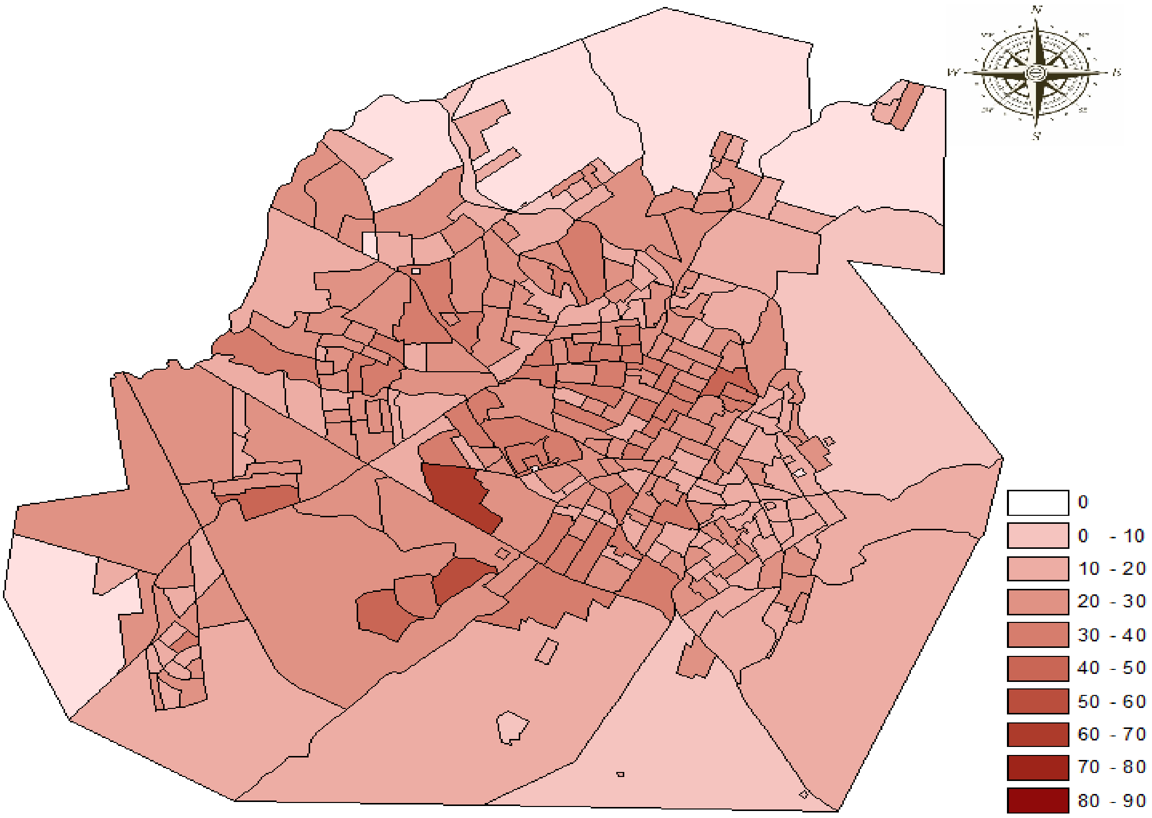
Source: Author’s own elaboration

Figure 62 – Maximum diversified demand in kW - year 2.



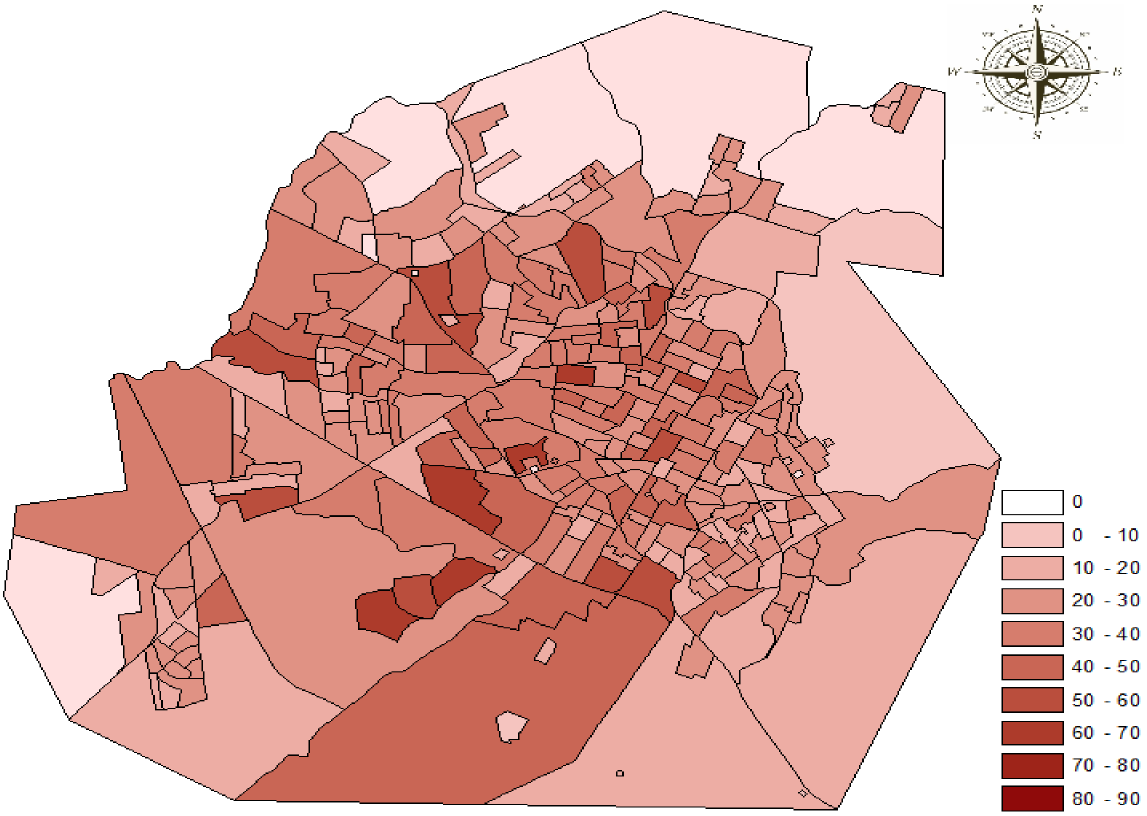
Source: Author’s own elaboration

Figure 63 – Maximum diversified demand in kW - year 3.



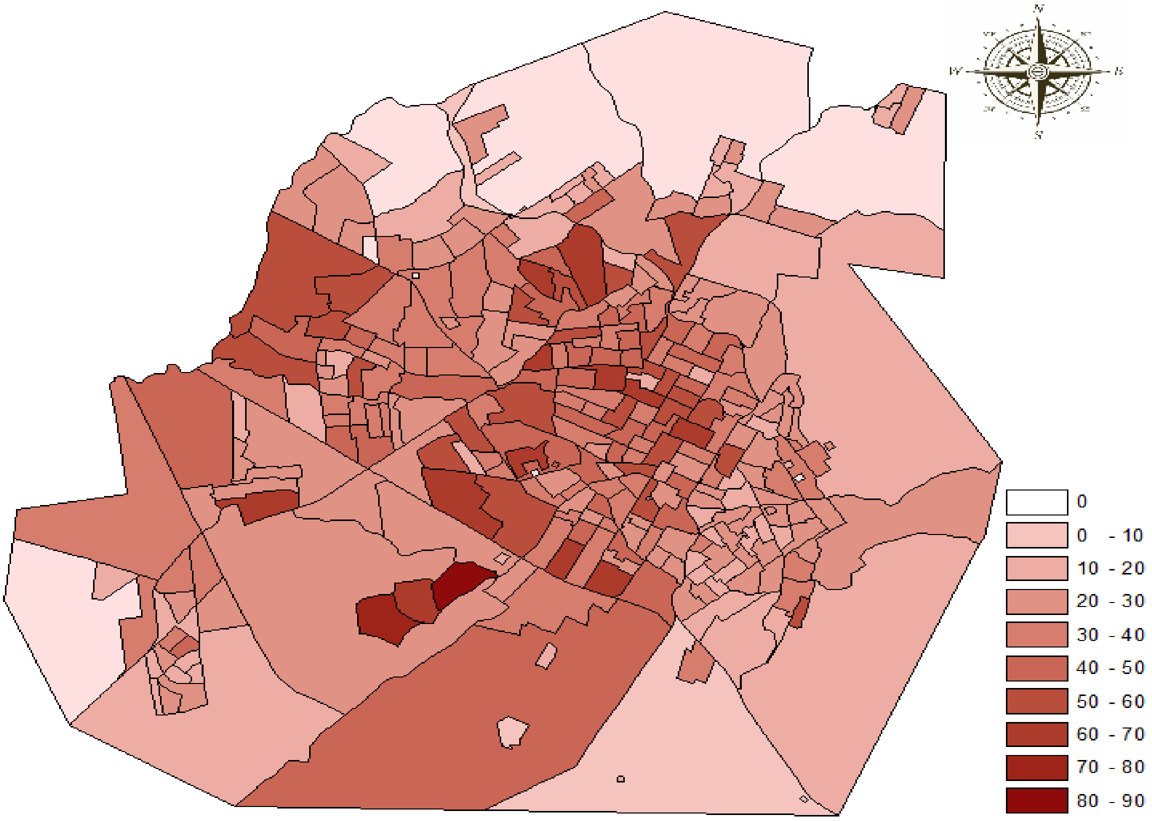
Source: Author's own elaboration

Figure 64 – Maximum diversified demand in kW - year 4.



Source: Author's own elaboration

Figure 65 – Maximum diversified demand in kW - year 5.



Source: Author's own elaboration

From the figures of maximum diversified demand, it is possible to observe an increase in residential recharge over the years, as DNCEV are acquired. This increase occurs mainly in the subareas with the highest concentration of DNCEV, but not exclusively because factors such as the average SOC of all DNCEV influence the increase in demand. The results are expected to help distribution companies with future planning, as new investments, in critical regions and planning energy dispatch. The distribution company in the urban zone carried out reinforcement investments, the rated power of the transformers supports this increase in residential demand.

4.6 RESULTS OF CS CONNECTION

For the CS distribution network connection, the methodology proposed in (MORRO-MELLO *et al.*, 2021) and described in item 3.5.2 was used. With the CS spatially distributed in ArcGIS tool shown in Figs. 39 to 44, the maximum allowable expansion (e) for low voltage was 0.286 km obtained through Eq. (19) and all stations with one charger must be connected at low voltage according to the standards of the distribution company. Then, the radius of maximum allowable expansion was performed for all blue and gray CS. In this radius, all transformers with supply capability are marked as available. If no transformer is available for a station, new transformers are allocated in the existing lines. Segment losses cannot exceed predetermined percentages by standards according to (MORRO-MELLO, 2018), which are:

A) Losses in the power meter: 0.8%.

B) Losses in the connection: 0.7%.

C) Losses in the expansion of low voltage network: 2.0%.

D) Losses in transformer: 3.0%.

