UNIVERSIDADE ESTADUAL DE CAMPINAS

Faculdade de Engenharia Elétrica e de Computação

Eslam Mahmoudi

Urban Electromobility Modeling and Simulation Within Integration Framework of Electric Vehicle-Transportation-Land Use-Energy

Modelagem e Simulação da Mobilidade Elétrica Urbana na Estrutura de Integração de Veículo Elétrico-Transporte-Uso da Terra-Energia

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Supervisor: Prof. Ernesto Ruppert Filho

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- ORCID do autor: https://orcid.org/ 0000-0002-7531-371
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Prof. Dr. Ernesto Ruppert Filho

Profa. Dra. Luciane Neves Canha

Prof. Dr. Adson Bezerra Moreira

Prof. Dr. Gilmar Barreto

Prof. Dr. Marcelo Gradella Villalva

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Abstract

This thesis presents a novel urban electromobility modeling and simulation in the integration framework of EV-transportation-land use-energy to predict the spatial-temporal EV charging power demand of the urban area and optimal planning of the urban charging infrastructures.

In the first part of the thesis, the urban spatial model is constructed based on real-world data to provide the spatial platform for EV mobility simulation. To this end, the actual urban street network is built based on OpenStreetMap data and is integrated with urban land use constructed based on GIS data of the urban area. A new tool is developed to extract traffic data of all street segments from the Google map traffic layer to simulate the urban streets traffic.

In the second part, the EV user's travel behavior, including driving and charging behaviors, is modeled by considering the interdependencies between EV user and EV, transportation system, land use, and energy system. The EV user's driving behavior includes the user's decisions on the spatial-temporal attributes of the EV trip (i.e., purpose, departure time, destination, and route of the trip) and the driving pattern (i.e., driving speed on the trip route) are modeled based on user's preferences, EV technical attributes, and EV energy consumption in accordance to the dynamic urban traffic and spatial feature of the urban area. The EV user's charging behavior that implies a decision-making process on the charging, charging postponement, delay charging at the destination location, or en-route charging on the trip route is simulated based on the user's location priority and range anxiety, required energy for the next trip, etc.

In the third part, each EV trip, including driving and subsequent charging or parking, is simulated via developed models of user's travel behavior in integrating the EV-transportation-land use-energy. Accordingly, the EV's daily travels are simulated in the multi-location multi-purpose travel pattern so that the user departs from home at a specific time of the day, makes several trips between different locations, and finally returns home. The daily travels simulation of an EV leads to predicting the spatial-temporal daily charging demand of the EV in the urban area. The daily travels of all EVs in the urban area are simulated to forecast the spatial-temporal urban power demands, including the slow charging demand at land-use blocks and fast charging demand at fast charging station candidates.

In the fourth part, the slow and fast charging infrastructures planning models are developed to determine the site and size of slow and fast charging stations according to the predicted slow and fast charging power demands. The slow charging piles number of each land-use block is determined based on the daily power demand of the land use. The optimal number of fast charging stations are selected from the candidates to meet the fast charging demand of the urban area. The optimal number of chargers at the selected fast charging stations is determined regarding their daily charging power profiles.

Keywords: electric vehicle, urban electromobility, EV-transportation-land use-energy, driving and charging behaviors, spatial-temporal charging demand.

Resumo

Esta tese apresenta uma nova modelagem e simulação de eletromobilidade urbana no quadro de integração de EV-transporte-uso da terra-energia para prever a demanda de energia de carregamento de VE espaço-temporal da área urbana e o planejamento ideal das infraestruturas de carregamento urbano.

Na primeira parte da tese, o modelo espacial urbano é construído com base em dados do mundo real para fornecer a plataforma espacial para simulação de mobilidade EV. Para este fim, a rede viária urbana real é construída com base nos dados do OpenStreetMap e é integrada ao uso do solo urbano construído com base em dados GIS da área urbana. Uma nova ferramenta é desenvolvida para extrair dados de tráfego de todos os segmentos de rua da camada de tráfego do Google map para simular o tráfego de ruas urbanas.

Na segunda parte, o comportamento de viagem do usuário EV, incluindo comportamentos de direção e carregamento, é modelado considerando as interdependências entre o usuário EV e EV, sistema de transporte, uso do solo e sistema de energia. O comportamento de direção do usuário EV inclui as decisões do usuário sobre os atributos espaço-temporais da viagem EV (ou seja, propósito, hora de partida, destino e rota da viagem) e o padrão de direção (ou seja, velocidade de direção na rota de viagem) são modelado com base nas preferências do usuário, atributos técnicos EV e consumo de energia EV de acordo com o tráfego urbano dinâmico e características espaciais da área urbana. O comportamento de carregamento do usuário EV que implica um processo de tomada de decisão sobre o carregamento, adiamento de cobrança, atraso de cobrança no local de destino ou cobrança em rota na rota de viagem é simulado com base na prioridade de localização do usuário e ansiedade de alcance, energia necessária para a próxima viagem, etc.

Na terceira parte, cada viagem EV, incluindo a condução e subsequente carregamento ou estacionamento, é simulada por meio de modelos desenvolvidos de comportamento de viagem do usuário na integração do EV-transporte-uso da terra-energia. Consequentemente, as viagens diárias do EV são simuladas no padrão de viagem multi-local e multiuso para que o usuário saia de casa em um horário específico do dia, faça várias viagens entre locais diferentes e, finalmente, volte para casa. A simulação de viagens diárias de um EV leva a prever a demanda de carregamento diário espaço-temporal do EV na área urbana. As viagens diárias de todos os VEs na área urbana são simuladas para prever as demandas espaço-temporais de energia urbana, incluindo a demanda de carregamento lento em blocos de uso do solo e a demanda de carregamento rápido em candidatos a estações de carregamento rápido.

Na quarta parte, os modelos de planejamento de infraestrutura de carregamento lento e rápido são desenvolvidos para determinar o local e o tamanho das estações de carregamento lento e rápido de acordo com as demandas de energia de carregamento lento e rápido previstas. O número de pilhas de carregamento lento de cada bloco de uso do solo é determinado com base na demanda de energia diária do uso do solo. O número ideal de estações de carregamento rápido é selecionado entre os candidatos para atender à demanda de carregamento rápido da área urbana. O número ideal de carregadores nas estações de carregamento rápido selecionadas é determinado em relação aos perfis de potência de carregamento diários.

Palavras-chave: veículo elétrico, eletromobilidade urbana, EV-transporte-uso do solo-energia, comportamentos de direção e carregamento, demanda de carregamento espaço-temporal.

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SUMMARY

Chapter 1

1. Introduction

1.1. Background

The history of the invention of the Electric Vehicle (EV) dates back to the early nineteenth century in 1835 when a small-scale electric car was built that powered by non-rechargeable primary cells. However, in the twentieth century, Internal Combustion Engine Vehicle (ICEV) became very popular in the car manufacturing and transportation system, owing to the abundance and cheapness of crude oil. Excessive use of fossil fuel vehicles has increased carbon emissions worldwide, and the world has gradually become aware of the adverse effects of greenhouse gases. Urban transport systems alone account for a large portion of total greenhouse gas (GHG) emissions in cities, and many countries around the world are promoting environmentally sustainable transport to achieve energy-efficient and low-carbon development in cities. However, the rapidly growing demand for mobility and private-vehicle ownership in the urban areas have counteracted efforts to reduce GHG and other air pollutants. In order to reduce GHG emissions, the automobile industries and transportation systems trend has shifted from fossil fuels to clean energy fuels. EVs are considered a promising technology and an attractive solution for a low-carbon future. In recent years, many automakers have made significant efforts to transform from the ICEVs to EVs that offer reliable green solutions. The significant advantages of using EV are:

- Zero-emission results in a cleaner environment.
- The high-efficiency performance leads to maximum use of resources such as regenerative braking.
- Flexibility to charge at any location equipped with an electric power supply such as home, workplace, and public charging facilities.

- Ability to charge with renewable energy, especially solar energy.
- Noise-free pollution due to the use of fewer non-moving parts.

Although the EV offers a clean and quiet operation, it still suffers from limited battery capacity, long recharging time, higher costs, insufficient access to electricity in urban areas. Due to the many governments establishing increasingly stringent and ambitious targets supporting EV adoption, the deployment of EVs has been growing rapidly worldwide. In this context, some policy interventions like ICEVs bans and government purchase subsidies, improving EV technologies, and introducing new EV models by automotive industries can encourage people to buy EVs. As such, with the ambitious goals set by governments and continuous improvements in industrial technology, it is expected that the penetration of EVs will be increased rapidly across the world. Nevertheless, it is expected that EVs could gain significant market penetration in the near future, especially in urban areas. Hence, since transport electrification offers an option for a sustainable and decarbonized transport sector, it is essential to investigate the energy demand of EVs in the urban transportation system. In this context, electromobility is becoming a significant alternative for conventional mobility systems, aiming to reduce emissions of harmful substances into the urban environment by reducing the number of ICEVs and deploying EVs in the transportation system, especially in the urban areas characterized by high population density and heavy traffic. Electromobility is a concept that refers to the usage of the electrified transportation system. Therefore, an electromobility system should at least include the EVs and the charging facilities system. Electromobility is not just about technology but also acceptance within the population, hence the attempt of car manufacturers to produce energy efficient EVs and the government's subsidies can encourage the public to buy EVs and lead to electromobility expansion. However, one of the main reasons people accept EVs is the easy access to suitable charging facilities. In general, the charging facility can be deployed in homes, workplaces, and public locations. All EV owners can access public charging facilities, while their access to home and workplace charging is limited and depends on their residency and occupation location. However, charging location choice by EV users is determined by their interaction with charging facilities in different activity locations so that users meet several locations in a day to perform their activities.

Moreover, concerning their access to charging facilities in different locations, they may prioritize a charging location over others regarding factors such as personal mobility behavior, charging price, convenience, and personal preference. Hence, locating charging infrastructures in the future of urban areas cannot be independent of charging facility types at different locations and the charging behaviors of EV owners. Therefore, predicting the EV charging demands based on daily EV users' travel behavior, including driving and charging behaviors, is essential to locating adequate charging infrastructures in the urban areas, which ultimately leads to the spread of urban electromobility.

1.2.Research motivation

Due to the much higher efficiency of EVs than ICEVS and the zero-emissions property of EVs, transport electrification became the political agenda of governments worldwide. Thus, it is expected that the large-scale EV penetration in urban transportation will be realized in the near future. The large number of EVs brings high EV charging power demand in the urban areas, making the need to construct charging facilities in different locations of the urban area. However, the blind construction of charging infrastructures causes problems such as waste of land and financial resources and irregular fluctuations in the urban power grids. Predicting the spatial-temporal distribution of EV charging power demands can help solve these problems and design the charging infrastructures scientifically. In order to forecast urban charging power demand and scientifically design the charging infrastructures in the urban areas, EV mobility should be modeled accurately in the urban environment. Different systems are involved in urban mobility, such as EVs, EV users, the urban transportation system, urban activity locations, urban traffic patterns, and urban power grid. Due to the dynamic and interdependent nature of the different systems' behavior, the models must consider all influencing factors relevant to urban electromobility. In this context, it is essential to simulate urban electromobility by taking into consideration the travel behavior of the EV users, EV technical attributes, urban transportation system characteristics, urban traffic patterns, urban geographic features, urban energy systems, etc. Such simulation enables to achieve accurate forecasts of the spatial-temporal charging power demand at different locations of the urban area and plan the adequate charging facility to meet the urban charging demand. However, the available studies in the modeling and simulation of the EV mobility and EV charging demand prediction have proposed simple models that ignore the main influencing factors on urban electromobility. As such, the proposed models are not suitable to simulate urban electromobility.

Due to the complexity of the urban transportation system modeling, the previous studies have not considered the urban street network and urban traffic simulations in their proposed models.

In this regard, two studies groups are distinguished; one group that totally ignored the urban street network and another group that used a small graph as the street network to model EV mobility.

In the first group of studies, a virtual network was assumed that the EV mobility parameters (e.g., driving time, driving distance, etc.) are directly extracted from the travel survey data of conventional cars or modeled probabilistically based on the travel data. Furthermore, the traffic congestion of streets highly affects EV mobility, EV energy consumption, and the EV charging demand. While most studies did not consider the traffic influence, few studies assumed fixed traffic congestion value for their virtual network or simple graph. By adopting a simple speed-flow model, the constant speed was estimated for EV driving. Whereas the urban traffic is dynamic and stochastic, and EV driving speed should be modeled in a stochastic and dynamic framework to represent the stochastic nature of EV driving in urban transportation systems. Thus, the oversimplification in modeling EV mobility in studies cannot result in an accurate EV charging demand. Consequently, the proposed models are not suitable for urban electromobility simulation.

Moreover, there is a need for an actual dynamic model of urban traffic and taking into account the dynamic traffic on EV mobility regarding the speed limits and traffic congestion of the urban street network. One of the main influencing factors on EV charging demand is the EV consumption on EV driving. However, constant energy consumption per kilometer (KWh/km) is assumed in most existing studies. The EV energy consumption on each trip is calculated based on this assumed consumption rate and a trip distance randomly extracted from a PDF calibrated based on travel survey data. This overestimation of EV energy consumption results in inaccurate prediction of EV charging demand. Thus, the obtained results of these studies cannot represent the realistic EV energy demand in urban areas. However, besides the technical characteristics of EV's motor and powertrain, its energy demand depends on the street network topology and traffic conditions. A detailed model of the EV power train is required to calculate EV energy consumption while driving on the street with estimation speed, acceleration/deceleration according to street attributes, and dynamic traffic conditions.

In addition to the features mentioned above of urban mobility, EV mobility cannot be modeled independently of the EV users' travel behaviors. Even though besides the complexity of the urban transportation system and urban traffic pattern, the EV users' travel behavior adds another complexity in the urban electromobility simulation. Most studies used simple models to reduce the complexity of EV mobility simulations complexity by ignoring the EV users' behaviors or representing a simple model of users' behaviors. Therefore, these studies are not applicable for urban electromobility simulations since the main affecting factors on urban mobility were ignored. Hence, the results that are achieved by applying the proposed models for the urban areas are not accurate enough to be considered by city policymakers to design the future roadmaps of urban transportation and urban energy systems. Therefore, while EVs are not yet sufficiently integrated into the urban transportation system, comprehensive modeling and simulation of urban electromobility are required to predict the urban charging demand and planning urban charging infrastructure by taking into account the influencing factors on urban electromobility.