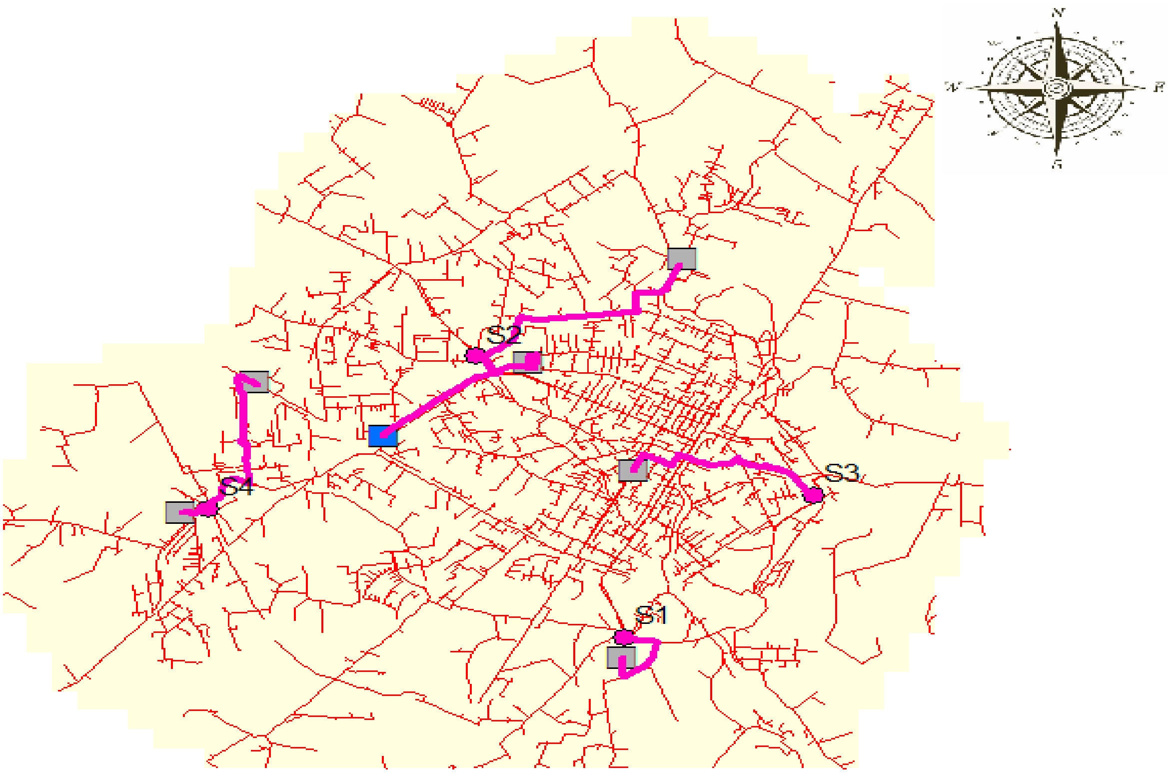
After the loss calculations by project segment, only connections that do not exceed the limits will be used to calculate the cost function. The candidate connection had voltages outside the acceptable range (at 9%, 9%, 12%, 13%, 17% and 19% in years 0 to 5, respectively). The proposed methodology disregarded all the possible connections outside the acceptable range. Black CS must be connected in medium voltage. The distribution company limit the expansion in 0.15 km ensuring adequate levels. A radius of maximum allowable expansion was performed for all black CS and all the expansions within these bounds are found.

The algorithm in Fig. 14 is modeled in a Python programming language. To start with the cost function, the unit cost per km (k) at low and medium voltages are, respectively, K1 = \$3088.77 and K3 = \$4247.06. The cost of system uses per km K2 is \$610.00 (MELO, ZAMBRANO, PADILHA-FELTRIN, 2017). The distance between elements is spatially modeled in ArcGIS tool, and the line resistances, current, n, and cp correspond to technical standards. The cost of additional equipment Ce1 is \$81.66 and \$1927.81 (without a new transformer and with a new transformer, respectively), and the cost Ce2 is \$2592.03.

The method searches for the minimum connection cost from the substation to the CS through an exhaustive search. A priority list has been constructed, since CS with more rated power are in more critical regions. The black CS will be allocated first, followed by gray stations and finally, blue stations. The average charging time is determined by initial SOC of the DNCEV and a function will be used. Some DNCEV will be fully charged and others (determined randomly) charged at a minimum of 50% of SOC or more (randomly characterized - 50% to 90%). The method analyses the path cost for all predetermined paths and chooses the lowest cost path to connect each CS to the electric network. The elements' supply capability is updated with this new load, and the process is repeated until all CS are connected to the electric network. Finally, the power-flow method guarantees adequate power levels after the allocation process has been completed. If some connection falls outside acceptable limits, photovoltaic panels are proposed to guarantee adequate levels of voltage. The algorithm used to allocate CS is run for all study periods. Figs. 66 to 71 shows the lower-cost connection for each CS identified by the proposed algorithm in each year.

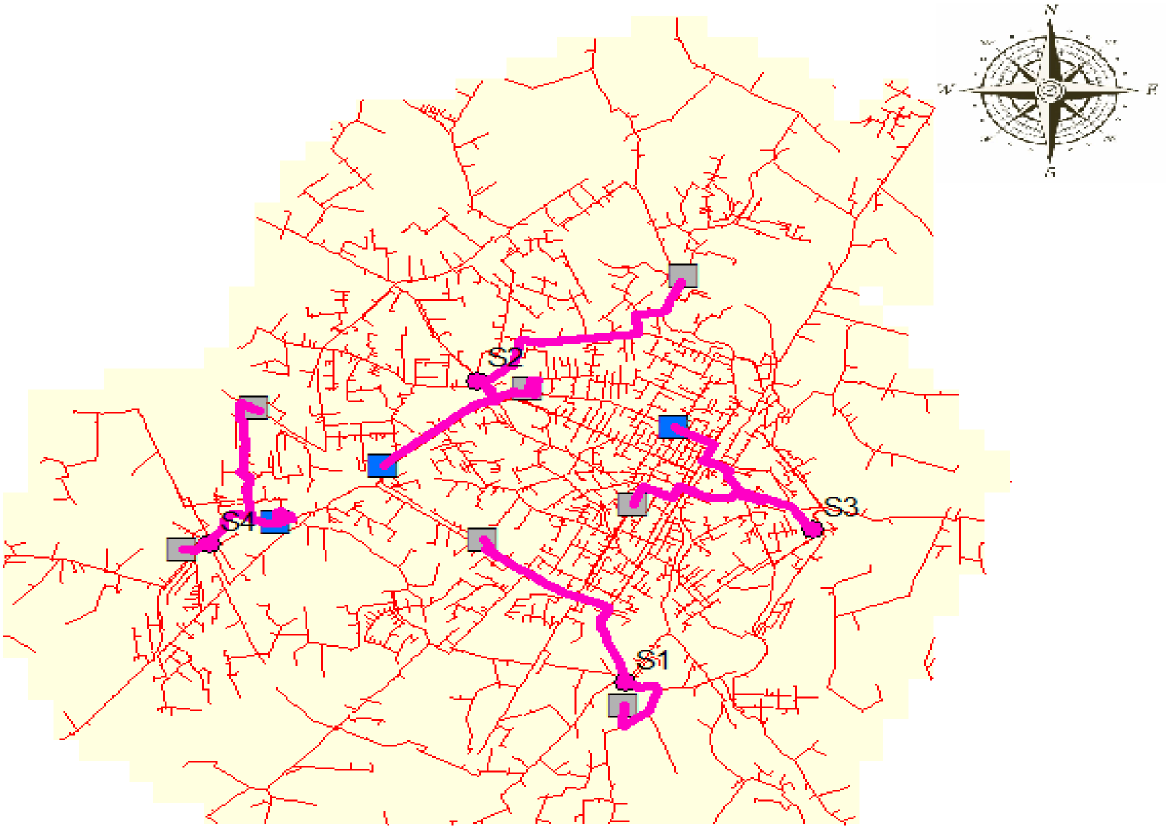
The pink lines indicate the minimum cost paths between CS and a substation with the connections at low voltage with the existing transformers or with new transformers (30 kVA for blue CS, 75 kVA for gray and black transformers - commercial transformers values) (WEG, 2015). In all study periods (years), it is observable that the CS is distributed among the four substations (S1, S2, S3 and S4), avoiding the overload of a single substation. Many transformers have excess supply capacity allowing for CS allocation with in low voltage because the electricity distribution company has reinforced the network. In all years, there are CS connected to current network elements, which is a benefit for the distribution company, reducing costs of purchasing additional equipment to establish a connection.

Figure 66 – Lower-cost connections - year 0.



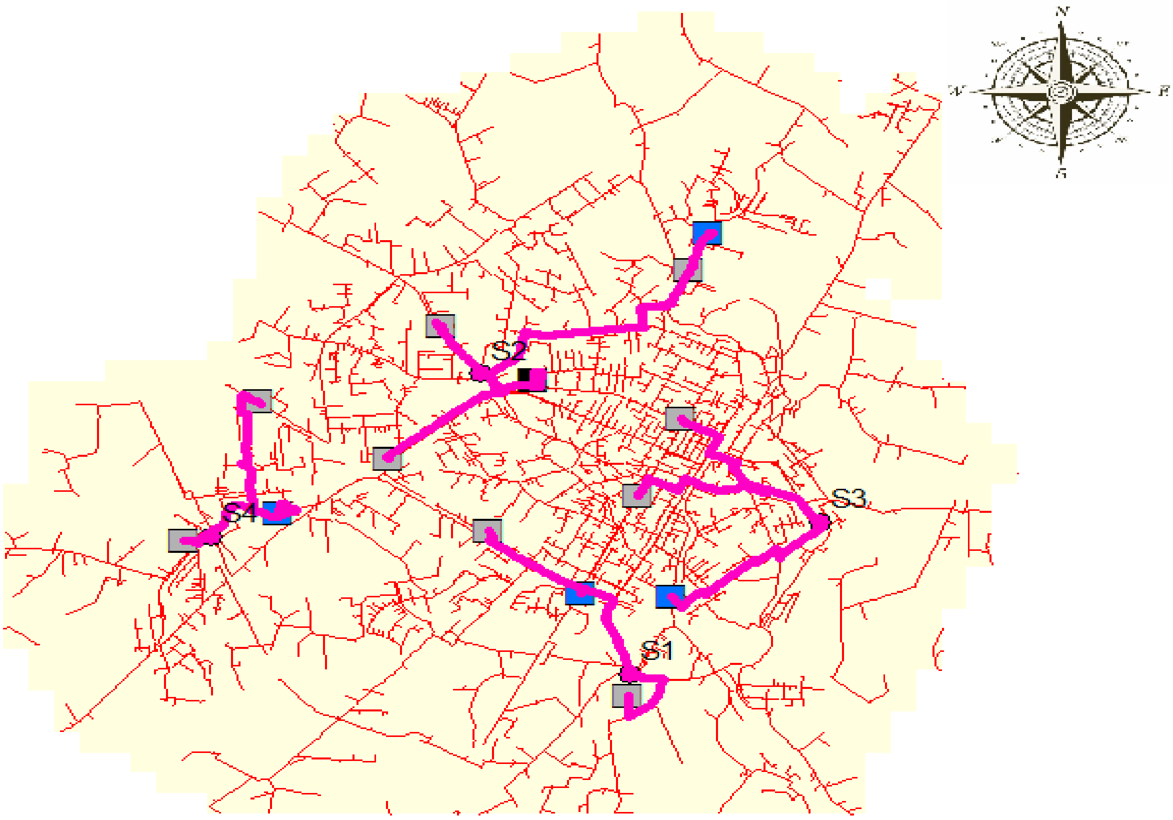
Source: Author’s own elaboration

Figure 67 – Lower-cost connections - year 1.



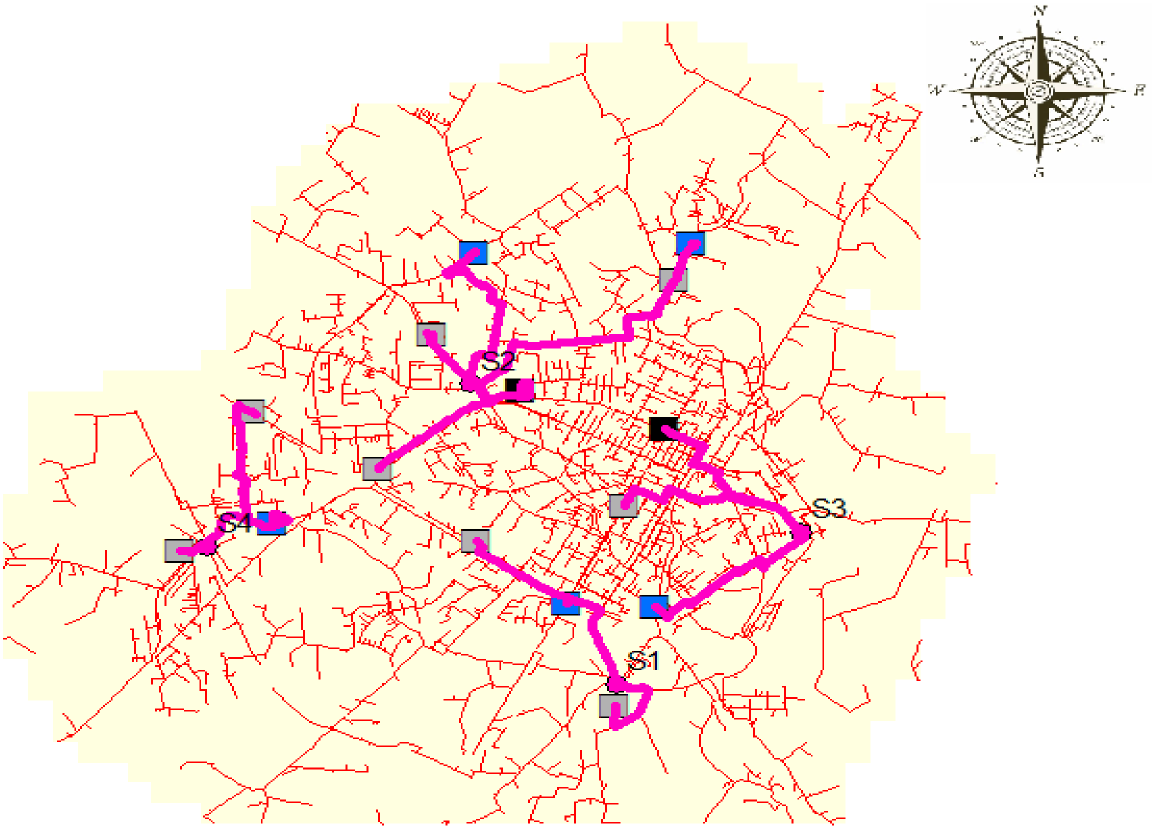
Source: Author's own elaboration

Figure 68 – Lower-cost connections - year 2.



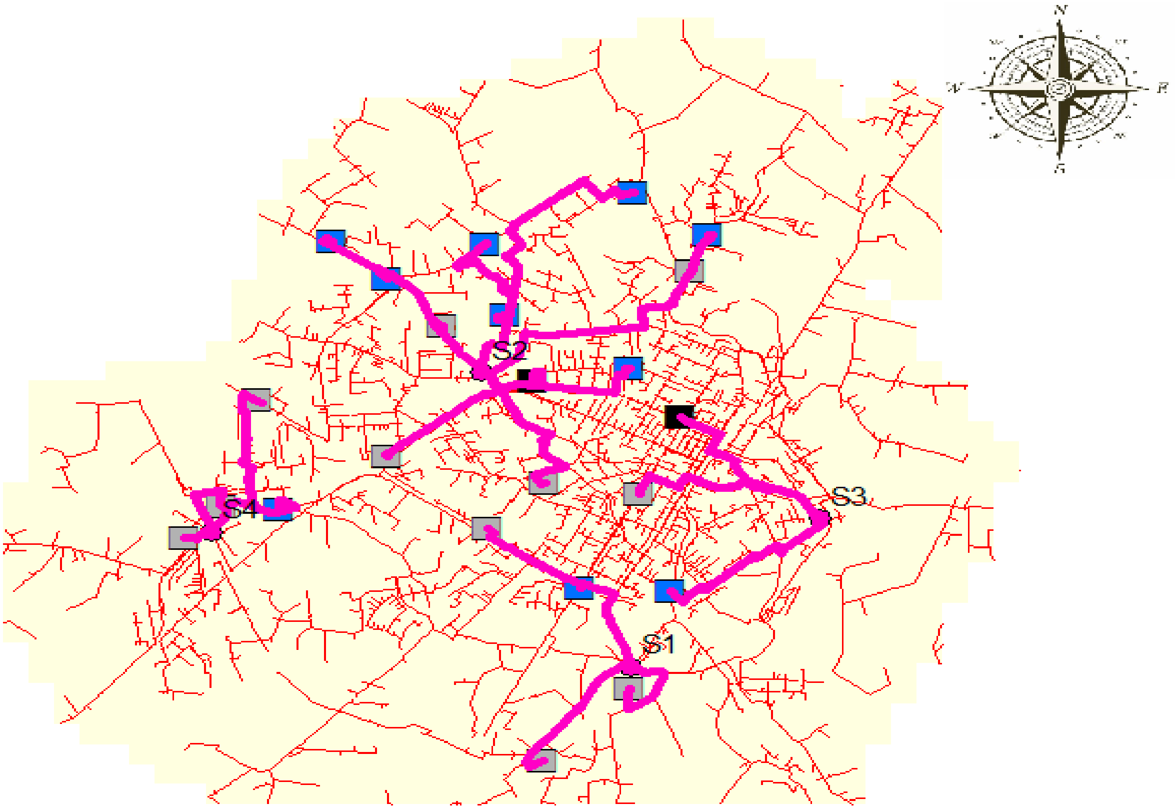
Source: Author's own elaboration

Figure 69 – Lower-cost connections - year 3.



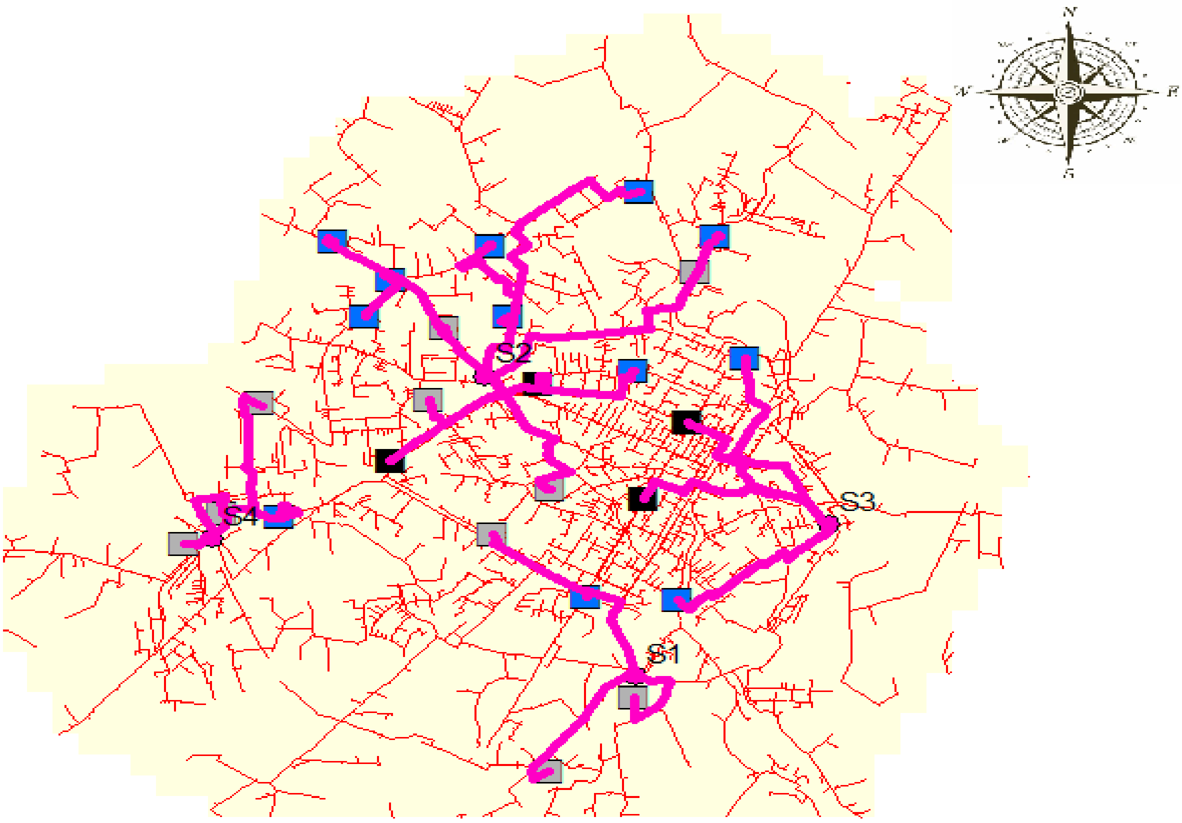
Source: Author's own elaboration

Figure 70 – Lower-cost connections - year 4.



Source: Author's own elaboration

Figure 71 – Lower-cost connections - year 5.



Source: Author's own elaboration

The final costs are shown in Table 5. Analysis using graph theory shows that the closest connection point (i.e., the one requiring the least connection) is not always the most cost-effective. Instead, to help distribution companies reduce costs, the analysis of other possible connections considers supply capacity, distance patterns, and technical losses.

The advantage of using the supply capability of the existing network elements by creating a zone to explore other points of the electrical network instead of connecting CS to the nearest network point can be verified mainly in year 4. Here the algorithm determines that 62% (thirteen CS) of the lowest-cost connections are connections to existing low-voltage transformers in low voltage. Eight CS needed new transformers and two CS were connected at medium voltage. The CS connected at low voltage with new transformers and those connected at medium voltage will have a higher cost due to the need to make reinforcements in the network due to the acquisition of new elements. The distribution company will analyze such reinforcements as part of planning for connections of its distribution network and transfer some costs to the CS owners.

TABLE 5 – FINAL COSTS.

	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
Final Cost ($)	34,929.15	43,807.81	68,222.66	80,009.87	106,462.92	132,356.09

Source: Author’s own elaboration

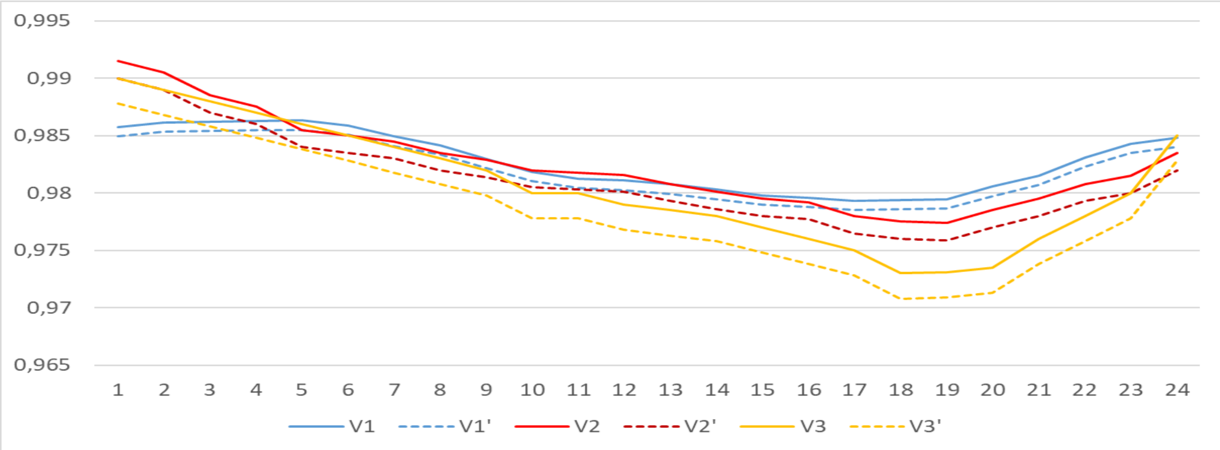
The power-flow method used in this study is divided into two parts. First, the technique was used to ensure that each possible connection initially proposed can guarantee energy delivery at appropriate levels while discarding the candidate connections that fail to meet power requirements (voltage levels). With the cost function, the least costly connections for the distribution company are chosen. After the cost function is performed, the power-flow method is used again because more than one CS can be allocated on the same feeder and, if this occurs, the power levels may be inadequate. The input data is the CS rated power (equivalent to the contracted power). In the case of the use of load controllers, the load curve must be provided. In the case of inadequate power levels, using the power-flow method, photovoltaic panels are proposed until the electric network stabilization.