Due to the limited knowledge and experiences of EV traveling in the urban areas and the absence of historical data about EV users' travel behaviors, this research aims to develop models of realistic human travel behaviors in the actual urban environment to predict the slow and fast charging demands of EVs in the urban area in a multi-location and multi-purpose framework in different urban land use and planning the slow and fast charging infrastructures for providing a vision of urban charging energy demand to develop and implement urban energy management solutions for its sustainable future.

1.3.Scope and Objectives

This thesis addresses the issues related to urban electromobility modeling and simulation to achieve accurate EV charging demand prediction to design charging infrastructures in the urban area. In this context, the interactions between EV users with the EV, transportation system, land uses, and energy system in the urban area are analyzed and modeled, leading to simulating daily EV mobility in the urban area. The EV mobility on the urban transportation system eventually results in spatiotemporal EV charging demand at the urban street network and urban land-uses, which provides the opportunity to determine the optimal location and size of charging infrastructure.

In a nutshell, the thesis aims to simulate urban electromobility by modeling the EV user driving and charging behaviors in integrating the EV, transportation system, land-use, and energy systems to predict spatial-temporal EV charging demand and slow/fast charging infrastructure planning in the urban area. The main objectives of this research are summarized below.

(1) Constructing the actual urban spatial model includes the urban street network and land use to provide a simulation framework to model the spatial attributes of EV mobility in the urban area.
(2) Creating a new tool to extract the real-world city-scale traffic data from the Google map traffic layer to model the dynamic traffic pattern of the urban street network.
(3) Developing a new simulation framework of EV mobility based on the interactions between EV, transportation system, land use, and energy system of the urban area to simulate the urban electromobility.
(4) Modeling the EV users' driving behavior to simulate the EV driving on the urban street network in accordance with the dynamic traffic of urban streets and streets topology.
(5) Modeling the EV users' charging behavior in accordance with the user's preferences and possible access to charging facilities in the home, workplaces, and public locations in the urban area to emulate the realistic human decision-making process on EV charging in the urban electromobility simulation.
(6) Forecasting the spatial-temporal distributions of urban charging power demand based on EV users' driving and charging behavior simulation in the integration of EV-transportation-land use-energy.
(7) Planning the slow and fast charging infrastructures in the urban area regarding urban energy system interaction with EV users, transportation system, and land use according to the slow and fast charging power demand predicted by urban electromobility simulation.

The thesis objectives are described briefly in the following.

1.3.1. Integration of transportation and land use

Despite the existing complexities in urban spatial modeling, a detailed model including the actual urban street network and land use is needed to achieve the electromobility objectives. In this regard, extensive data of urban street segments and land uses is required for the spatial modeling of the urban environment. Fortunately, the open-source data provided by the online map provider and the city's municipality are reliable data to model the urban areas. In this regard, the GIS data of the study area are collected to model the street network and land use integration. In this framework, the land use includes the locations (e.g., houses, workplaces, shopping malls, etc.) where EV users perform their activities. The spatial distribution of activities in different urban land uses creates the need for travel on the urban area to cover the distance between the locations of activities. Transportation networks provide the connectivity between activities and consist of different street segments which are hierarchical by nature, like the motorway, primary, secondary, etc. Intending to model the spatial aspects of EV mobility in the urban area, the urban street network and land-use integration enable to identify of the possible destination locations and route of EV trips, in which the EV users can decide the trip's destination and route based on their preferences and according to the limitations imposed by the urban traffic.

1.3.2. Integration of transportation-land use-energy

The main objectives of urban electromobility simulation are EV charging demand forecasting and charging infrastructures planning. EVs' energy consumption of driving on the street network leads to charging demands that are met through the charging facilities located at street networks or deployed in different urban land-uses. Hence, the charging infrastructures link the urban energy system with the integrated urban transportation and land-use system. Integration of the energy into transport-land use integrated model could improve the representation of energy issues in the urban electromobility, such as EV charging demands and charging infrastructures deployment in the urban area. The prediction of spatial-temporal distributions of urban charging demand provides a reference for locating the charging facilities in the land-uses or at the street network. Therefore, to achieve urban electromobility purposes, EV mobility in the urban area should be modeled by taking into account the interactions between EV users with the transportation system, land uses, and energy system. The integration framework of transport-land use-energy allows EV users to satisfy their travel demand and charging demand in their daily itinerary.

1.3.3. EV user interaction with the transportation-land use-energy integration

In the daily itinerary, the EV users travel on the street network between their activity locations and may decide to charge their EVs with the charging facilities at homes, workplaces, or public locations. The interactions of EV users with transportation-land use-energy systems refer to the ways that EV users pursue to travel on the street network between different activity locations in the urban land uses as well as utilize the charging facilities, which is interpreted as EV user's travel behavior including driving, charging/parking behaviors. One of the objectives of this research is to develop models to simulate the EV user's travel behaviors in the integrated framework of EV-transportation-land use-energy.

1.3.4. EV user's travel behavior

An EV trip includes driving and charging or parking afterward. In other words, the EV has different states over travel, including driving, charging, or parking states. Travel behavior refers to the decision-making process of the EV user during the travel regarding the state of the EV. In each state, the EV user decides on the corresponding parameters based on his/her preferences, the existing conditions, and information on the urban environment. Besides, it is assumed that EV users are rational and have sufficient information about the feasible alternatives for making a decision.

1.3.4.1. EV user's driving behavior

The users' driving behavior refers to their decision-making on the related parameters of the trip (i.e., trip purpose, departure time, destination location, trip route) and the driving pattern (i.e., EV's speed profile or driving cycle). EV users decide the trip parameters based on their preferences and by regarding the urban streets' topology, dynamic traffic conditions, and activity location distributions in urban land use. Currently, there are very few EVs in the urban transportation system, and it isn't easy to get the real-world EV users' travel behavior and driving pattern data. But it is acceptable to assume that the EV users will more or less have the same driving pattern as the conventional cars. Therefore, travel survey data and driving speed data of conventional vehicles are used to simulate the driving behavior and driving patterns of EV users.

EV user's driving behavior modeling aims to simulate the user's decision-making on purpose, departure time, destination location, and route of each trip. Besides, the purpose of driving patterns modeling is to generate the instantaneous driving speed on the predicted trip route under the dynamic traffic pattern of the urban street network. Contrary to the previous studies that neglect the comprehensive model of user's driving behavior, this research aims to represent the realistic model of EV driving, which mainly affects the EV energy consumption, EV charging demand, and finally, the urban charging demand.

1.3.4.2.EV user's Charging behavior

The objective of users' charging behavior modeling is to determine their decisions on the desire to charge, selecting the charging mode, and selecting the charging location. Due to the stochastic nature of EV mobility and energy consumption, there is the possibility that the EV user decides to charge EV at any time of day and in any location of the urban area. Hence, the EV users charging behavior that highly affects the spatial-temporal EV charging demand distributions should be modeled realistically by taking into consideration the main influencing parameters on users' decisions. The main influencing parameters include charging location type, State of Charge (SoC) of EV's battery, required energy for the next trip, user's range anxiety, charging convenience, price, and user's preferences.

Owing to the lack of empirical data on the EV users' charging behavior, users' decision-making process in response to the mentioned influencing parameters is modeled to emulate the realistic human behavior. To this end, by considering the availability of charging facilities in different activity locations, the users are classified, and for each user group, the charging behavior is modeled separately. Therefore, in contrast to the studies that assumed simple rules for charging EV at fixed locations, this research intends to develop charging behavior modeling in a multi-purpose multi-location framework for achieving the accurate prediction of spatial-temporal urban charging demand distributions.

1.3.5. Spatial-temporal charging demand prediction

One of the main objectives of the electromobility simulations is to predict the EV charging demands. In some of the studies, without considering the dynamic nature of EV mobility, the charging load in a charging station is estimated by assuming the arrival flow to the station by a Probability Distribution Function (PDF) like Poisson distribution. Contrary, some studies predict the charging demand load by considering simple trip chains for daily trips for EVs in a virtual network. The forecasted charging load distributions in these studies are not accurate due to the oversimplification of EV mobility. In order to predict more accurate charging load demand in the urban area, this research simulates the daily EV mobility in a multi-purpose and multi-location framework into EV-transport-land use-energy integrated context based on the users' travel behavior, dynamic urban traffic, actual EV energy consumption, etc. For this purpose, the daily trips of EVs in the urban area are simulated in the mentioned frameworks to predict the time, location, power demand of each charging event of each EV at the urban charging locations. Accordingly, the daily spatial-temporal charging power distributions of urban locations are obtained.

1.3.6. Slow and fast charging infrastructures planning

Besides the spatial-temporal charging demand prediction of urban charging demand prediction, the other main objective of the urban electromobility simulation is the slow and fast charging infrastructures planning in the urban area. In the urban electromobility simulation, three charging location types are distinguished; home, workplace, and public. The EVs charging at homes and workplaces can only be with slow charging facilities. In contrast, the slow and fast charging modes are possible for public charging of EVs. The slow charging demands of EVs at homes and workplaces are met by their dedicated charging piles. Hence, the charging infrastructures planning problem is not implemented for the home and workplaces. Thus, the charging infrastructure planning aims to find the size and site of slow and fast-charging stations to meet the slow/fast public charging demand predicted by the urban electromobility simulation. EVs' public slow charging demands are met locally by the slow charging piles located at user's activity locations or at the nearby public parking lot within an accepted walking distance (less than 300meter). Thus, the slow charging facility planning is performed at the land-use block level. The land-use-based slow charging planning is selected because the slow demand's spatial attributes are ignored in point-based slow charging planning. The further drawback of point-oriented models is the partial coverage problem. However, the use of land-use blocks eliminates the drawbacks. Thus, the spatial-temporal distributions of public charging load predicted by electromobility simulation are used to determine the required charging piles number via land-used based planning.

Contrary the slow charging, to satisfy the fast charging demand of EVs, the Fast Charging Stations (FCS) are planned according to the distribution of public fast charging load distributions and the structure of the urban street network. In this regard, the streets with a large amount of traffic are considered the best candidates for locating the FCSs. Hence, the actual urban street network and urban traffic model provide the opportunity to find the candidate street segment for FCS locating. The arterial streets with heavy daily traffic are identified as candidate street segments. The midpoints of the candidate street segment are selected as FCS candidate locations. The optimal FCS planning is often based on the multi-objective optimization methods that lead to taxing computational efforts for urban transportation networks. As such, this research aims to utilize an evolutionary heuristic approach to find the optimal site and size of FCS to meet the fast changing demands of EVs in the urban area. To this end, at the first step, the required FCS candidate locations that cover all urban street networks are determined so that the geographical distance of each node of the urban street network (as a potential fast demand point) to the nearest FCS candidate be less than the maximum detour distance considered for planning. At the second step that is performed during the electromobility simulation, each EV with fast charging demand is assigned to the nearest FCS candidate by assuming that each FCS has enough chargers to charge all incoming EVs. The third step, called the reallocation step, is implemented at the end of electromobility simulation when the daily charging demand and the number of EVs assigned to the FCS candidate are obtained. At this step, the FCS candidates are combined, EVs reallocated to other FCSs while satisfying the planning objectives (e.g., minimizing the number of FCSs and economic objective) and constraints (e.g., EV reallocated to other FCS if their distance is less than maximum detour distance). At the fourth step of planning, a capacity constraint is determined by both technical and economic objectives. Considering a finite capacity, the service level is then defined based on the waiting times of the EV users at each FCS. At this step, the number of required chargers for each selected FCS is established considering the arrival times of the EVs. Therefore, the optimal sizing solution is obtained based on a trade-off between the waiting time and the number of active simultaneous chargers.

1.4.The major contributions of the thesis

The relatively high complexity of real street networks and traffic conditions of urban areas, the high diversity of urban land uses, and the complicated travel behaviors of EV users are expected to pose serious challenges to employing the models and approaches of existing studies in urban electromobility modeling and simulation. To address the existing challenges, this thesis proposes a novel urban electromobility simulation that compared with existing studies the main contributions are as follows.

(1) The actual urban street network graph is constructed based on real-world geospatial street data of OpenStreetMap (OSM), consisting of all street types such as the trunk, motorway, primary, secondary, tertiary, residential, etc. Although some studies have used a simple graph to show the network of urban streets with a few types of roads, the graph of the entire actual street network has not been used to simulate EV mobility in the urban area. Construction of the actual street network facilitates the urban traffic simulation, EV user driving pattern models, EV energy consumption model, etc.

(2) Collecting the traffic data of all urban street segments is almost impossible. To overcome the difficulty of collecting city-wide traffic data, a tool is developed to extract real-world traffic conditions of the streets from Google Map Traffic Layer (GMLT). To this end, the GMLT images of the study area are captured, and by processing the captured images, the traffic state of each street segment is specified according to the traffic colors of the streets provided by GMLT.

(3) Besides EV technical aspects, driving speed, and acceleration/deceleration, the EV driving energy consumption depends on the slopes of streets. In this regard, the constructed actual urban street network provides the opportunity to obtain the slope of streets. In this thesis, the open-source Digital Elevation Model (DEM) data provided by the Shuttle Radar Topography Mission (SRTM) of NASA is used to calculate the average slopes of all street segments of the urban area.

(4) The polygon-based model of urban land use is created based on the GIS-land use data of the study area. The urban land-use blocks and urban street networks are integrated to represent the urban spatial model. The integrated street network and land use allow modeling the spatial characteristics of EV mobility in the urban area that is ignored in the previous studies.

(5) To overcome the oversimplification of EV mobility simulation in the previous studies, in this research the EV user driving behavior, which includes decision-making on trip parameters (purpose, departure time, destination, and route of trip) and driving pattern (driving speed, acceleration/deceleration), is comprehensively modeled in the integration framework EV-transportation-land use-energy in the urban area.

(6) Contrary to the existing studies that simply model the charging decision of EV users, this research proposes a model to emulate the realistic EV charging behavior based on the following.