Figs. 72 to 74 shows the daily evolution of the voltage for a three-phase system in PU before (continuous line) and after (dotted line) CS connections (point of connection) in year 5 to substation 3, feeder 6 (blue CS), substation 4, feeder 1 (gray CS) and substation 2 (black CS). The three straight lines in blue, red, and yellow represent voltage for a, b, and c phases, respectively, before the CS connection. The dotted lines of the same colors represent the voltage for a, b, and c, respectively, after the CS connection. If the network is out of range, photovoltaic panels are proposed.

The OpenDSS software calculates these voltage values at the point of the CS connection to the electric network. Figs 72 to 74 show that the voltage drop is more considerable in low voltage, with greater sensitivity when introducing the CS. The medium voltage network has higher levels of supply capability to have a lower voltage drop in PU (Fig. 74). If the medium voltage network is not overloaded, CS connections will not cause any voltage-drop problems. In year 4, a gray CS fell outside the range and required the introduction of photovoltaic panels. Therefore, photovoltaic panels, through OpenDSS, were introduced until the CS was within the allowed limits (0.93 PU). This was the only case of CS outside the range that required photovoltaic panels. Fig. 75 shows the daily evolution of the voltage for a three-phase system in PU before (continuous line) and after (dotted line) CS connections without the photovoltaic panels. Fig. 76 shows the daily evolution of the voltage for a three-phase system in PU (dotted line) without the photovoltaic panels and after (dash dot line) with the photovoltaic panels installed next to CS.

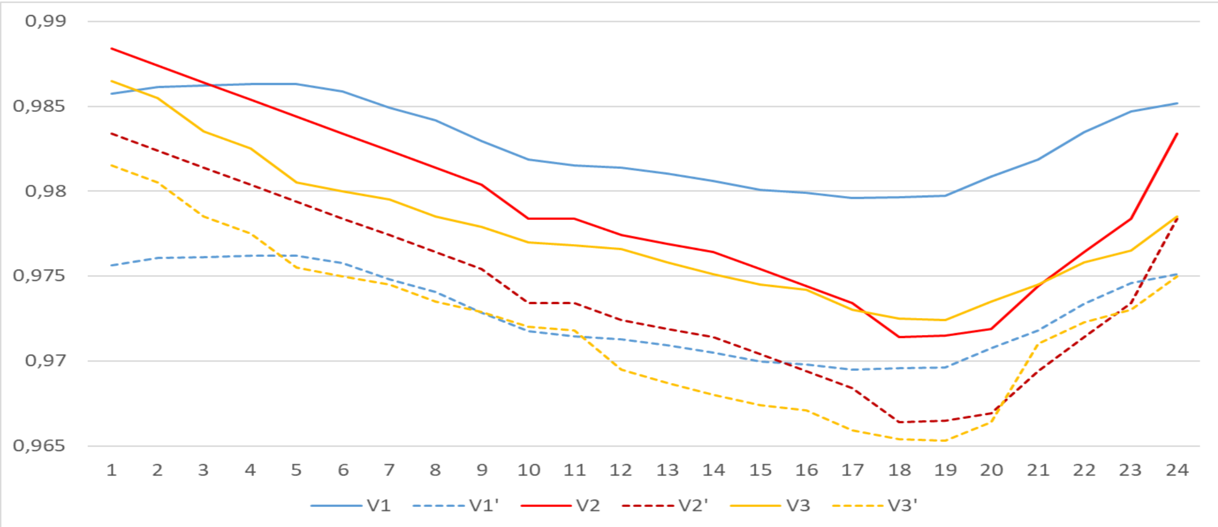
It is possible to observe that the introduction of photovoltaic panels, in addition to taking the CS connection to the appropriate range, can help to improve the quality level that was previously without the connection, thus helping the distribution network.

Figure 72 – Daily voltage curve in low voltage connection for a blue CS.



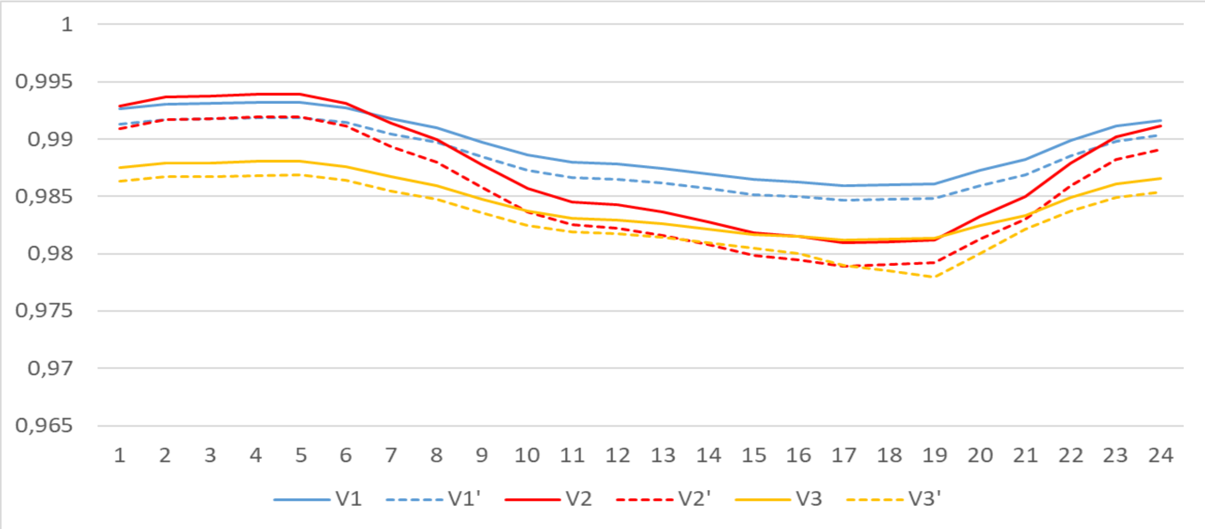
Source: Author’s own elaboration

Figure 73 – Daily voltage curve in low voltage connection for a gray CS.



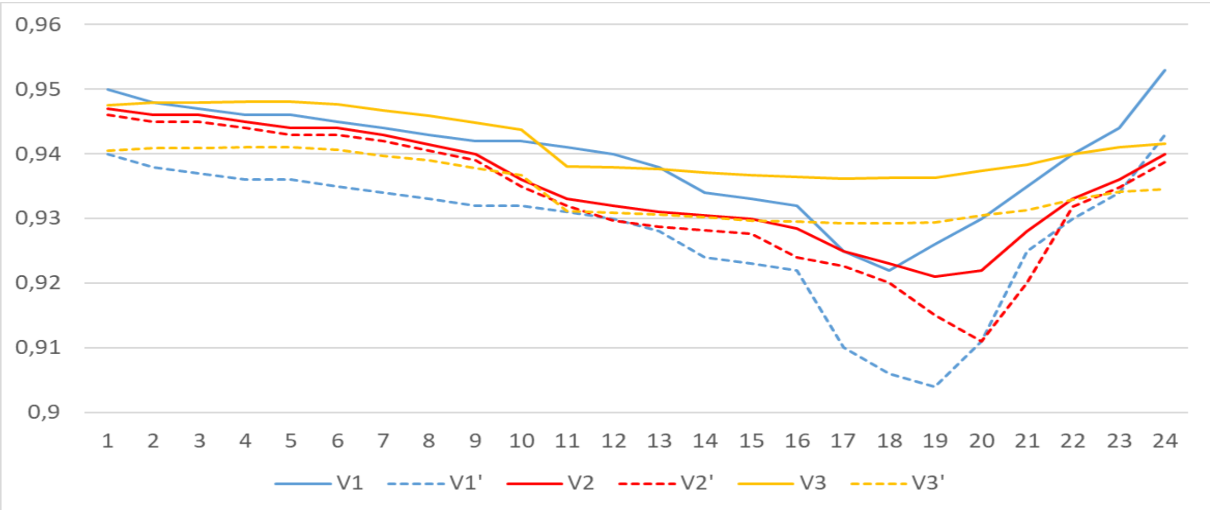
Source: Author’s own elaboration

Figure 74 – Daily voltage curve in medium voltage connection for a black CS.



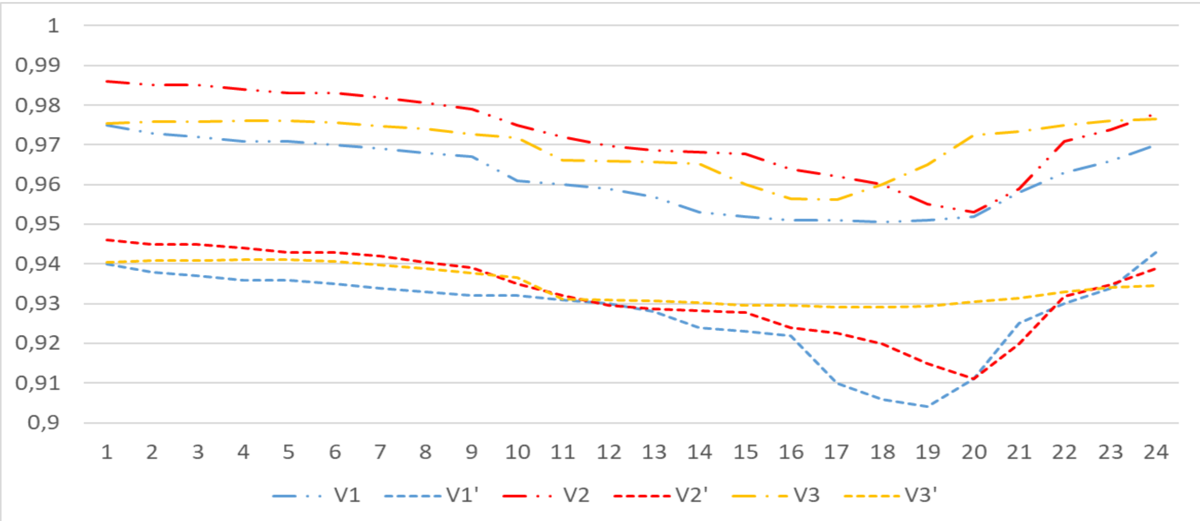
Source: Author's own elaboration

Figure 75 – Daily voltage curve in medium voltage connection for a gray CS.



Source: Author's own elaboration

Figure 76 – Daily voltage curve in medium voltage connection for a gray CS.



Source: Author's own elaboration

Tables 6 shows the overload elements (only substations and feeders) and the final supply capability after the CS have been allocated in each of the years. The proposed methodology provides a database for planning the expansion of the electric network. With better use of existing facilities, less investment for expansion will be needed. The elements' final supply capability is calculated by subtracting the initial supply capability after the CS has been installed. Due to the spatial distribution of CS and the distribution network, substation 2 was the one that allocated the most CS over the years. However, there is enough supply capability to meet the entire demand in substation 2 as well as substations 1, 3 and 4.

TABLE 6 – OVERLOAD ELEMENTS.

		Year 0		Year 1		Year 2		Year 3		Year 4		Year 5	
	Initial supply capa-bility (MVA)	Over-load (MVA)	Final supply capa-bility (MVA)	Over-load (MVA)	Final supply capa-bility (MVA)	Over-load (MVA)	Final supply capa-bility (MVA)	Over-load (MVA)	Final supply capa-bility (MVA)	Over-load (MVA)	Final supply capa-bility (MVA)	Over-load (MVA)	Final supply capa-bility (MVA)
S1	108.530	0.065	108.465	0.130	108.400	0.152	108.378	0.152	108.378	0.217	108.313	0.217	108.313
S2	209.560	0.152	209.408	0.152	209.408	0.347	209.213	0.369	209.191	0.544	209.016	0.696	208.864
S3	873.000	0.065	872.935	0.087	872.913	0.152	872.848	0.217	872.783	0.217	872.783	0.304	872.696
S4	131.610	0.130	131.480	0.152	131.458	0.152	131.458	0.152	131.458	0.217	131.393	0.217	131.393
S1F1	16.110	0.000	16.110	0.000	16.110	0.000	16.110	0.000	16.110	0.000	16.110	0.000	16.110
S1F2	16.100	0.000	16.100	0.000	16.100	0.022	16.078	0.022	16.078	0.022	16.078	0.022	16.078
S1F3	16.820	0.000	16.820	0.065	16.755	0.065	16.755	0.065	16.755	0.065	16.755	0.065	16.755
S1F4	19.900	0.065	19.835	0.065	19.835	0.065	19.835	0.065	19.835	0.065	19.835	0.065	19.835
S1F5	16.110	0.000	16.110	0.000	16.110	0.000	16.110	0.000	16.110	0.065	16.045	0.065	16.045
S1F6	15.710	0.000	15.710	0.000	15.710	0.000	15.710	0.000	15.710	0.000	15.710	0.000	15.710
S2F1	14.190	0.000	14.190	0.000	14.190	0.065	14.125	0.065	14.125	0.065	14.125	0.065	14.125
S2F2	18.210	0.065	18.145	0.065	18.145	0.065	18.145	0.065	18.145	0.065	18.145	0.065	18.145
S2F3	16.600	0.000	16.600	0.000	16.600	0.000	16.600	0.000	16.600	0.065	16.535	0.065	16.535
S2F4	18.540	0.000	18.540	0.000	18.540	0.130	18.410	0.130	18.410	0.130	18.410	0.130	18.410
S2F5	16.490	0.065	16.425	0.065	16.425	0.065	16.425	0.065	16.425	0.065	16.425	0.065	16.425
S2F6	15.580	0.000	15.580	0.000	15.580	0.000	15.580	0.022	15.558	0.022	15.558	0.152	15.428
S2F7	14.680	0.000	14.680	0.000	14.680	0.000	14.680	0.000	14.680	0.000	14.680	0.022	14.658
S2F8	19.890	0.022	19.868	0.022	19.868	0.022	19.868	0.022	19.868	0.044	19.846	0.044	19.846
S2F9	16.260	0.000	16.260	0.000	16.260	0.000	16.260	0.000	16.260	0.088	16.172	0.088	16.172
S3F1	16.100	0.000	16.100	0.000	16.100	0.000	16.100	0.000	16.100	0.000	16.100	0.000	16.100
S3F2	15.570	0.000	15.570	0.000	15.570	0.065	15.505	0.130	15.440	0.130	15.440	0.130	15.440
S3F3	17.200	0.065	17.135	0.065	17.135	0.065	17.135	0.065	17.135	0.065	17.135	0.065	17.135
S3F4	14.440	0.000	14.440	0.000	14.440	0.000	14.440	0.000	14.440	0.000	14.440	0.000	14.440
S3F5	15.380	0.000	15.380	0.000	15.380	0.000	15.380	0.000	15.380	0.000	15.380	0.000	15.380
S3F6	13.370	0.000	13.370	0.000	13.370	0.000	13.370	0.000	13.370	0.000	13.370	0.022	13.348
S3F7	14.950	0.000	14.950	0.000	14.950	0.000	14.950	0.000	14.950	0.000	14.950	0.000	14.950
S3F8	16.110	0.000	16.110	0.000	16.110	0.000	16.110	0.000	16.110	0.000	16.110	0.130	15.980
S3F9	16.100	0.000	16.100	0.022	16.078	0.022	16.078	0.022	16.078	0.022	16.078	0.022	16.078
S4F1	15.540	0.065	15.475	0.065	15.475	0.065	15.475	0.065	15.475	0.065	15.475	0.065	15.475
S4F2	19.610	0.000	19.610	0.022	19.588	0.022	19.588	0.022	19.588	0.022	19.588	0.022	19.588
S4F3	19.610	0.065	19.545	0.065	19.545	0.065	19.545	0.065	19.545	0.065	19.545	0.065	19.545
S4F4	15.790	0.000	15.790	0.000	15.790	0.000	15.790	0.000	15.790	0.000	15.790	0.000	15.790
S4F5	19.990	0.000	19.990	0.000	19.990	0.000	19.990	0.000	19.990	0.065	19.925	0.065	19.925
S4F6	17.850	0.000	17.850	0.000	17.850	0.000	17.850	0.000	17.850	0.000	17.850	0.000	17.850
Total		0.412		0.521		0.803		0.890		1.195		1.434	

Source: Author’s own elaboration

4.7 RESULTS OF STATIONARY WPT CS FOR BEB

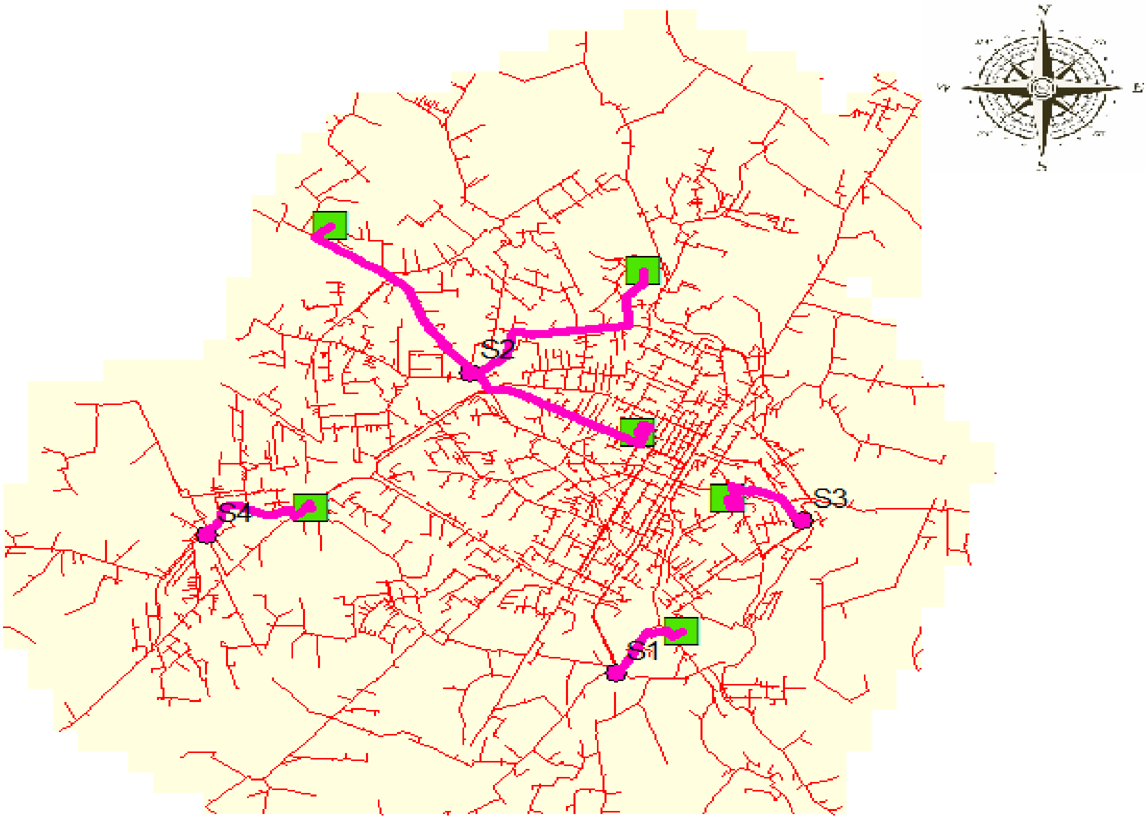
To provide guidelines for urban agents who may install stationary WPT CS in bus terminals, the routes of BEBs in the urban zone were simulated and stationary WPT CS allocated in each integration of public transport (Fig. 77). With the simulations, it was found the power needed to meet the demand for BEB throughout the day, with the amount of stationary WPT CS that meets their demand. Total fleet (25 BEB) replacement was considered. With the simulations carried out, it was possible to coordinate the BEBs so that they perform their recharges at different times in each of the 6 integration of public transport locations, therefore requiring only a 400kW single stationary WPT CS in each of six locations (BRYDEN *et al*, 2019).

The connection with the distribution network was simulated for the six stationary WPT CS following module 5. None stationary WPT CS connected at medium voltage were out of range. The cost for the connection was high compared to the cost of a common station for CS owner (which can be the city hall or a private agent) over $40,000.00 (US DEPARTMENT OF ENERGY, 2015) and for the distribution company (may reach $50,020.03 according to the simulations in Fig. 78).

Figure 77 – Integration of public transport

Source: Author's own elaboration

Figure 78 – Lower-cost connections stationary WPT CS



Source: Author's own elaboration

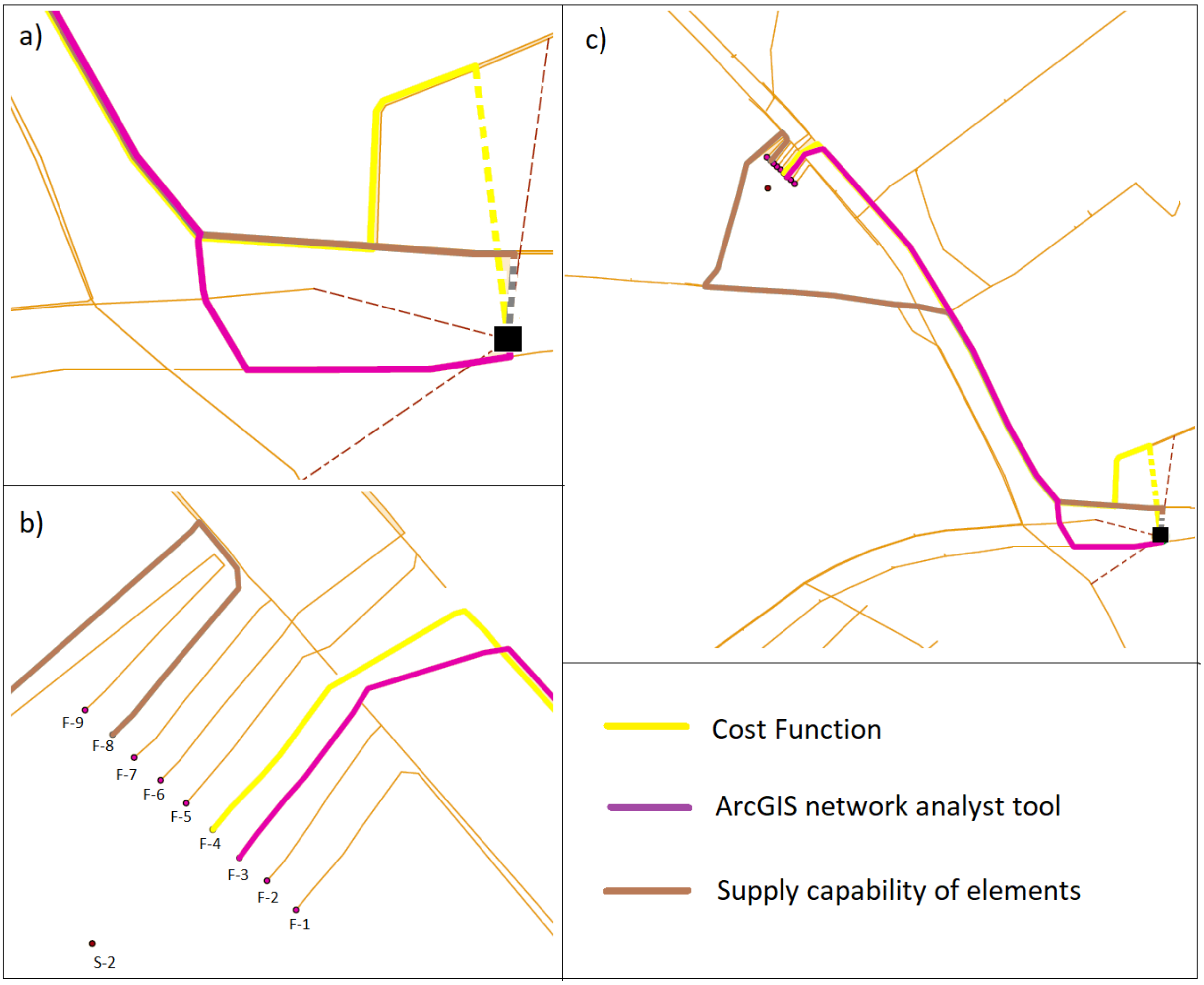
Connection costs for the six stationary WPT CS were $43,032.32 (S1F3); $42,565.14 (S3F5); $45.254,32 (S2F2); $48,510.23 (S2F1); $50,020.03 (S2F5); 44,254.60 (S4F6) respectively. The costs are higher compared to CS installation costs. Public-private partnerships are recommended to make such installations feasible and guarantee rapid recharge to BEB. Note that the load increase was not included in Table 6 for the stationary WPT CS for BEB. Urban planners must define when such stations should be allocated based on the replacement of buses by BEB. The increase in substations and feeders will not cause problems for the distribution network.