- EV users are classified based on their access to charging facilities at different locations such as home, work, and public locations of the urban area
- Different charging strategies are considered based on EV users' preferences, including obligatory charging, convenient charging, charging postponement, and charging delay.
- The slow charging mode at land-uses and fast charging mode at FCSs are considered to simulate the EV user charging mode decision.

(7) In the absence of a detailed model of slow/fast charging demand prediction in the actual urban environment in the available studies, this thesis simulates the EV daily travels in a multi-purpose multi-location framework in the integration of EV-transportation-land use-energy to forecast the spatial-temporal slow and fast EV charging power demand in the land-use blocks and FCS candidates.

(8) The spatial attributes of the integrated urban model and dynamic traffic simulations provide the opportunity to determine the suitable FCS candidates' locations, which are located along the arterial urban streets with two or more one-way lanes with heavy daily traffic. Moreover, an evolutionary heuristic model proper for large-scale urban transportation systems is developed to optimally site and size of FCSs by considering the EV user preferences, FCS constraints, and the urban environment constraints.

1.5.Thesis overview

In order to reduce the usage of conventional vehicles, which burn fossil fuels and emit greenhouse gases, electromobility as a viable alternative has been considered a practical means of sustainable urban mobility. In this context, comprehensive electromobility models are required to provide a suitable framework for increasing EVs in the urban transportation system.

Due to the dynamic and interdependent nature of the system's behavior, the models need to consider all affecting factors relevant to urban electromobility. To this end, the interdependencies between EV users, EVs, transportation systems, and urban land use should be comprehensively analyzed to forecast the urban charging power demand and plan the charging infrastructures in the urban environment. In this regard, EV mobility is simulated in the integration framework of EV users, transportation systems, land-uses, and energy systems. Users travel between different locations that are located in different urban land-uses to perform their activities. The transportation system provides connectivity between the activity locations through the street network. EV consumes energy when driving on the street network, which its amount depends on the EV technical attributes and user driving behavior. Regarding the available energy in EV's battery and required energy to support EV travel, the user may decide to charge EV at any time and any location of the urban area. The charging infrastructure as the energy system at urban land use or urban streets provides energy to charge EVs supplied by the urban power grid or RES.

Therefore, the EV user's travel behaviors modeling in the integrated context of the street network and land use allows predicting the spatial-temporal distributions of urban charging demands and charging infrastructure planning in the urban environment, which are the main objectives of this research. The EV user travel behavior in integrating the urban street network and functional zones considering the urban traffic should be modeled accurately to simulate the EV daily travels, eventually leading to achieving the EV energy demand in the urban area. Based on GIS data of the street network and land-uses, the integrated urban area is modeled spatially so that a street segment is identified as a line between two intersection nodes with a given latitude and longitude (Lat/Long). Polygons specify Land-uses boundaries with specific Lat/Longs for their vertices. The specific Lat/Longs identify the activity locations in each land-use block to determine each EV trip's Origin-Destination (OD).

The travel behaviors of users are interpreted as their decision-making on the spatial-temporal characters such as departure time, trip purpose, destination location choice, trip route choice, driving acceleration/deceleration, charging mode. These users' decision-making processes are modeled under the user's preferences within the urban environment and in response to the dynamic traffic of the urban street network. Moreover, to consider the travel behavior of the study area's drivers, the study area's travel data is used in developing the models.

For each EV trip, the EV user decides to travel to perform an activity, chooses a destination location related to the activity (trip purpose) in an urban land-use block, chooses an optimal-energy trip route on the street network from O location to D location. Then, the user leaves the origin location at a specific departure time. During the driving, the second-by-second driving speed of EV is generated stochastically based on the user's driving behavior in response to traffic conditions and the speed limit of each street segment of the trip route. Traveling on the trip route continues until the EV arrives at the destination at a specific arrival time. When the EV arrives at the destination location, the user decides whether to charge or not. If the user decides to charge, the EV will be charged during parking at the destination location. Otherwise, it will be idle. The spatial-temporal characteristics of an EV trip include OD locations and street intersections of the trip route, departure time from origin location, arrival time at the destination location, and times to reach or leave the street intersections. In other words, an EV travel can be represented as three typical EV behaviors, namely driving, parking, and charging, which can be thought of as three states which an EV traverses over time.

EV daily trips are considered home-to-home trips in which the EV user departs from home at a specific time of the day, performs several activities in different locations, and finally returns home. For each trip of EV daily trips, the spatial-temporal characteristics of the driving, charging, or parking are recorded during the simulation. By simulating the daily trips of a number of EVs in the study area, the start time, end time, location, energy demand amount of charging events of the EVs are extracted from the recorded data of EV daily trips to obtain the spatial-temporal charging demand distributions in the urban area.

The thesis overview is shown in the flowchart of Figure 1.1.

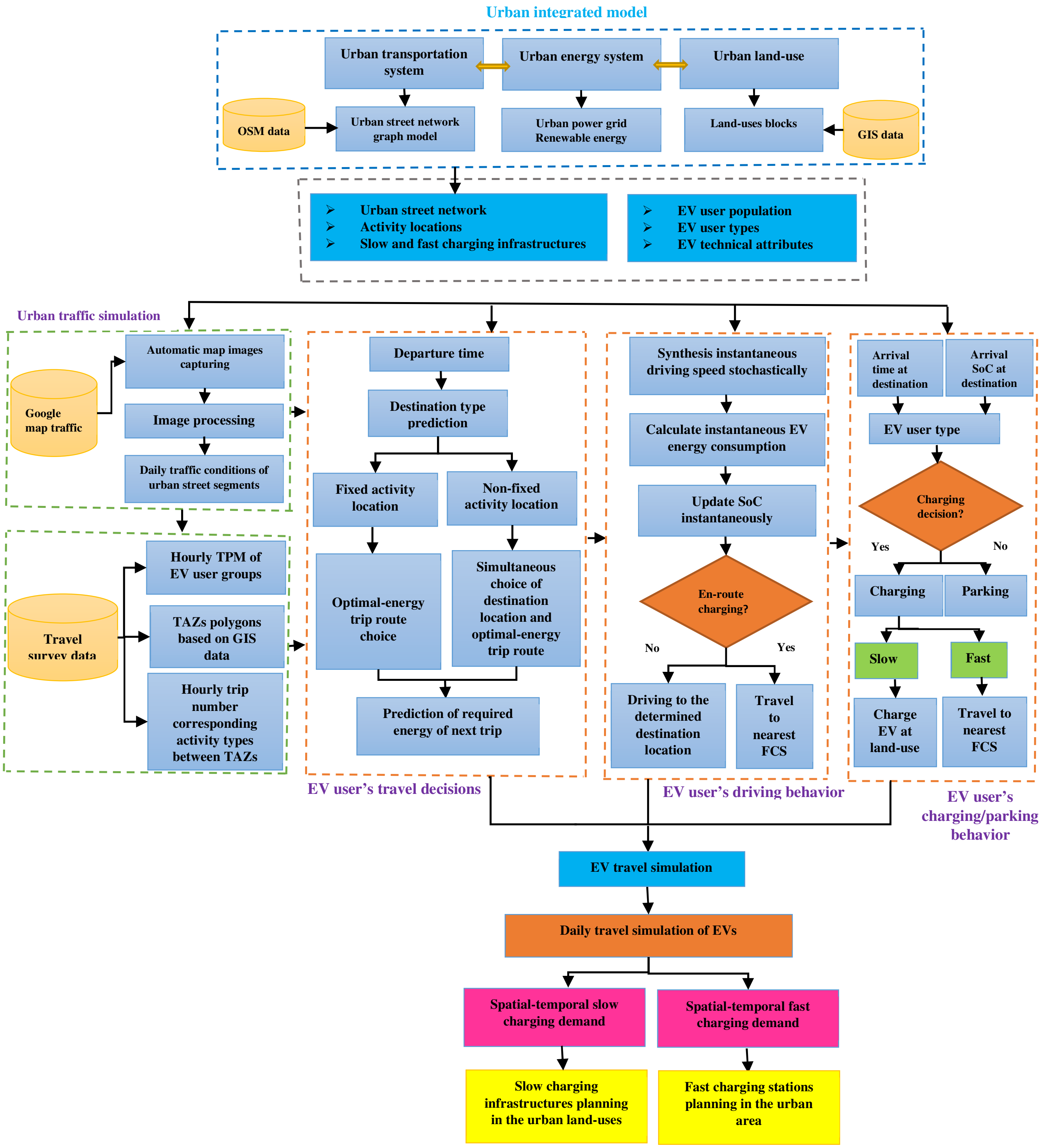


Figure 1.1. Thesis overview flowchart

1.6. Organization of the Thesis

This thesis consists of five chapters that are listed below:

Chapter 1: Introduction

In this chapter, an introduction to urban electromobility modeling is introduced briefly. In addition, the research motivations, objectives, main contributions, overview, and organization of this thesis are also discussed in this chapter.

Chapter 2: Literature Review

In this chapter, basic concepts related to urban electromobility are explained briefly. The state-of-art about various models and simulation methods used for EV mobility simulation are discussed. Along with this detailed review of previous studies, drawbacks from the previous studies have been identified. These drawbacks in the existing studies led to the research on the urban electromobility modeling and simulation in the integration framework of EV-transportation-land use-energy system.

Chapter 3: Integrated Urban Model

This chapter creates the spatial urban model by integrating the urban transportation system and land use. To this end, the urban street network and urban land use are constructed based on GIS data to provide the opportunity to model the spatial attributes of EV mobility in the urban area. Moreover, the tool developed to extract data traffic of the urban area is described in this chapter.

Chapter 4: EV users travel behavior modeling in the urban electromobility framework

This chapter presents the driving and charging behavior models developed to simulate the behavior of EV users in the integration of EV-transportation-land use-energy systems. Accordingly, the spatial-temporal attributes of EV trips are simulated.

Chapter 5: Forecasting Spatial-temporal Charging Demands and Charging infrastructure planning in the urban electromobility simulation

In this chapter, based on the models developed in previous chapters, the daily travels of EVs in the study area are simulated to predict the spatial-temporal charging power in the urban area. The slow charging demand at urban-land uses and fast charging demand at FSC candidates are predicted, which are then used to charging infrastructure planning. Finally, the charging infrastructure planning models are developed based on the economic and convenience objectives of FCS and EV users by considering the urban constraint.

Chapter 6: simulation results and analysis

This chapter provides the numerical simulation for a given EV penetration rate in the study are to represent the efficiency of proposed models in predicting the slow and fast charging demand and planning of charging infrastructures, which are the main objectives of urban electromobility simulation.

Chapter 7: Conclusion and Recommendations for Future Research

This chapter provides an overall assessment of this thesis. The recommendations for future research directions are discussed regarding the extension of research in the urban electromobility for integrating renewable energy to the EV charging system, leading to increasing the synergy between EV and renewable energy and reducing dependency on the urban power grid.

Chapter2

2. Literature Review

2.1. Introduction

The state-of-art various modeling techniques used for modeling electromobility are discussed. Along with this detailed review of previous studies, drawbacks from the previous studies have been identified. These drawbacks led to the research on urban electromobility modeling and simulation in the EV-transportation-land use-energy integrated framework.

Replacing conventional combustion-engine vehicles with EVs is unavoidable in the world due to concerns about the depletion of fossil fuels and urban environmental pollution issues [1]. With the development of EV technology, government incentives for the purchase of EVs, and a significant decrease in EV prices, the number of EVs in the urban transportation system is expected to grow rapidly in the coming years [2]. The large-scale penetration of EVs in the urban transportation system helps increase energy security and reduce emissions [3]. Meanwhile, the uncertainty and flexibility of EV charging power demand pose both challenges to and opportunities for the operation of charging infrastructure, distribution grid, and Renewable Energy Sources (RES) [4]. The great number of EVs will demand a significant amount of charging power and require the construction of a large number of charging infrastructures in urban areas [5]. On the other hand, unscientific construction of charging infrastructure leads to excessive or insufficient charging facilities in different urban zones and causes irregular fluctuations in the urban distribution grid [6]. From the distribution grid perspective, on the one hand, EV will result in a random and uncertain load that leads to increased peak load and load pattern changes [7], the need for capacity expansion and grid reinforcement [8], etc.

On the other hand, EV as distributed energy storage can help improve the operation of the grid by increasing the integration of RES [9-10] and providing ancillary services [11-12]. Furthermore, EV charging with clean energy generated from RES leads to positive environmental effects from EV penetration in urban areas [13] and decreases the distribution system's pressure [14]. Therefore, analyzing and predicting the spatial-temporal distribution of EV charging load demands in urban areas is essential to scientifically determine the optimal site and size of charging infrastructure, reducing the harmful effects of EV charging load on the distribution grid and increasing the synergies of EVs with RES.

2.2. Simulation framework

The electromobility simulations can be implemented within a wide range of simulation frameworks and using various modeling techniques. The probabilistic travel parameters extracted from travel survey data were used to simulate the spatial-temporal driving and charging patterns of EVs to obtain the charging load demand at different times and locations by using stochastic methods like Monte Carlo Simulation (MCS) [15-20], Markov chain [21-22], Markov chain Monte Carlo [23-24], trip chain [25-28], trip chain and Markov decision process (MDP) [29-30]. Nevertheless, most of these studies considered three destination types – home, work, and others – to model the daily travels of EVs, whereas traveling in the urban transportation system should be modeled on a multi-location and multi-purpose framework to reflect realistic traveling in the urban area [31].

The primary purpose of EV charging load modeling is to deduce the traveling behavior of EV drivers in the transportation system to predict the spatial-temporal distribution of the charging power demand in different locations [32-34]. The spatial characteristics of the street network and destination locations and the drivers' decisions in response to the traffic flow of streets connecting destination locations significantly influence the EV travel pattern, EV energy consumption, and the resulting charging demand. In this context, the existing studies on modeling and predicting EV charging load were conducted according to two main frameworks. (1) The first group of studies was performed based on virtual road networks. In these studies, regardless of the topological features of the street network, all travel parameters (e.g., travel distance, travel time, etc.) were modeled by PDFs calibrated by vehicle travel data (mainly the NHTS dataset). Thus, the spatial characteristics of the destination locations and routes of EV trips are neglected, and the travel distance is extracted from PDF (generally lognormal). Moreover, the energy consumption of the trips was estimated based on energy consumption per kilometer of EV driving, which is assumed to be a constant value or a random number obeying a specific PDF. At the same time, the topological characteristics of street networks, OD locations, and traffic flow of the road network significantly affect EV travel behavior, energy consumption, and the resultant charging demand of EVs. (2) In the second group of studies, EV charging demand modeling was conducted based on a simple road network graph containing several edges and nodes. The edges represent the streets, and the nodes are considered the charging locations or functional areas.

Transportation network modeling based on graph theory makes it possible to incorporate the transportation characteristics and traffic flow in the spatial-temporal modeling of EV trips. However, previous studies utilized a graph model to represent transportation systems only containing a few street segments that cannot represent an actual urban transportation system. Although modeling a city-scale transportation system with a huge number of nodes and street segments by graph increases the complexity of the simulation, it leads to obtaining a more accurate and realistic model of urban electromobility.

2.3. Urban traffic simulation

The traffic congestion of urban street networks is an essential factor affecting EVs' energy consumption and charging demand by increasing the driving duration and service time of air conditioning and reducing driving efficiency. The driving behavior of EV users is also affected by the traffic congestion level of streets, so it is assumed that the EV users are aware of the traffic conditions of the urban street network and choose the optimal travel route based on their preferences. In this context, the traffic simulation methods that determine the dynamic traffic conditions of street networks help to model the realistic driving behavior of EV users in more detail. Despite the traffic significantly affecting EVs' driving and charging behaviors, it is rarely considered in the existing studies in electromobility simulations. Only a few recent studies the traffic and speed-flow relationships are considered to model the EV travel patterns. In [35], by considering the topological characteristics of the traffic network and simulating the movement process of the vehicle on the road by using the cellular automata, the space-time prediction of the EV charging load is performed. In [29], the traffic congestion of different roads of assumed transportation network graph in a time period is set to a uniform value, assuming that the congestion degree of different roads has a generally consistent temporal trend, to estimate the EV speed with a simple speed-flow model on the trip route that determined by Dijkstra algorithm as the shortest path. In [36], a Markov-chain traffic model was used to describe the EV traveling characteristics, simulate the EV flow on a traffic network, and determine the fast-charging demand from the spatial and temporal perspective. In [37], a forecasting method based on neural networks is established to predict the hour-by-hour traffic flow of EVs on the traffic network model in the EV charging model. In addition, a road network testbed based on the Dublin traffic network is established to study the willingness of EV drivers to choose the FCS with the lowest travel time considering the network's traffic. In [38], an EV charging demand forecasting method based on real-world traffic volume data collected by the Traffic Monitoring System in the highway, national route, and local roads of South Korea every hour is forecasting the EV charging demand in the residential and commercial sites. The collected traffic data was used to determine the EV charging starting time without considering the traffic impact on travel behaviors of EVs like driving time, driving speed, and travel route. In [39], the daily EV charging is simulated by incorporating the impacts of traffic congestion on the energy consumption of EVs. To this end, the road congestion level of three road types, i.e., express road, main road, and secondary road, and the congestion level of each road was determined according to the calculated driving speed and its road grade, as smooth, basically smooth, slight congestion, medium congestion, and severe congestion. In addition, two indexes are defined to measure the level of traffic congestion and to correct the driving duration and speed. In [40], consider traffic conditions on the EV's route towards its destination by minimizing the total trip duration. It is assumed that the traffic conditions are locally available, either from the vehicular network itself or from an external traffic service, and can be used to estimate the EV's arrival time towards a specific charging speed. Therefore, this paper focuses on the influence of considering traffic conditions on the EVs' charging planning and not on the travel routing based on the dynamic traffic pattern of the city.

Therefore, the influence of traffic congestion of street networks on the driving behavior of EV users includes the driving speed, driving time, driving energy consumption, and the EV user decision on travel route choice rarely considered in previous studies. Moreover, these mentioned studies only considered the traffic for a small traffic network or a city zone. In contrast, the city-wide traffic simulation is needed in the realistic electromobility simulation. In this context, a city-scale traffic simulation is required that be able to determine the traffic condition of actual urban streets to simulate the traffic impact on the driving riving behavior of EV users in urban electromobility simulation. To simulate the urban traffic pattern, the developed countries invest in intelligent transportation research where researchers collect traffic data through loop detectors [41], Radio Frequency Identification (RFID) [42], and sensor networks [43] to model and predict the traffic patterns of urban areas.

Due to the need for a substantial budget to collect traffic data by using advanced instruments and the non-grid structure of the urban street network in developing countries, the mentioned techniques are not still used to collect the traffic data in the cities of Brazil. Moreover, the traditional data collection processes at the city level are tedious and require considerable human effort and instruments. Thus, one solution could be to use a platform like Google Maps. In this context, in this research, the traffic data of the urban street network of the study area is collected from Google Map Traffic Layer (GMTL) to simulate the urban traffic patterns.

2.4. EV user driving behavior

In the studies that used virtual networks for the transportation system, driving behavior is not modeled explicitly. Instead, the related parameters are directly extracted from the travel data of conventional cars or the PDFs fitted on travel data. The spatial attributes of trips (OD locations, trip routes) are ignored in these studies, so they did not propose a framework to analyze and model driving behaviors. Hence, the proposed models are not adequate for urban electromobility simulation.

Several of mentioned studies used a simple small graph to model the travel behavior of EV drivers realistically. In these studies, nodes of the graph are considered destination locations or functional zones (e.g., residential, commercial, etc.). In order to model the travel behavior of drivers, in these studies, the trip destinations were randomly selected from the graph's nodes without considering parameters that affect the destination choice of EV users, such as travel time and attractiveness. In addition, the trip route was randomly selected or determined as the shortest path between nodes of the network graph. The traffic conditions of road networks were mostly considered free-flowing or set to a uniform value over a period of time, assuming that the congestion level of roads has a generally consistent temporal trend. Only a few studies considered real-world traffic to analyze the characteristics of spatial-temporal charging load [44-45]. In these studies, the trip distance was calculated based on the length of edges, and the energy consumption of trips was estimated based on trip distance and energy per kilometer (kWh/km), which was assumed to be a constant value or calculated from the empirical equation corresponding to the assumed road type of edges. However, the virtual road networks or oversimplified road network graphs used in the existing studies cannot accurately represent the actual topological characteristics of real street networks.

Moreover, the choice of random destination and the shortest trip route cannot describe the realistic travel behavior of EV drivers. In addition, underestimated or overestimated energy consumption leads to unrealistic EV charging demand. The assumed traffic conditions or real-world traffic data collected from a small area cannot represent urban transportation systems' real-world city-scale dynamic traffic. Therefore, the proposed models in the existing study cannot be adequate to model the realistic driving behavior of EV drivers in the urban environment, including the extensive street network with dynamic traffic patterns that highly affect the driver behavior. Hence, to model the driving behavior of EV users, it is essential that their decision-making on the spatial-temporal attributes of their trips in the urban area explicitly are modeled, which is one of the objectives of this research.

Besides the driver behavior in destination and route selection for each trip, the EV driving pattern of EV on the urban selected trip route on the street network should be modeled to determine the driving time, driving energy consumption, etc. In this regard, the instantaneous driving speed of EV on the trip route must be modeled according to the street speed limits and traffic conditions. In this context, the driving cycle generation methods can be used to model the instantaneous velocity, acceleration, and driving distance of EV driving patterns. In [46], the standard driving cycles include Environmental Protection Agency (EPA), Urban Dynamometer Driving Schedule (UDDS), Highway Fuel Economy Cycle (HWFET), and high acceleration aggressive driving (US06) are incorporated by power train model to calculate the energy consumption of EVs and determine the SoC profiles of EV trips. Although this paper represents a more accurate model than papers that only consider constant energy consumption for EVs, standard driving cycles cannot display realistic driving conditions because the standard cycles are only recorded under certain, precise conditions and may not always represent real-world driving conditions [47].

Due to the stochastic nature of driving in the urban transportation system, stochastic driving cycles can represent realistic driving patterns. In [48], the stochastic driving cycles are generated from standard driving cycles UDDS, HWFET, Artemis Urban (AU), and Artemis Road (AR). However, the stochastic driving cycles generated in these papers cannot represent the real-world driving condition because they are generated from standard driving cycles with limited datapoint despite being stochastic. Therefore, stochastic driving cycle generation needs a sizeable real-world dataset to better demonstrate the realistic driving conditions. In this regard, in the absence of EV driving cycle data, the large-scale driving dataset of the National Renewable Energy Laboratory (NREL) [49], which has been used widely in previous studies, is used to generate the stochastic driving cycle for each EV trip in this thesis.

Therefore, the integration of urban street network and land use provide a platform to model the driving behavior of EVs accurately based on the developed models of destination type prediction, destination location choice, route choice, and synthesis stochastic driving cycle for each EV trip, which are not considered in previous studies.

2.5. EV user charging behavior

Besides the EV user driving behavior, the user charging behavior affects the EV charging demand of the urban area. In this regard, realistic models should be developed to simulate the user charging behavior by considering the main affecting parameters on user decision in the charging EV. Moreover, the user preference for charging mode, charging location, and charging time should be considered to achieve more accurate urban charging demand prediction.

2.5.1. Classification of EV charging modes

When the EV is connected to the power grid through the EV charger, its battery is charged through the AC/DC power converter. This converter can either be on-board (inside the EV) or off-board (outside the EV). The power level of these chargers varies for various manufacturers [50-52]. In addition, there are multiple types of battery technologies used by the EV manufacturers, such as lead-acid batteries [53], lithium-ion batteries [54], and nickel-metal hydride (NiMH) batteries [55]. With the recent progress in lithium-ion battery technology, it has used almost all of the current EV models in these recent years. EV charging mode can be classified based on the charging power rate that the EV is charged. The EV charging mode is mainly classified into slow and fast charging modes [56]. Besides the slow and fast charging modes, EV charging can also be classified into Level I, Level II, and Level III.

Levels I and II chargers are considered slow charging due to their relatively low power ratings. Level III chargers are considered fast chargers due to their higher power ratings, usually known as DC fast chargers. The DC fast charging is the most helpful method to decrease the range anxiety of EV users [50]. However, DC fast charging brings an increased rate of battery degradation. It also shows disadvantages such as voltage sags and voltage flickers in the power distribution system [57].

2.5.2. Charging decision

The threshold-based charging behavior models are used in studies by assuming that the charging decision is made at a destination when the SoC is reached below certain SOC thresholds. For instance, in [58], charging is assumed to occur whenever EV arrives at a destination with a SOC of below 30% or when their SOC falls below 60%, and the parking duration is longer than two hours. Similarly, [59-62] stipulates fixed charging thresholds. Contrary to realistic charging behavior, users might decide to charge in anticipation of their impending energy consumption. Threshold-based behaviors assume that users blindly use their EVs until charging becomes unavoidable. Like SOC thresholds, the en-route charging is decided by EV users if they cannot complete their ongoing trip due to an empty battery [63-65]. Few studies considered charging opportunities within the context of their overall mobility behavior. In this context, authors in [66-67] show that more realistic charging behavior can be simulated when future demand is considered. [68] implement plan-aware agents who choose to charge whenever their SOC is below their estimated SOC requirements for future trips plus a safety margin. None of those mentioned above models considers influencing variables other than the vehicle's SOC.

2.5.3. Charging location choice

Charging location choice is another important aspect of modeling user charging behavior in electromobility simulations. Usually, both charging decisions and charging location choices are made simultaneously, especially for slow charging mode. The simplest forms of integrated location choice assume users always charge at home [69] or–even more bindingly–at any destination with charging opportunity [70]. In the vast majority of studies mentioned above, especially to choose an FCS, charging is modeled to occur at the nearest charging station as soon as the respective charging behavior calls for recharging. In simulations where trips cannot be interrupted, or chargers are available at only a few dedicated facilities, agents charge at their trip destinations or the nearest charging station after completing their trip. Ref. [71] expressed that drivers prefer to charge at the home and workplace rather than public charging stations. The [72] used a mixed logit model to determine the charging choice at the end of each trip and assumed that charging usually occurs after the last trip when returning home. Ref. [73] shows that most users prefer to charge at midnight. The study in [74] concluded that the main predictors for choosing the charging location and mode are the battery capacity, midnight indicator, SoC, etc. However, a few existing studies investigated the choice of charging stations (private/workplace or public) and the charging preference of public stations of users. While EV users meet several destination types in their daily trips and have the opportunity to charge their EV at home (private), working places, and public charging stations, most studies consider one or two fixed locations to charge EVs. Therefore, to model the user charging behavior in urban electromobility, it is essential that charging behavior is modeled in a multi-purpose, multi-location context of EV trips in the urban environment by taking into account the user preferences and influencing factors on the user's charging decision such as SoC, required energy for next trip, range anxiety, charging convenience, midnight charging, etc.

2.6. Spatial-temporal charging demand predictions

In recent years, extensive studies have been conducted on EV charging load modeling and forecasting. Two datasets are used to model EV charging demand in the studies: historical charging data and travel data of conventional vehicles. The historical charging data were collected from the private and public charging infrastructure in the form of charging power (kW) and energy (kWh), and the State of Charge (SoC) of EV batteries was directly employed to predict and model the charging load demand through data-driven and machine learning [75-78]. Historical data-based forecasting models can only be used for a specific area from which the data comes, making the models less scalable.

Unlike historical charging data that was only used in a few studies, vehicle trip datasets are widely used in most existing studies. Since nowadays EVs are not yet widespread in the transportation system, especially in developing countries, travel data of conventional vehicles are used to model EV travel patterns on the assumption that EVs have similar driving patterns to traditional vehicles and the advent of EVs will not affect the daily travel patterns of cars in the transportation system. The vehicle travel datasets include household travel survey data, e.g., National Household Travel Survey (NHTS) [79], Origin-Destination (OD) travel data [80], and vehicle GPS data [81] that were collected from a specific region over a period of time. Travel parameters such as start and end times of trips, travel distance, and driving time are modeled by Probability Density Functions (PDFs) calibrated by travel data. With these input parameters, probabilistic models were developed to simulate the stochastic nature of EV driving and charging patterns to obtain EVs' charging demand [82-86].