4.8 COMPARISON OF RESULTS

This section compares the module 5 proposed with other approaches described in the literature to show our methodology's advantages. The CS in each year of our work were modeled in a routing method for optimizing resources according to (CAMPOS, 2014), with the help of the ArcGIS route optimization tool (contained in the network analyst functions in ArcGIS for solving complex routing problems). The tool application results in shorter paths and lower costs, helping analysts identify the possible routes between two or more points by aggregating the criteria of price, restrictions, impedances, and others. The parameters are modeled with the starting point in a determined CS, leading to several endpoints in the possible substations. Finally, the tool identifies the best criteria route, obtaining the costs for CS's connection in the distribution network.

Another comparison can be made with the standards that distribution companies apply when adopting strategies to connect new loads using more supply capability components (ENERGISA, 2018). To compare these standards with the proposed methodology, it is shown the final cost of these allocations, which have been made using allocating the CS via the components with more excellent supply capability. Two methods for using supply capability to determine allocations were analyzed. In the first, the most extensive supply capability of the nearest element is used. (If the connection is made at medium voltage, the feeder's supply capability is determinant; if the connection is made at low voltage, the transformer's supply capability is determinant). The second strategy is to identify the most extensive supply capability considering the sum of all the elements involved. To compare all these strategies, it is used a black CS, in year 5. Fig. 79 a-c show the spatial allocation using the proposed methodology (yellow), using the ArcGIS tool (pink), and using supply capability (brown). Fig. 79 a) show CS possible connections to feeders 3, 4, and 8. Fig. 79 b) shows the connection feeder using cost function (feeder 4), ArcGIS network analyst tool (feeder 3), or supply capability of elements (feeder 8). Fig. 79 c) shows an aerial photo of the CS connection to substation 2 using the proposed methods and the other two methodologies. In this case, when supply capability is taken as the criterion for allocation, the cost is the same whether the nearest element's capability or the sum of all elements is determinant. The value found by all methodologies is summarized in Table 7. For this allocation, the proposed method reduces computational time by up to 30% if compared with conventional planning methods.

Figure 79 – Spatial Comparison of allocation methodologies.



Source: Author's own elaboration

TABLE 7 – VALUES FOUND BY THE METHODOLOGIES.

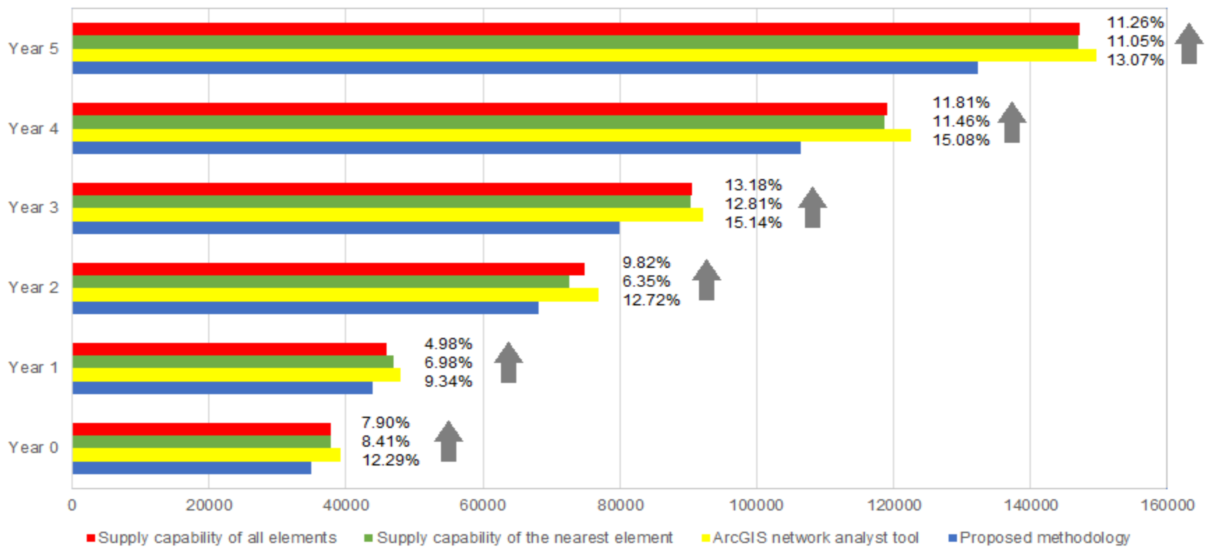
	Proposed Methodology	**ArcGIS network analyst tool**	**Supply capability of the nearest element**	**Supply capability of all elements**
Cost ($)	13,849.61	15.022,12	14.855,28	14.855,28
Computational time (s)	66	86	79	81

Source: Author's own elaboration

The methodology (using the cost function - yellow) achieves the lowest cost value in this example. It is found that the difference in the costs of connections is mainly due to the increase in equipment and operating costs that would be added to the network following the guidance of other methodologies. Please note that the possible connections may be tied to different transformers, feeders, distances. Supply capacities are various from one viable connection to another, eventually leading to different total connection costs. Furthermore, to show the cost function's effectiveness and prove that this example is not unique, all the CS in each of the years were allocated according to all methods. The final costs are shown in Fig. 80, where it can be observed that the lowest price for all years is obtained using the cost function proposed in this study. Fig. 80 also shows the percentage increase in costs if the other methodologies are used.

Ultimately, the method proposed for allocating CS in the electric network can help electricity distribution companies reduce their costs, as shown in Fig. 80. In years 3 and 4, the costs will be reduced by up 15%. It considers the elements' supply capability and the distances involved and all the other information that planners need to consider. It guarantees adequate energy levels through the power-flow method and allows the costs of operation, connection, losses, and additional equipment to be calculated. Furthermore, in Fig. 80, it can be observed that the results of the proposed methodology, through graph theory, find good solutions according to the costs that the planners define. Compared to other approaches, our methodology resulting in at times in a cost reduction of 15%.

Figure 80 – Comparison of allocation methodologies.



Source: Author’s own elaboration

4.9 FUTURE WORKS

Future works can be further expanded to model new, other loads (hydrolyzers) or complementary technologies (battery storage systems), thus providing a flexible methodology to assist in connecting loads with high power requirements. For this work, it was not necessary to use battery storage systems. As the number of CS increases, depending on the study zone and condition of the distribution network, the use of energy storage may be necessary. For future works, with the increase in the number of DNCEV and consequently increase in residential charging, an TI infrastructure for coordinated residential charging must be implemented. For this work, such infrastructure was not necessary as the increase in residential load is supported by the distribution network.

It was not possible to apply prices in kWh for the CS within the replication of the methodology proposed in (NYOTHIRI *et al*., 2021), helping vehicles to choose the CS with the lowest price and quantifying this price both for the utility, for the consumer (owner of DNCEV) and for the owner of CS. The use of differentiated kWh prices in different periods of time (hours of the day) and in different locations led DNCEVs to look for CS very far away, and in some cases to avoid CS even in need of recharge. Thus, it was decided to withdraw this step. However, for future works, a more elaborate kWh pricing approach can be implemented.

This work has an approach and a multidisciplinary spatial database with the use of socioeconomic data, transport infrastructure and data from the distribution network. Such data are provided by public and/or private companies operating in the urban zone. Thus, for the application of the proposed methodology, it is necessary to obtain these databases. These may be restricted, due to municipal, state or federal legislation, in the case of public entities and restricted to confidentiality in the case of private companies. The proposed methodology was applied in an urban study zone in which the *Electrical Energy Systems Planning Laboratory (LaPSEE) of the São Paulo State University – UNESP FEIS* had agreements with private companies that provided the necessary database. Therefore, for this work it was not possible to apply the methodology in other urban zones, due to the complex integration of databases and availability of these databases. However, as part of future work, new study groups have been created to apply and improve the methodology of this work. An example is that the methodology proposed in this work serve as the basis for writing and approving the "Green corridor" RD&I project. This project is being carried out with a company funding from, with the practical application of the conclusions drawn from this work. The Green Corridor will be the largest electric mobility corridor in the Northeast of Brazil, being developed to connect six Brazilian states. Thus, new databases will be used, with investments, public and private partnerships to encourage the use of DNCEV with a focus on the process of solutions to promote sustainability in transport infrastructure.

5 CONCLUSION

The present work presented a methodology that consists of five parts for the introduction of DNCEV in urban zones. The proposed methodology was based on the spatial-temporal approach of DNCEV with the introduction, traffic, infrastructure, decrease in local pollution, recharge, and impact on the electric network.

This proposed method is applied in a medium-sized Brazilian city. The introduction of DNCEV shows the spatial-temporal acquisition of them with thematic maps over the years. These maps and the total number of DNCEV help vehicle dealerships in their sales strategies and urban planners with strategies for a sustainable city.

In the traffic simulation results, the driving pattern of DNCEV and their SOC along the streets are found after simulations in the transport system. Such results in thematic maps along the years show the most concentrated and low SOC streets and avenues. Such locations will serve as the basis for the infrastructure module, with the spatial allocation of CS. In this module, CS was proposed in places with the highest concentration and lowest SOC of DNCEV. To guarantee recharge in CS for all those who need it, simulations in the TSS tool showed the amount of CS required, and thus regions of influence were proposed. The traffic and infrastructure modules will assist urban planners in their studies, plans, and sustainable mobility actions, CS owners with the correct spatial allocation, owners of DNCEV with CS where they need it, and distribution companies in the planning and energy dispatch.