In Ref. [87], probabilistic models of time of departure from home, time of arriving at home, and daily travel distance were used to model EVs stochastic travel by assuming that the EVs are charged once per day at home. In [88], the charging load of EVs is estimated at the home and workplace without considering other locations. The charging load of EVs in public charging stations is modeled in [89], while EV load demands in the other locations are not considered. The charging demand obtained by these studies cannot be accurate enough because of ignoring the possibility of EV charging in multiple locations. Thus, these models cannot be used to model the urban EV charging demand, which should be modeled in multi-locations of urban areas, including private and public locations. Tao et al. [90] utilized the Monte Carlo method to draw the trip chain of EVs based on NHTS data and developed a charging demand prediction probability model to evaluate the charging load in different locations and times. Wang and David [91] allocated a dynamic trip chain for each EV in a region through the Markov chain Monte Carlo (MCMC) approach, simulated vehicle travel and charging behaviors, and proposed a dynamic charging demand model to analyze the uncertainty of charging effects in homes, workplaces and commercial areas. Ref. [92] proposed a dynamic probabilistic spatial-temporal model for EV charging demand. The temporal characteristics include the driving time and parking time. The spatial attributes of travel include the travel distance and destination transitions modeled by Probability Distribution Functions (PDFs) calibrated by travel survey data. Ref. [93], probabilistic spatial-temporal model to simulate the daily profile of EV charging load based on the refined probabilistic models and Monte Carlo algorithm. In the above studies, all spatial and temporal parameters of EV travel patterns are extracted from the travel survey data without considering the impact of road networks on the EV travel patterns modeling.

2.7. Charging infrastructures planning

The EV users prefer to charge their EVs at their daily itinerary's primary activity locations (home and work). However, since all EV users have no access to charging facilities at home or workplace, or when EVs need emergency charging, the public charging facilities are selected by users to meet their changing demands. Thus, the lack of enough slow and fast public charging infrastructure can be one of the main barriers to accepting electromobility by the people and urban transportation electrification. Thus, comparing the models for slow charging stations with those for FCS in the literature, it is clear that models for FCS are based on the street network while models for slow charging stations are based on zones. Most existing models in literature only consider FCS planning without considering the actual street network. As such, most of the models are not realistic and not applicable in urban charging infrastructures planning.

2.8. Slow charging infrastructures planning

According to the estimated charging demand of city zones, some studies investigated slow charging stations. In [94], the daytime and nighttime charging demands in each Traffic analysis zone (TAZ) are estimated based on employment and residence data. An optimization model maximized the total coverage with a given number of charging stations. [95] estimated the charging demand for each TAZ, and the assigned slow charging stations aim to maximize the chargers' usage. In [96], regression analysis based on travel survey data was also used to estimate charging demand in each TAZ and develop an optimization model to minimize the total access cost of EVs to their nearest charging stations. In [94,96], the centroid-to-centroid distances between TAZs were estimated to assign EV to a TAZ, and a charging station was located at the centroid of each TAZ. However, the proposed models in these studies are problematic and inaccurate because they did not distinguish whether a TAZ is partially covered or fully covered. A TAZ of a city includes different land use and activity locations. Hence slow charging station planning at the TAZ level is not realistic because EV users choose a charging station for slow charging in or near (walking distance up to 300 meters) their activity locations.

Moreover, in these studies, the dynamic EV mobility in the city is neglected, and charging demands are estimated based on simple assumptions.

2.9. Fast charging infrastructures planning

A large number of studies can be found in the specialized literature devoted to locating the FSC with a particular focus on developing mathematical optimization models. However, in order to implement the mathematical optimization models on the urban transportation system, two main issues should be taken into account: firstly, the optimization models will be multi-objective optimization include constraints related to the EV user preferences, transportation system, and FCS make the problem more challenging to solve and need very high computational time [97-100]. In other words, due to a large number of constraints, the optimization problem is NP-hard, which is impractical to apply on large systems [97,101]. Secondly, the optimization problem for an extensive urban transportation system leads to a high computational burden. As a result, it is impossible to solve the mathematical optimization models for a comprehensive urban transportation system within an acceptable time. Therefore, the FCS planning problem as an NP-hard problem is mainly solved by clustering algorithms and heuristic methods. The clustering methods were used to determine the FCS locations by clustering the fast charging demand points and assigning FCSs into the cluster centers. In [102], a hybrid algorithm based on K-means clustering was developed to site and size charging systems to satisfy the EV fleet's changing demands. In [103], the iterative clustering technique was proposed to deploy fast charging infrastructures in large urban areas for electric taxis. In this regard, an iterative version of Density-based Spatial Clustering of Applications with Noise (DBSCAN) was used to find the charging station locations that satisfy the charging demand of an electric taxi fleet. In [104], a taxi trajectory data-based FCS planning was developed based on iterative K-means clustering to meet the hourly demand of an e-taxi fleet. Although the clustering methods can find the solutions quickly for an extensive system, they only consider the distance between demand points to find the centers of the clusters as FCS locations. Due to ignoring the urban structure, they may allocate FCSs at unfeasible locations.

Contrary to the clustering methods, the heuristic methods consider the optimization criteria to develop an algorithm to find optimal size and site of FCS with trad-off between different constraints imposed by the urban environment, street network structure, urban traffic, and economic constraint investments, user preferences, etc. AS such, it is more officinal than clustering algorithms. In [105], an FCS locating model named the multipath refueling location model was proposed and solved using heuristic algorithms to locate FCS in Sioux Falls. In [106], the FCS planning problem was carried out through the heuristic method to avoid the high computational effort that results from traditional optimization models. In [107], a heuristic method was designed for charging infrastructure planning in virtual urban contexts based on distance, economic objective, and infinite capacity constraint to meet the estimated hourly demand of charging demands. In [108], presented a heuristic methodology for urban transportation networks, considering the deployment of the FCS for coverage objective and the fulfillment of user preferences and constraints.

2.10. Research gaps

According to the above literature review, although the available research investigates the EV mobility, spatial-temporal prediction of charging load, charging facilities planning, due to the following issues, the proposed approaches in existing studies are not suitable to urban electromobility simulations.

(1) The actual urban street networks and their traffic conditions are neglected in most studies. Nonetheless, several studies used a small graph to represent the street network. The proposed models in these studies to EV mobility simulation are not applicable for the urban area with a large street network and dynamic traffic.

(2) In most existing studies, the energy consumption of EV trips is simply calculated by assuming constant energy consumption per kilometer. This oversimplification leads to an inaccurate estimation of EV charging demand and the urban charging power demand.

(3) The previous studies mainly utilized the travel survey data to model the travel distance and travel time of EV trips. While these parameters should be calculated based on urban street network topology and dynamic traffic conditions. As such, the EV mobility models in these studies are not suitable for urban electromobility simulation.

(4) In existing studies, the daily travels of EVs are widely modeled as simple trip chains with few trip purposes in a virtual network. This model of EV daily trips is not realistic for urban electromobility simulation. In the accurate urban electromobility simulation, the EV daily trips should be modeled in a multi-purpose framework between different

activity locations in the actual urban land-uses to obtain accurate spatial-temporal charging power demand.

(5) The effect of traffic on EV mobility is ignored in most studies. Some studies considered constant traffic congestion levels for EV driving on a small street network graph. A few studies used the actual traffic data of a small region to simulate EV mobility. While, in urban electromobility, the city-scale dynamic traffic simulation is needed to model EV mobility on a large-scale urban street network.

(6) In almost all studies, the destination choice and route choice behavior of EV drivers are neglected in EV mobility simulation. Few recent studies modeled the destination and route choice by a random process in which destination and route of trips are randomly selected from available destinations and routes. The random choice model ignores the factors influencing user decisions on destination and route, such as user preferences, traffic, EV energy consumption, activity locations attractiveness, etc.

(7) The threshold-based modeling of EV user charging behavior, charging at a fixed location at a fixed time of day that widely were used in previous studies, cannot represent the realistic charging behavior of EV users. For urban electromobility simulation, it is essential to model the charging behavior in a multi-location framework by considering the main influencing parameters on the users' behaviors such as charging location access, location priority, range anxiety, as well as considering different charging strategies and charging modes.

(8) The charging infrastructure planning models in the studies are mainly developed to determine the location of charging facilities in a small area of the city or a hypothetical network. These studies ignored the urban spatial attributes, and the proposed models are applicable in greenfield planning. However, in urban electromobility simulation, the urban spatial structure and urban traffic should be considered in charging infrastructures planning.

To address the mentioned research gaps, this thesis proposes the urban electromobility simulation based on the EV user driving and charging behavior modeling in the integration framework of EV-transportation-land use-energy to predict spatial-temporal urban charging power demand and slow/fast charging infrastructures planning.

Chapter 3

3. Integrated Urban Model

3.1. Introduction

An integrated urban model would be able to consider land use–transport–energy interactions with explicit spatial-temporal representations at the zonal scale. In an integrated urban model representing interplays between transport land use and energy, EV consumes energy while driving on the transportation system and can be charged at charging infrastructures located at land-uses and the street network at any time. The interaction of EV driver with an integrated framework of transport-land use- energy is translated into EV driver driving and charging behaviors.

3.1.1. Transportation system and land use integrating

Transportation in urban areas is highly complex, and its complexity is related to the urban spatial structure. The spatial distribution of human activities in the urban area creates the need for travel to overcome the distance between the locations of activities. Urban land use represents the location and level of spatial accumulation of activities and is characterized by social, cultural, and economic activities forming an activity system at separate locations. Land use is the characterization of land based on what can be built on it. It determines what kind of community, environment, or settlement can be used on a particular type of land. It is worth noting that land use and zoning are not the same, so that land use is the way that people adapt the land to suit their needs, and zoning is how the government regulates the land. Transport networks provide connectivity between activity locations in land-uses through the street network. Therefore, transportation and land use are interrelated because of urban activities' locational and interactional nature. Two-way interaction of land use and transport led to the notion of the 'land use transport feedback cycle' that theorizes the complex relationships between the transport network and land use, which can be briefly summarized as follows.

- The distribution of land uses, such as residential, industrial, or commercial, over the urban area determines the locations of human activities such as living, working, shopping, education, or leisure.
- The distribution of human activities in space requires spatial interactions or trips in the transport system to overcome the distance between the locations of activities.
- The distribution of infrastructure in the transport system creates opportunities for spatial interactions and can be measured as accessibility.
- The distribution of accessibility in space co-determines the destination location and route decisions of daily travels

According to the land use transport feedback cycle that is shown in Figure 3.1, the accessibility, availability, and attractiveness of locations in different land-use are indicators to choose an activity location in a land-use. The transportation system creates spatial accessibility so that there is a path between every two locations of land uses, including different street types. Therefore, integrated transportation and land use outcomes provide the potential activity locations in different land uses and possible street paths between activity locations.

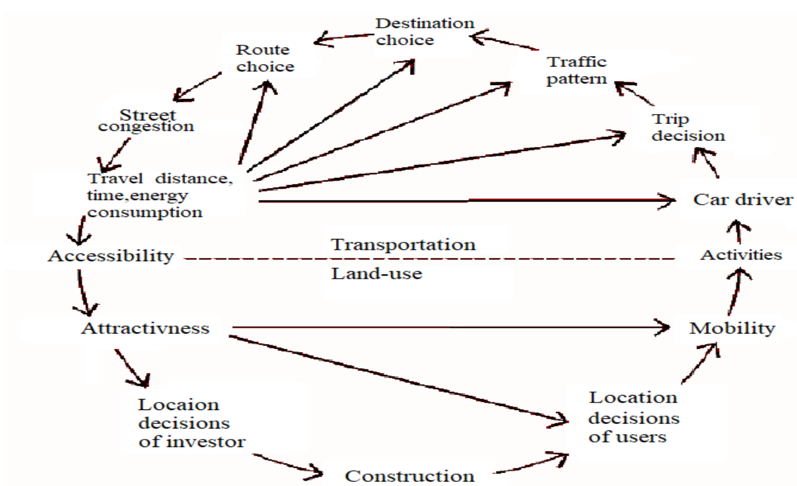


Figure 3.1. The land-use transport feedback cycle

Transport networks, together with land-use patterns and sociodemographic traits, attitudes, and preferences–co-determine EV users' travel behavior, that is, the way they use the transport networks to connect their activity locations. As such, the transportation system and land-use integration provide a framework to model the travel behaviors of EV users. The outcomes of this integration for EV drivers are the potential activity locations in different land uses and the possible paths on the street network to reach these activity locations.

3.1.2. Urban Transportation, land use, and energy integrating

Land use and transport are intertwined and correlate with energy consumption, particularly in urban areas. Thus, urban mobility is not only affected by transport-land use but also by energy consumption and demand. In this context, EVs consume energy while driving on the street network and are charged charging stations located at land-uses. The energy system can include energy demand not only from the EVs but also from conventional stationary demand sources related to activity locations at land uses (e.g., households, offices, firms, etc.). Moreover, it is essential to note that EV diffusion may increase CO2 emissions if EVs are charged with carbon-intensive electricity. RES, especially Photovoltaics (PVs), prevents such an adverse effect. On the other hand, if EVs are completely charged only from RES, the negative correlation between the energy system and CO2 emissions from the transport sector might be changed. Hence, the conventional fossil energy sources of the energy system in the integrated urban can be included in the RES urban energy system to supply the traditional and EV demands.

3.2.Urban transportation system spatial modeling

To achieve an accurate model of EV mobility in the urban electromobility simulation, the EV position and its status (driving, parking, or charging) must be monitored at each time of day. The instantaneous EV's position in driving state is on the urban street network, and at the parking/charging states is at activities locations or charging stations. The spatial integrated urban model, which integrates transportation-land use systems, provides the opportunity to determine the instantaneous EV's position. For each trip, EV departs from an origin location at specific land use and passes from several street segments to reach a destination location at another land use. Urban transportation system provides the connectivity between Origin-Destination (OD) locations of trips by the street network with different attributes. Therefore, to simulate urban electromobility, a spatial model of the transportation system is needed with the following attributes.

- A street network consisting of all actual urban streets that provides the connection between each pair of locations in the urban area.
- The different street types of the street network must be known to predict the EV driving characteristics regarding the traffic and speed limit of the streets.
- Regarding the EV driver preference to choose an optimal trip route on the street network between OD locations, the routing algorithm is needed to find the optimal route. Hence, the street network should be able to be modeled as a graph to determine the optimal trip route between locations by routing algorithm.

To model the urban street network with the specifications mentioned above, the GIS data of all actual streets are required to create a fully connected graph of the street network. The street network data can be collected from different government agencies, and map providers, who often deliver data in non-standard formats, and datasets provided by various agencies are typically not explicitly referenced to each other. OpenStreetMap (OSM) [109] offers geospatial data of streets and their attribute. OSM provides an open-source collection of real-world street network data, including geospatial information about streets and intersections, along with attribute data about street types. Hence, it is suitable for modeling the urban street network in urban mobility studies. Moreover, OSM data allows modeling the street network as a graph with nodes representing street intersections and edges representing street segments. However, OSM data cannot be automatically extracted into a graph, and an interface with computing environments (like MATLAB) is required to process the data and generate a graph.

3.2.1. The general structure of OSM data

The OSM data structure comprises two essential elements to assess spatial data: geometry and attributes. The attributes are described with tags on any geometry. Tags provide information to the user about the particular element to which they are attached. They contain two free-format text items, such as key-value pairs. The geometry consists of three components: nodes, ways, and relations. The node geometry basically represents a specific point on the Earth's surface by its latitude, longitude, and ID. The way geometry consists of the lines connecting two or more nodes. The relation geometry logically defines geographic relationships between geometry and tags with respect to their order. As nodes, ways, and relations describe the spatial distribution of the elements, and tags contain all non-spatial information. A tag is a combination of a key and a value which are both arbitrary strings. It can be attached to nodes, ways, and relations. A road feature is stored as a way element in OSM data, which includes a geometric part composed of ordered referenced nodes and an attribute part consisting of several key-value pairs. A referenced node contains an ID that can be used to retrieve its latitude and longitude.

3.2.2. Extracting GIS data of OSM

The GIS formatted data files of the desired urban area are downloaded and imported in MATLAB to extract information contained in the files by a parsing script. As such, the geometry and attributes of streets are obtained. The streets are stored as ways with the tag 'highway' and one of the following values: "motorway," "primary," "secondary," "tertiary," "residential," etc. There are several steps required to produce the street network segments. Firstly, the OSM ways that contain a 'highway' tag are extracted and inserted into a street segments table, keeping the complete tag contents. Secondly, according to road hierarchy using the associated tags, the street segments are classified into the motorway, trunk, primary, secondary, tertiary, residential, motorway_link, trunk_link, primary_link, secondary_link, tertiary_link. Thirdly, the street segments are corrected for possible geometry and topology problems. In this research, the urban area of Campinas, Brazil, is considered the study area. The study area is 116.525 km^2 that includes the 113062 street segments and 49532 intersections. Figure 3.2 shows all the study area's actual streets with different street types (determined with different colors).

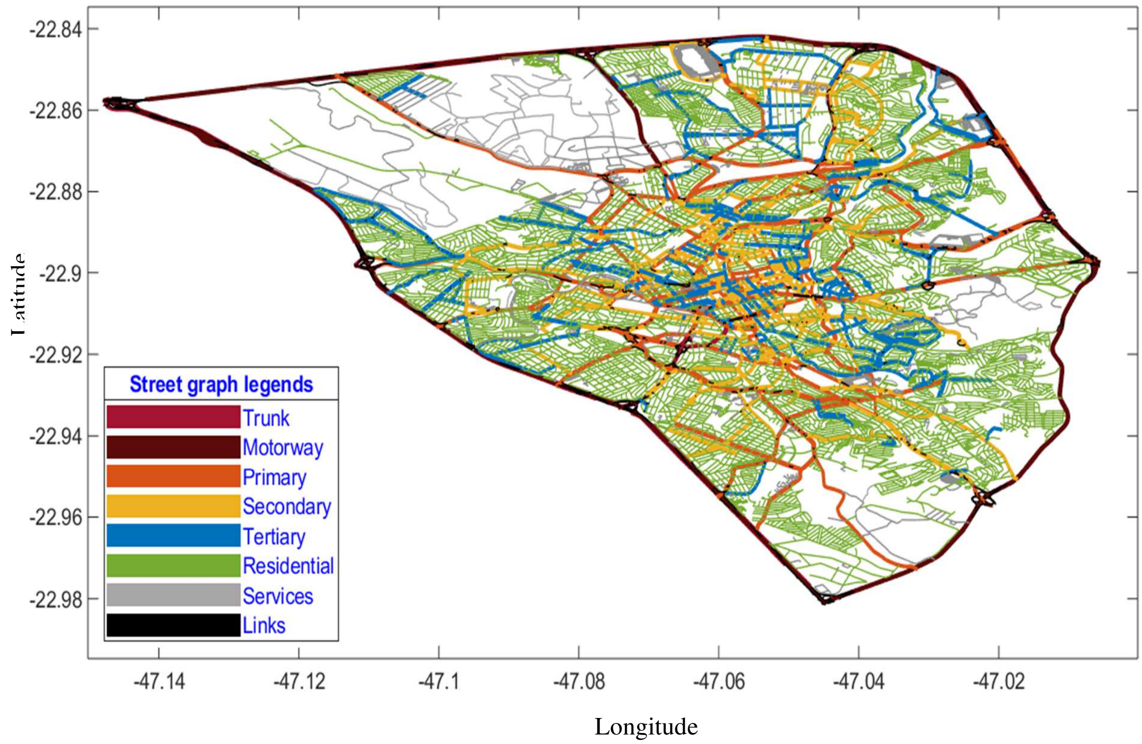


Figure 3.2. Urban street network.

3.2.3. Graph-based Street Network Model

Graph theory is considered a meaningful way to study street network analysis**.** The transportation network is spatially modeled by a street network graph, where nodes are intersections and edges are road segments. The extracted urban streets GIS data from OSM is used to construct the street network graph $G = (V, E)$, in which the vertex set V consists of street intersections, and the edge set E includes street segments between intersections.

An adjacency matrix is required to construct this graph that indicates the adjacent relation between nodes in the network. Some intersections may appear multiple times in the streets connectivity matrix because different streets may meet at the same intersection, and various directions are considered different streets.

To obtain the adjacency matrix, the unique nodes are identified, and a square orthogonal matrix is obtained with the size equal to all unique nod numbers. The square adjacency matrix is generated so that the corresponding entry of two nodes is one if there is a connection between them and otherwise is zero. Finally, the fully connected graph is created based on nodes' adjacency matrix and geographic information (latitude and longitude).

The procedure of constructing the street network graph from OSM data is summarized below.

(1) The desired area's OSM data is downloaded, the data files are imported in MATLAB, and a parsing script extracts part of the information contained in the files.

(2) The OSM ways that contain a 'highway' tag are extracted as street segments.

(3) According to road hierarchy, according to the associated key-value, the street segments are classified into the motorway, trunk, primary, secondary, tertiary, residential, motorway-link, trunk-link, primary-link, secondary-link, tertiary-link, etc.

(4) The street segments are corrected for possible geometry and topology problems.

(5) A square adjacency matrix is generated so that the corresponding entry of two nodes is one if there is a connection between them and otherwise is zero.

(6) The street network graph is created based on the adjacency matrix and intersection nodes' latitudes and Longitudes (Lat/Longs).

The street network graph constructed according to the above procedure for the study area is shown in Figure 3.3. In the created graph, between each pair of graph nodes, there is a path consisting of several edges. Each edge is represented as a street segment with the specified type, and its length is calculated by the Haversine function using the latitude and longitude of nodes at the two ends of the edge.

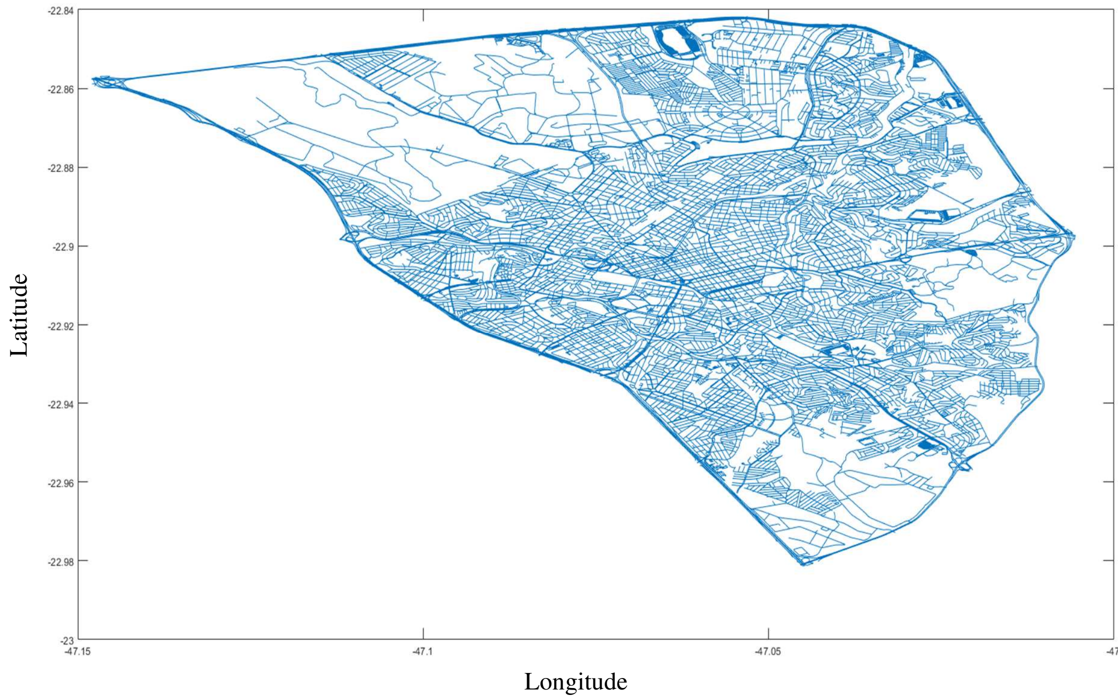


Figure 3.3. Urban street network graph

3.3.Urban land-use model

Each EV travel is taken to perform an activity at the destination location. The EV user's decision in selecting the destination location is influenced by the distribution of activity locations in the urban area. The actual urban land use information helps model the destination choice of trips more realistically, which was ignored in the existing studies of EV charging demand modeling.

In this research, the GIS data of the actual land use of Campinas provided by Prefecture Municipal de Campinas [110] are used to develop the polygon-based model of urban land use. The land uses are classified into residential, commercial and service, industrial, mixed, shopping mall, hypermarket, education, institution, leisure and sport, park, greenfield, and especial. The residential land use is divided into single-family, single and multi-family, and multi-family land uses. The mixed land uses consist of residential-commercial (RC), residential-industrial (RI), commercial-industrial (CI), and residential-commercial-industrial (RCI). The special land uses include military, and cemetery land uses.

In order to integrate land uses with the urban street network constructed based on OSM data, the GIS data of urban land use polygons are converted to geographic coordinates. As such, the polygon vertices specified by Lat/Longs determine the geographic boundaries of the land use. Figure 3.4 shows the urban land use of the study area.

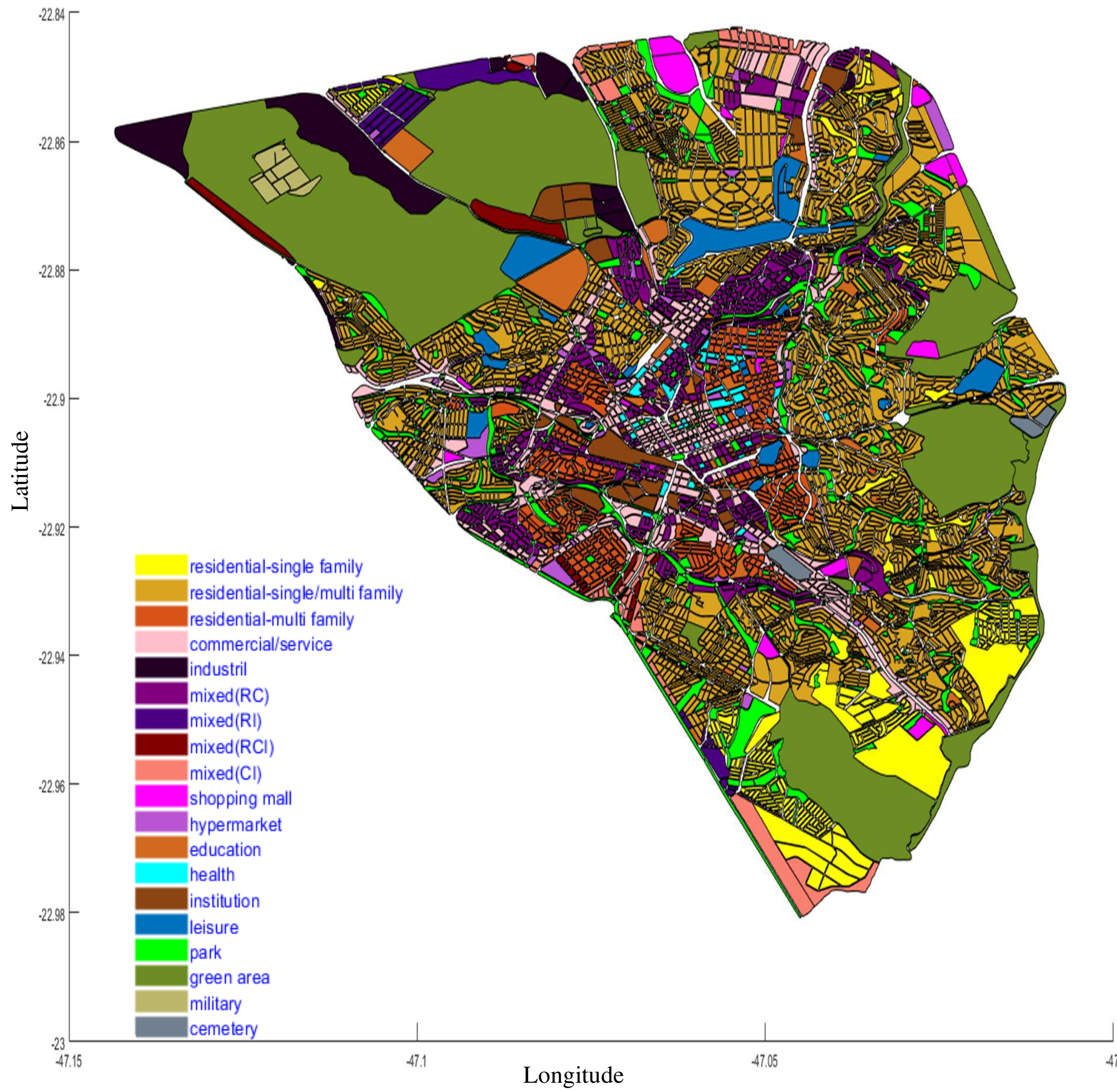


Figure 3.4. Urban land-use of the study area.