In the local pollution reduction module, a GHG emission model was used in the TSS tool to find the streets, avenues, and regions of the urban zone to reduce pollution as DNCEV was allocated. Thematic maps over the years with the reduction of CO_2 and NOx were shown, and it was observed that visually the decrease in pollution levels occurred in some specific locations, such as the decrease in NOx in bus routes. There was a reduction of about 3% for CO_2 and 10% for NOx at the end of the study period. Such results will support urban and sustainability planners, creating an effective strategy for reducing local pollution in strategic locations and ensuring better air quality. In module 5, a methodology was proposed to find the impact of increasing the residential nightly recharge. The results found were shown in spatial maps, divided by subareas. Such results will assist distribution companies in planning, improving the distribution network, and energy dispatch.

The entire methodology proposed in this work was developed with some pillars such as spatial database use and a time horizon for planning and simulation. Thus, the methodology of this work uses programming tools - Python; GIS tools - ArcGIS; TSS tool - AIMSUN and DSS tool - OpenDSS to model, simulate, generate results and discussions in a spatial-temporal manner. Thus, as a contribution, this work introduces a methodology that integrates computational tools and has a spatial database that produces visualized results on thematic maps. Finally, the work helps several public and private agents introduce DNCEV in cities over the years, contributing in a multidisciplinary way to the introduction, traffic, infrastructure, local pollution reduction, and impact on the network.

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APPENDIX 1

The master's work completed in 2018 creates a methodology for placement and connection of CS in the electric network for ETs. The methodology helps in decision-making for installing CS, considering some criteria, and cost functions for connection. The results help in the analysis of the lowest-cost places and connection CS. With this work, some papers were produced and were published in congresses:

a) I. Morro-Mello; J. D. Melo; A. Padilha-Feltrin. Estimação do fluxo de veículos elétricos em zonas urbanas. In: VI Simpósio Brasileiro de Sistemas Elétricos, 2016, Natal, p. 1-6.

b) I. Morro-Mello; A. Padilha-Feltrin; J. D. Melo. Fluxo de Veículos Elétricos em Zonas Urbanas. O Setor Elétrico, p. 86 - 93, 15 nov. 2016.

c) I. Morro-Mello; A. Padilha-Feltrin; J. D. Melo. Spatial-Temporal Model to Estimate the Load Curves of Charging Stations for Electric Vehicles. In: IEEE PES Innovative Smart Grid Technologies Latin America, Quito, 2017.

d) I. Morro-Mello; FREITAS, A. B.; J. D. Melo; A. Padilha-Feltrin. Spatial Analysis of Residential Load Growth due to Electric Vehicle Recharge. In: VII Simpósio Brasileiro de Sistemas Elétricos - SBSE, 2018, Niterói - RJ.

In the doctorate, new studies are carried out, improving, and creating new methodologies for EVs. Thus, during the doctorate, some papers were produced and were published in periodicals and congresses and are described below:

Periodicals:

e) MORRO-MELLO, IGOOR; PADILHA-FELTRIN, ANTONIO; MELO, JOEL D; CALVIÑO, AIDA. Fast Charging Stations Placement Methodology for Electric Taxis in Urban Zones. ENERGY, 2019.

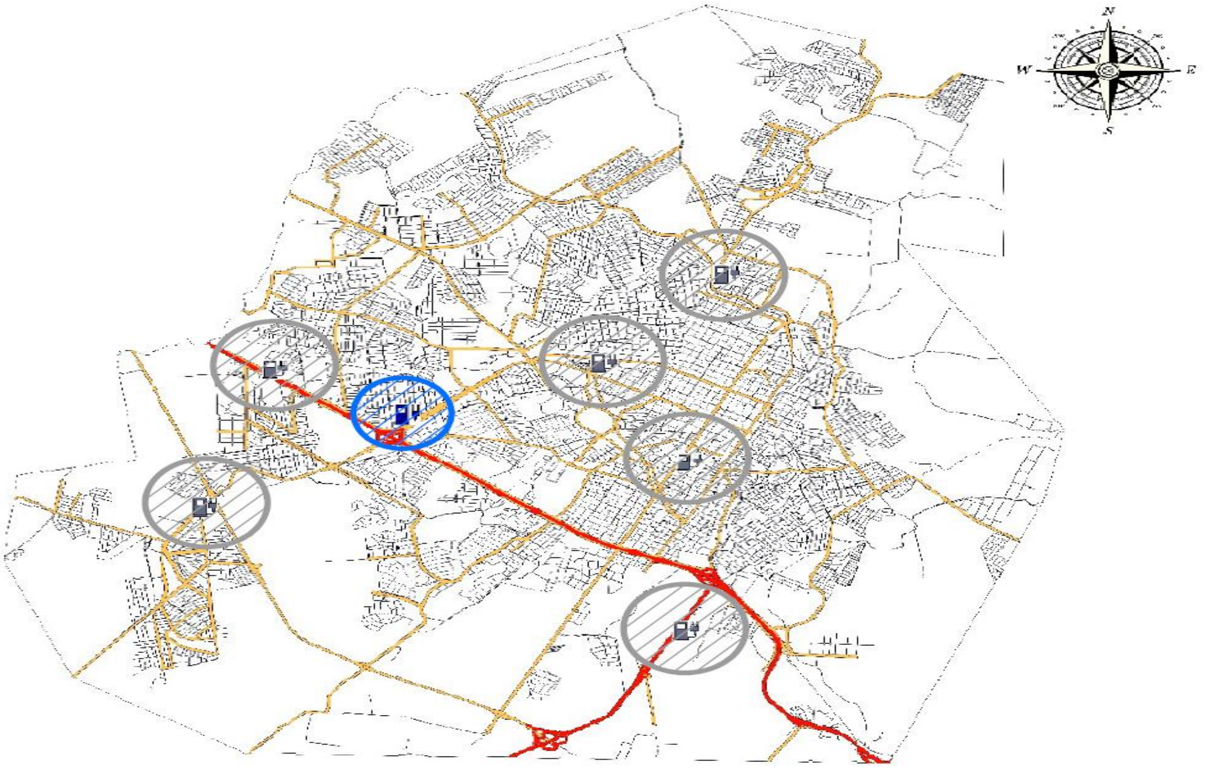
f) MORRO-MELLO, IGOOR; PADILHA-FELTRIN, ANTONIO; MELO, JOEL D; HEYMANN, FABIAN. Spatial Connection Cost Minimization of EV Fast Charging Stations in Electric Distribution Networks Using Local Search and Graph Theory. ENERGY, 2021.

Congresses:

g) RODRIGUES, J. L.; MORRO-MELLO, I.; MELO, J. D.; PADILHA-FELTRIN, A. Estimation of Electric Demand from Electric Vehicles Using Spatial Regressions. In: 2019 IEEE PES ISGT - Latin America, 2019, Gramado - RS, 2019. p. 1.

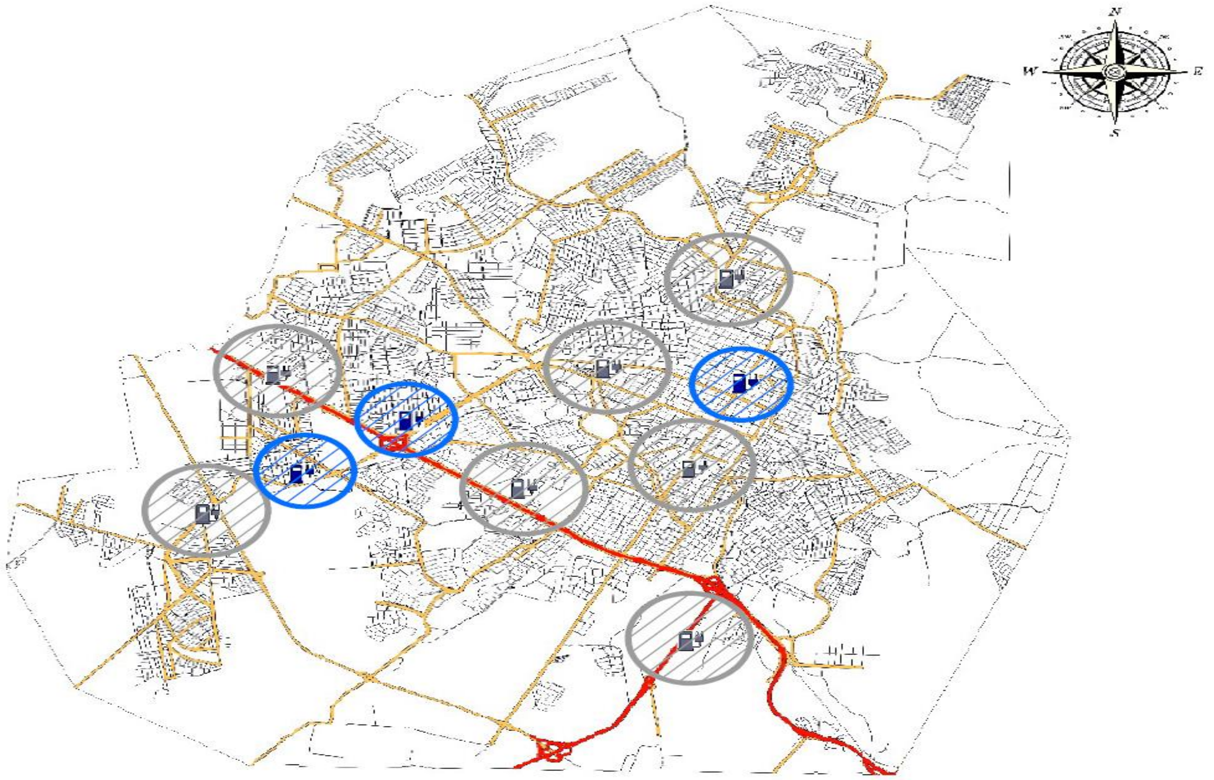
h) MELLO, IGOOR MORRO; FAUSTINO, FAUSTA J.; MELO, JOEL D.; FELTRIN, ANTONIO PADILHA. Greenhouse Gas Reduction Through the Introduction of Electric Vehicles in Urban Zones. In: 2020 IEEE PES Transmission & Distribution Conference and Exhibition Latin America (T&D LA), 2020, Montevideo.

Figure 81 – RI of CS in year 0.



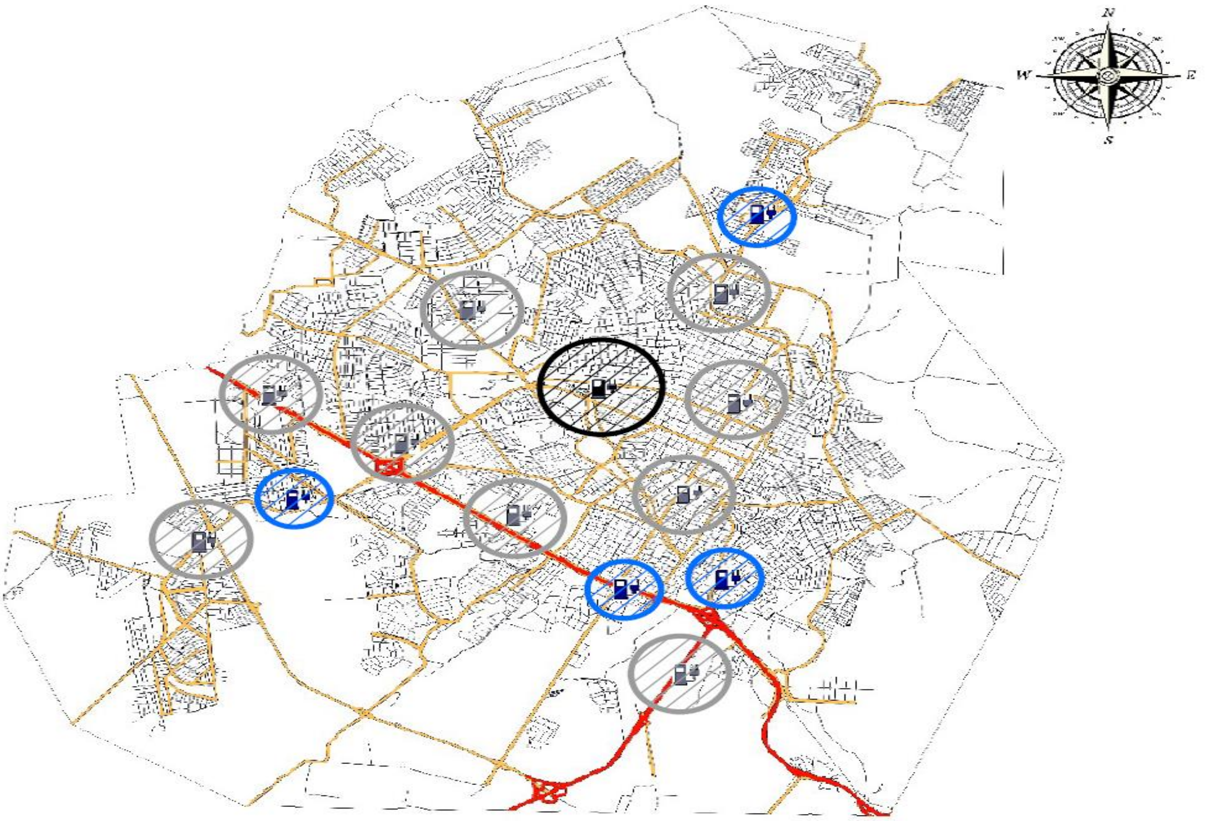
Source: Author's own elaboration

Figure 82 – RI of CS in year 1.