The urban street network and urban land-use blocks are integrated to model the spatial attributes of EV mobility in the urban electromobility simulation. Figure 3.5 shows the integration of the street network and land-uses block of the study area.

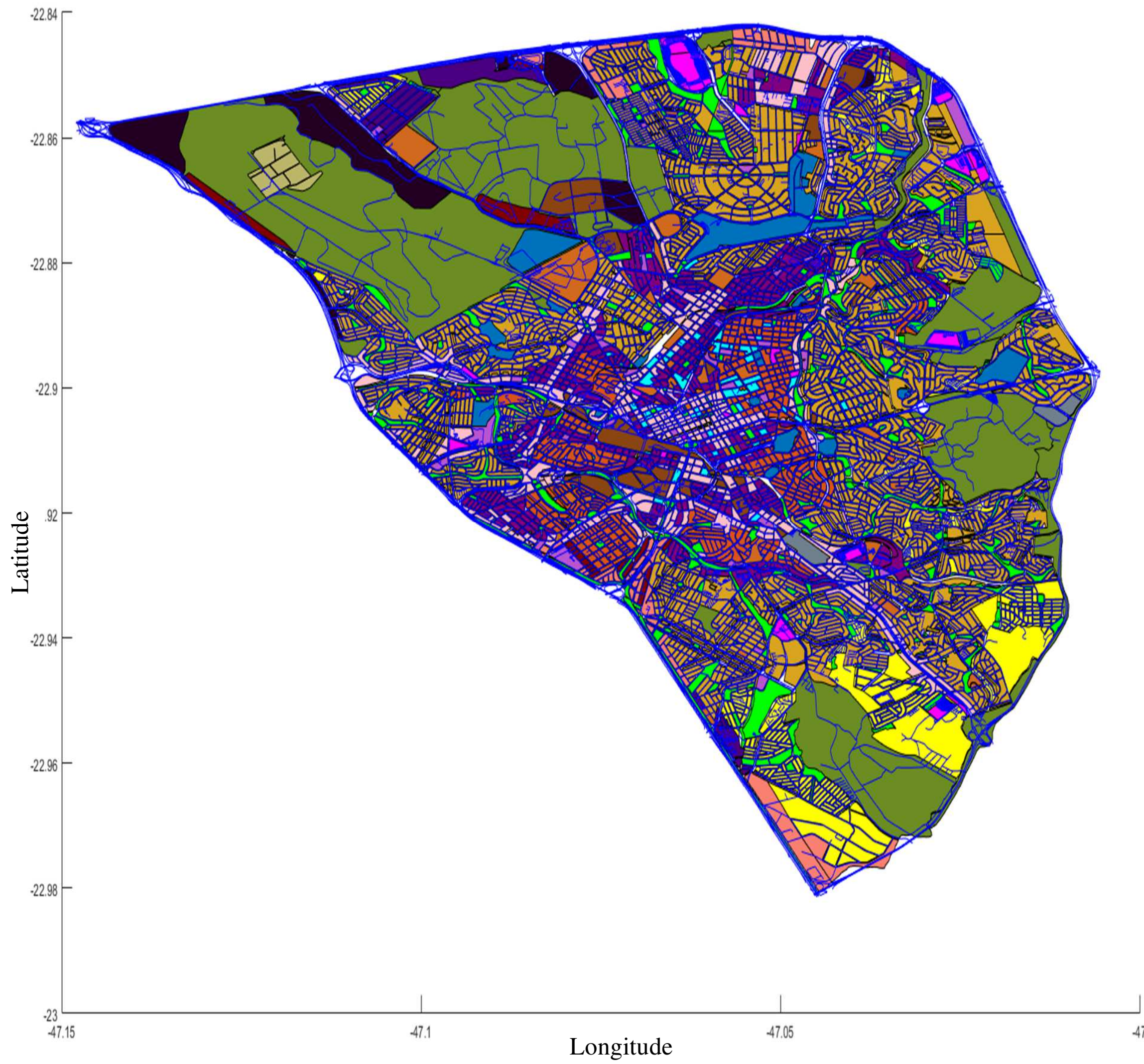


Figure 3.5. Integration of the street network and land-uses of the study area.

3.4.Transportation Analysis Zones

Since the travel data of the study area was collected at the Transportation Analysis Zone (TAZ) level, to utilize this dataset in proposed models in the thesis, the urban zoning based on TAZs is also considered. The travel data for the study area is extracted from the Origin and Destination survey of the Metropolitan Region of Campinas, OD-MRC, which was carried out by the Metropolitan Transportation Secretariat of São Paulo (MTSSP) [111], comprises the spatial and temporal information of the travels made by the population in the city. To capture the spatial characteristics of travels, the city was divided into TAZs. The trips' spatial characteristics were collected at the TAZ level, including the OD’s TAZs of trips. Moreover, the temporal attributes include the trip’s start time and end time, travel time, and dwelling time at the destination are recorded for each trip. The study area consists of 30 TAZs from the TAZs defined by MTSSP. Each TAZ is represented by a polygon that shows the geographical boundaries of the TAZ. Figure 3.6 shows the TAZ polygons of the study area.

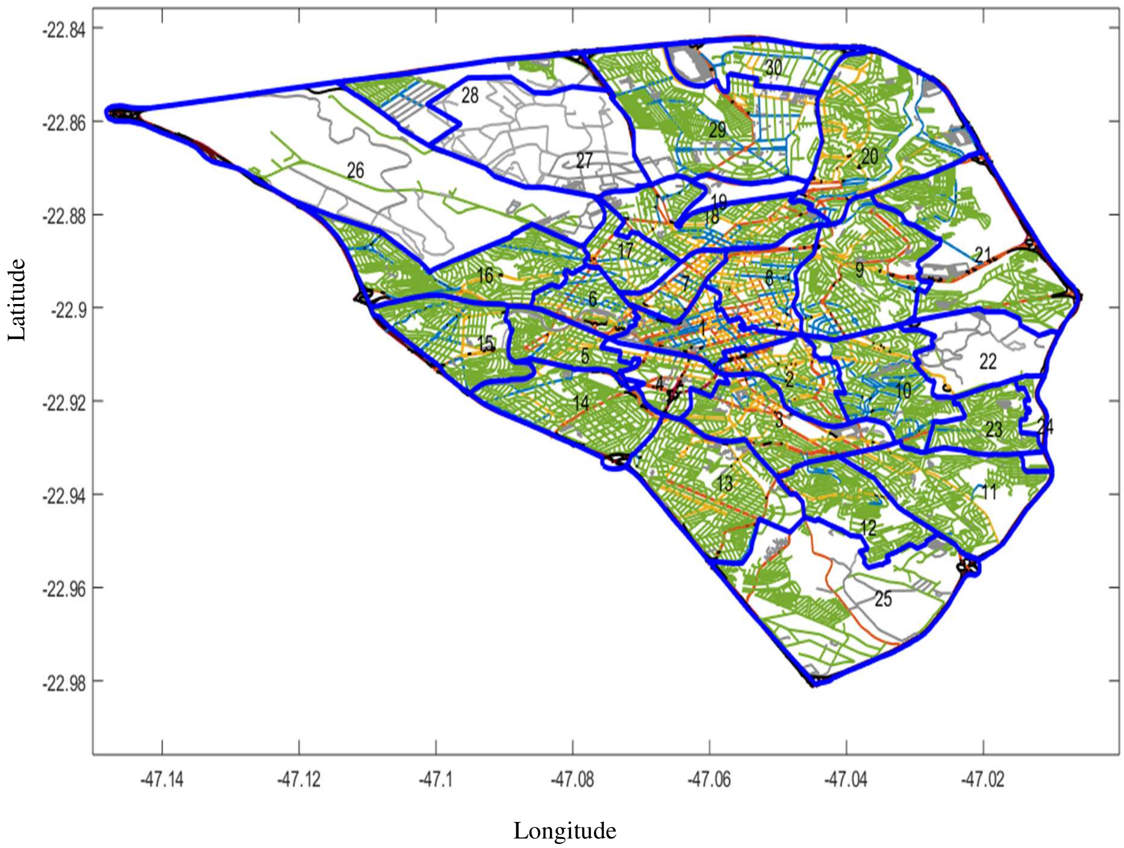


Figure 3.6. TAZs of the study area.

3.5.Urban traffic simulation

The urban traffic simulation methods proposed in the literature are essentially different in terms of traffic data collection. The approaches used to collect traffic data include data collection through advanced instruments (e.g., loop detectors, Radio Frequency Identification (RFID), sensor networks, etc.), traffic data collection using GPS data (e.g., taxi GPS data, cell phones in vehicles), manual counting (manual traffic volume count) of cars in a specific case study area, etc. Data collection with advanced instruments is costly, and traditional traffic data collection is time-consuming and requires significant human effort. Moreover, these approaches are not scalable for city-wide traffic data collection, and it is practically impossible to collect traffic data for all street segments of the city.

The modeling of urban street networks based on OSM geographical data makes it possible to use traffic information data provided by mapping systems such as Google Maps. Customizable, scalable, and cost-effective traffic data can be obtained by using Google Map Traffic Layer (GMTL), which provides valuable and continually updated traffic information of streets at the city scale. GMTL represents the traffic conditions of the streets by colors at any given time: green (smooth traffic), orange (moderate traffic), red (heavy traffic), dark red (Traffic jam), and white (no traffic).

However, GMTL does not provide the traffic dataset of streets, and it updates the traffic conditions of streets by colors at each moment. Hence, a method is needed to automatically capture GMTL images off streets and detect their traffic colors. In this regard, a tool is developed that captures GMLT images with a certain time-step over a desired period to provide the traffic data of the study area. This tool includes pre-processing GMTL images of the study area, automatically capturing GMTL images over the day, image processing, and determining the traffic condition of each street segment of the urban street network. The following subsections describe each step of the proposed tool in more detail.

3.5.1. Pre-processing of GMTL images of the study area

Urban traffic simulation aims to specify the traffic state of the urban street network dynamically over the day. To this end, the traffic condition of each street segment is recognized from the corresponding streets in the GMTL images.

In the urban street network graph created based on OSM data, each street segment (an edge of graph) is a straight line between two consecutive intersections (two nodes of the graph) with specific Lat/Longs coordinates. While, in the GMTL images, the street coordinates can be extracted from their pixel location coordinate regarding RGB values obtained from the image processing of map images. Thus, it is required to match the OSM street network and streets of GMTL images. For this purpose, firstly, the GMTL images containing all study area streets are captured, and secondly, the street pixels of captured images are extracted. Finally, the corresponding street pixels to each street segment of the OSM street network are obtained by matching the OSM street network and street pixels.

GMTL does not provide images of a particular area and shows the traffic of streets of the world's map with mentioned traffic colors. To collect the study area's traffic data, the GMTL images containing all streets of the study area should be captured. To make the color of the streets clearly visible, the GMTL map needs to be zoomed in enough. A zoom level of 15 is enough to clearly show the streets' colors. Since only one image of a zoomed-in map cannot cover all streets of the study area, several images should be captured. Each map image is specified by a center defined by Lat/Long and a zoom level. Hence, by considering the zoom level of 15, the six images of the GMTL map should be captured to cover the study area.

In addition to the traffic colors, the GMTL shows the additional information on the map like the street name, location name, bus stops, etc. These labels and tags should be removed to more accurately specify the color of street traffic. To this end, for each GMTL image of the study area, an HTML file is created to load and control the map by removing the labels, tags, and generally all additional information on the map except the colored street pixels. The map images that can be used to identify all streets of the study area are the images that contain all streets specified with only white and orange colors. These images that are called white images, are illustrated in Figure 3.7.

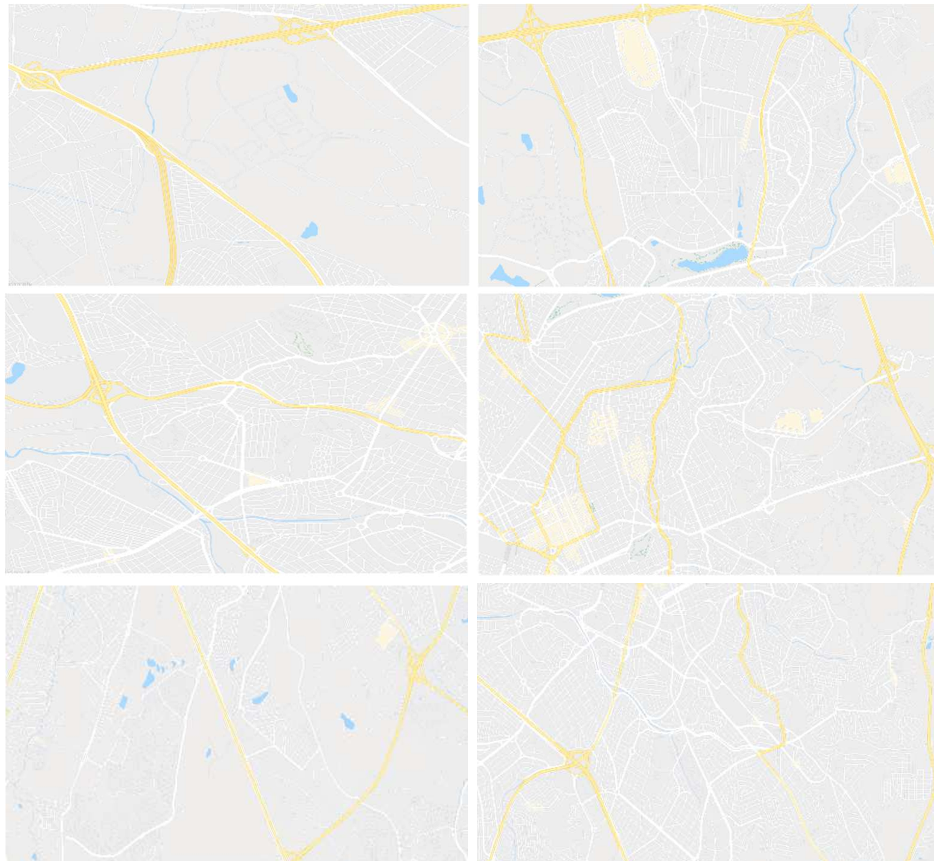


Figure 3.7. White images contain the street network of the study area.