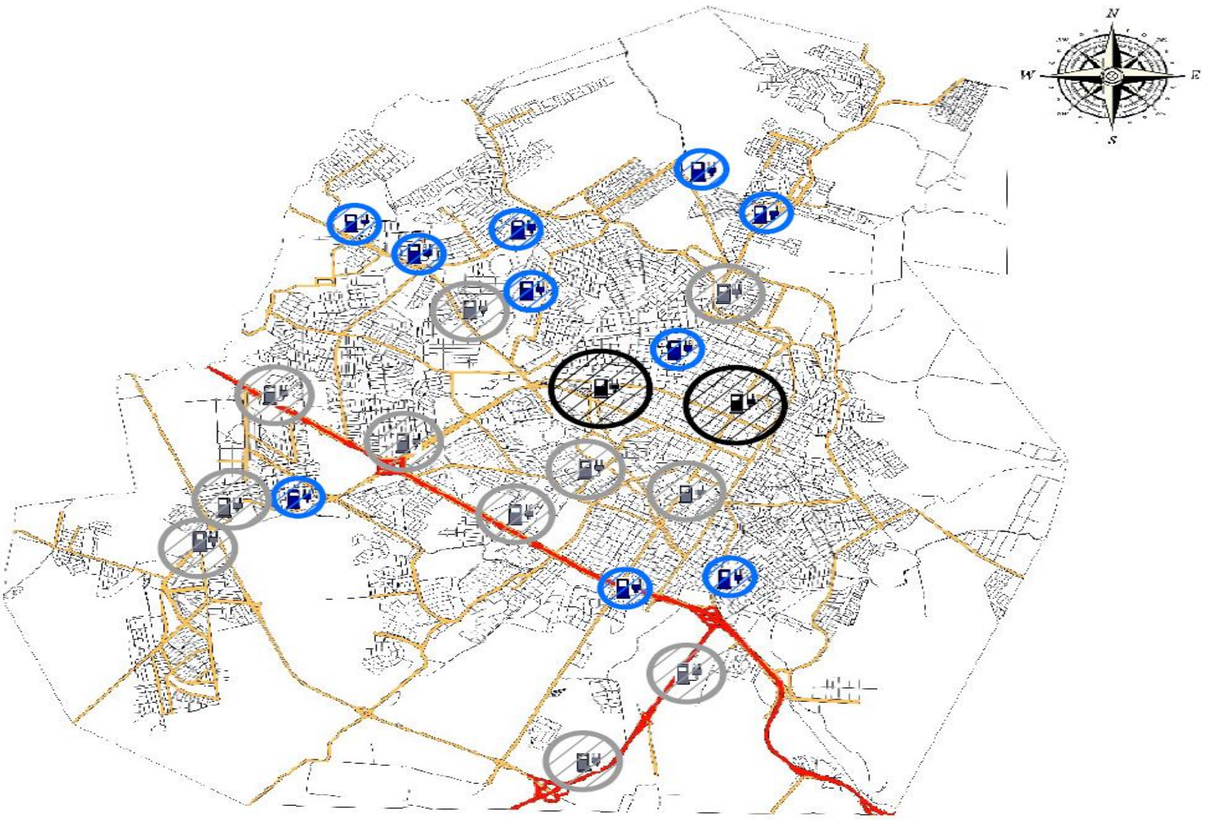
Source: Author's own elaboration

Figure 83 – RI of CS in year 2.



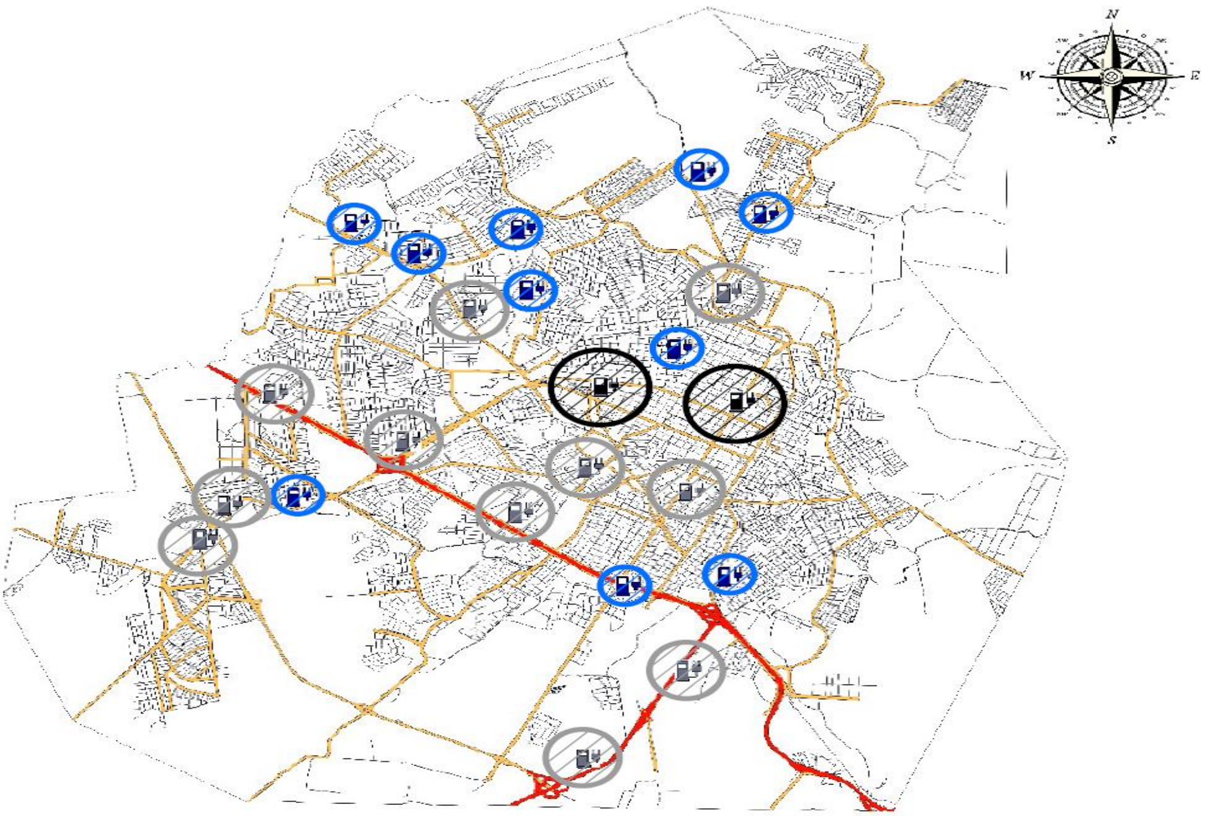
Source: Author's own elaboration

Figure 84 – RI of CS in year 3.



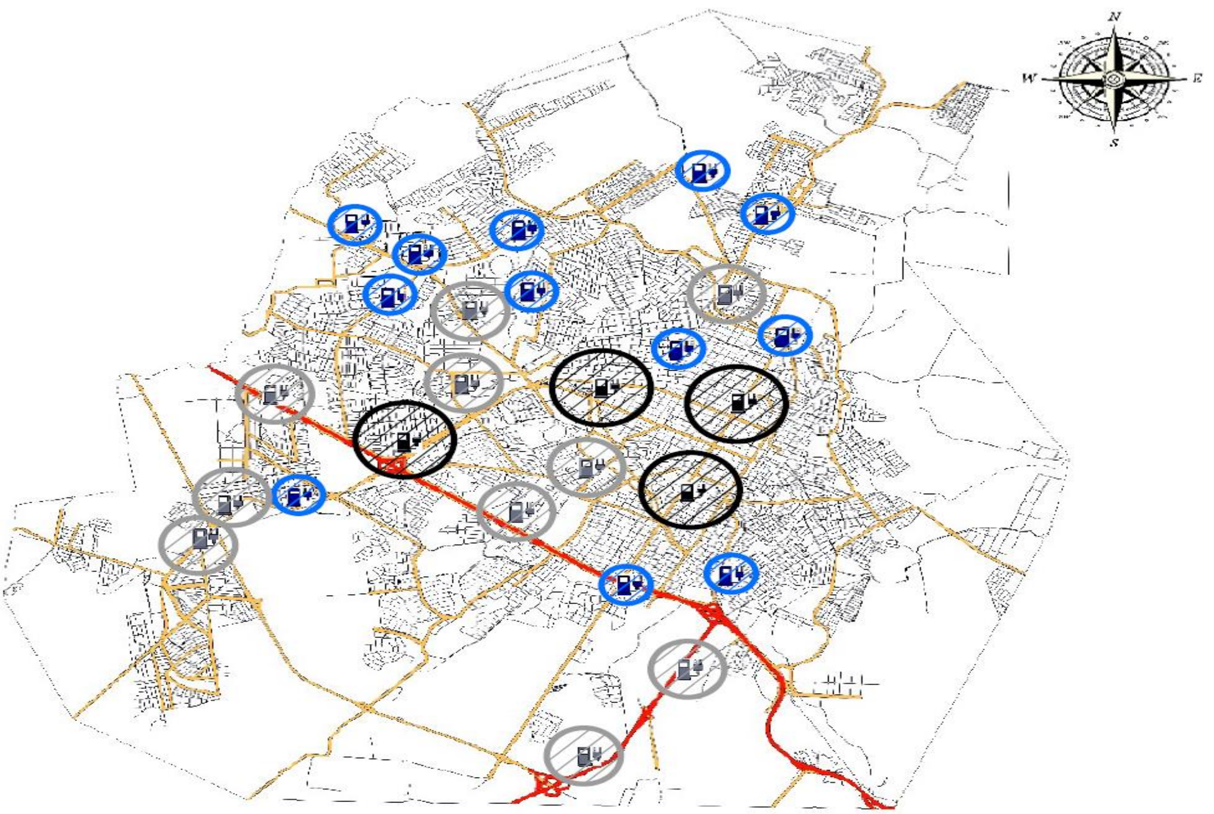
Source: Author's own elaboration

Figure 85 – RI of CS in year 4.



Source: Author's own elaboration

Figure 86 – RI of CS in year 5.



Source: Author's own elaboration