These white images are captured and processed to extract the streets edge's pixel's locations coordinates according to assigned RGB values. Then, by manually cleaning and incorporating the pixels of these white images, the edge's pixels of the streets of the study area are obtained, as shown in Figure 3.8.

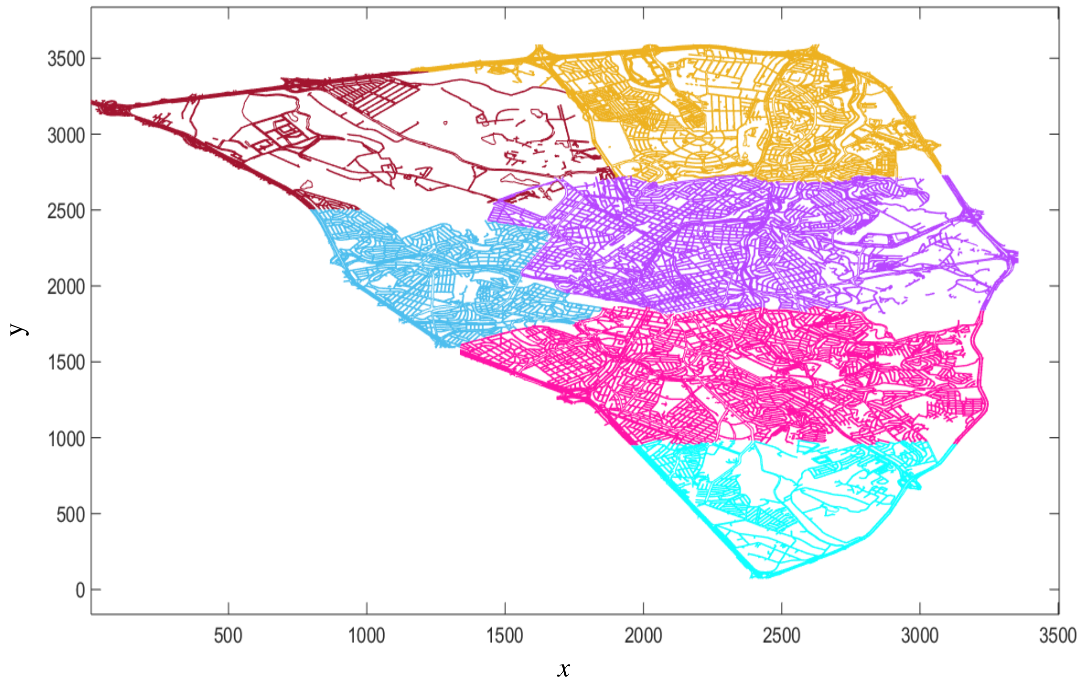


Figure 3.8. Street edge pixels for all streets in the study area are extracted from white images.

The streets edge's pixels coordinates are specified with *x* and *y* in the cartesian coordinate system, while the OSM street segments are defined by Lat/Longs coordinates. To obtain the streets edge's pixels corresponding to OSM street segments, they should be defined in the same coordinate system. Accordingly, the Lat/Longs of the OSM street network are converted to *x* and *y* coordinates, and then they are scaled and shifted horizontally and vertically to match with the street edge's pixels.

Since it is not possible to match all street segments by all streets edge pixels by only one scaling and shifting, the matching process is accomplished for the street segments in each TAZ. Due to this, each TAZ is divided into several sub-TAZs, and the street segments in each sub-TAZ are scaled and shifted to match with the corresponding street edge's pixels. After matching the OSM street segments and edge pixels, a rectangular buffer is created around each street segment to determine the edges pixels corresponding to the segment. Figure 3.9 shows the street segments matched with edges pixels and corresponding rectangular buffer for a sample area.

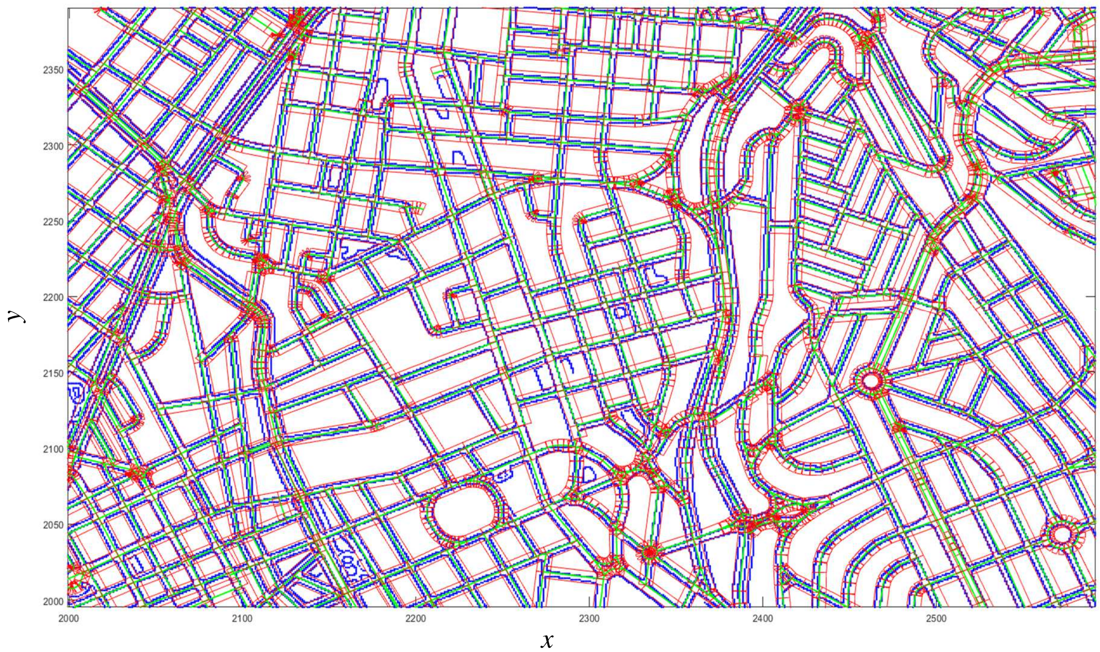


Figure 3.9. Rectangular buffers (in red color) corresponding to street segments (in green) containing the street edges pixels (in blue) for a sample area.

Therefore, for each OSM street segment, a rectangular buffer with *x* and *y* coordinates contains corresponding street edge pixels of GMTL images. Since the colored pixels are located at the street edge pixel's locations, capturing and processing the GMTL images at each moment and extracting the colored pixel locations, the colored pixel in each rectangular buffer and consequently the traffic color of each OSM street segment is obtained.

3.5.2. Automatic image capture

The GMTL does not show map images of a specific time; instead, it updates every second the traffic information of the streets, marked with the above traffic colors. To capture GMTL images automatically with a predefined time-step, a tool is developed using the Java robot and web reader of MATLAB. At each time-step, the web reader reads the HTML file of each map image, the 2.5-second pause is imposed to ensure that the map is loaded with the updated traffic information, and the Java-robot captures a screenshot of the web map image and saves it in image data format corresponding to the step-time. This process is repeated for each map image of the study area and each time-step over the desired time to collect the traffic data of the street network. Figure 3.10 shows the captured images from GMTL at a sample time step.

Figure 3.10. Traffic images of the study area are captured from GMTL at a sample time step.

3.5.3. Image processing of captured images

Image processing aims to identify the colored pixels and their location coordinates of captured images from GMTL. These images were saved as image data corresponding to each time step. As such, for each image of the study area at each time step, the locations of the colored pixel are extracted using their assigned RGB values. The extracted colored pixels are then incorporated to show the streets of the study area. Figure 3.11 shows the colored pixels of the street network of the study area at a sample time-step.

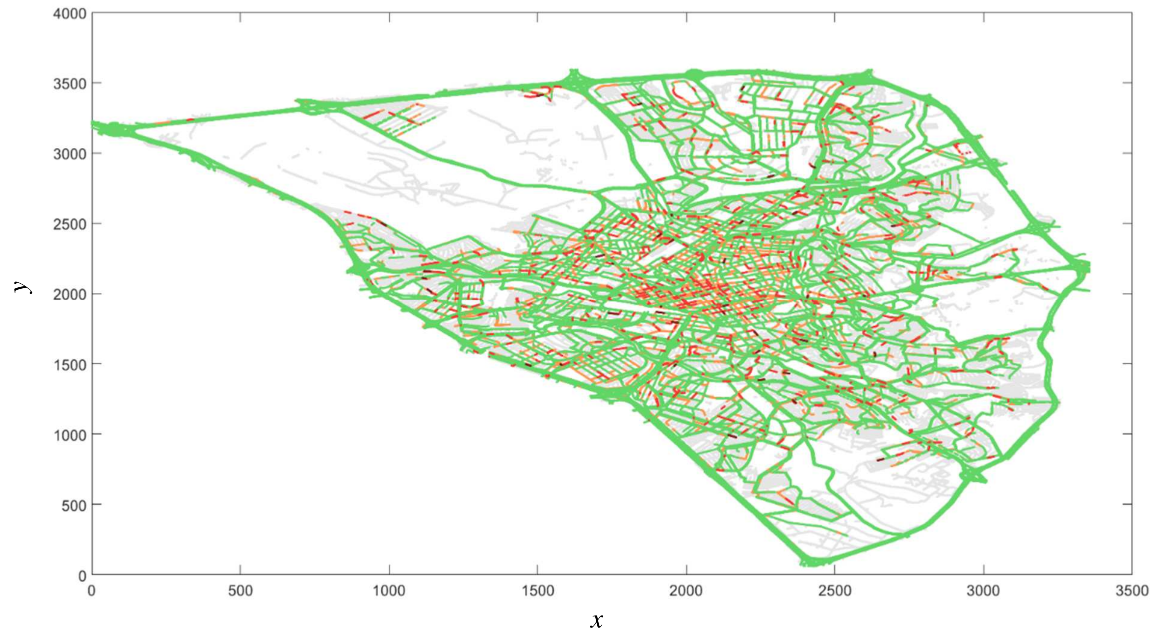


Figure 3.11. Extracted colored pixels of the traffic images of the street network for the study area.

3.5.4. Determining the traffic condition of urban street segments

By matching colored pixels and street segments' rectangular buffer, the colored pixels surrounded by each buffer are obtained regarding the location coordinates of colored pixels and rectangular buffer vertices coordinates. For example, the matching of colored pixels and buffers for the sample area of Figure 3.12 is illustrated in the following figure.

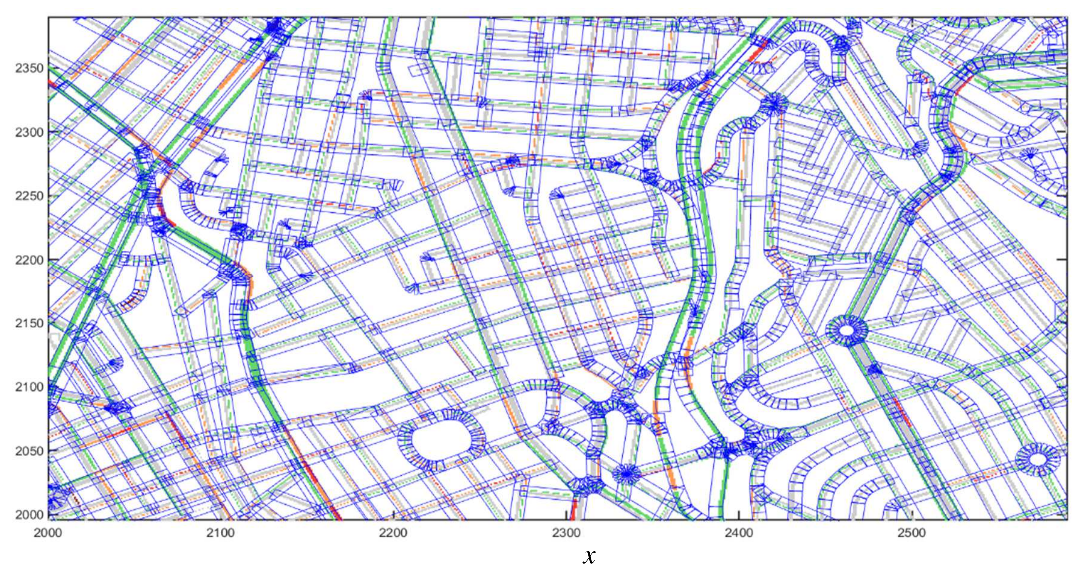


Figure 3.12. Matching of colored pixels and rectangle buffer for sample area.

Finally, the dominant color of colored pixels in each street segment's buffer is considered as the traffic color of the street segment. At each time step, the traffic color of each street segment is determined and stored with a numeric value: 1, 2, 3, 4, and 5 for green, orange, red, dark red, and white colors, respectively. By considering the time-step of two minutes, the traffic data for a weekday are collected by the developed tool from hour 5:00 to 5:00 of next day. Thus, traffic data for each street segment comprises 720 numbers of 1-5. The Historical Average (HA) traffic model is developed based on the extracted traffic data of five weekdays to predict the traffic conditions of the street network for a typical weekday.

Chapter 4

4. EV users travel behavior modeling

4.1. Introduction

In the travel demand modeling of EVs in the urban electromobility simulation, it is essential to model the user's travel behavior in the integrated framework of transportation and land-use systems. Users' daily trips are performed between different activity locations in the urban area. In this context, EV users' travel behavior is the way they use the street network to travel between OD locations of each trip. The EV users' travel behavior refers to the users' decision-making process on selecting the spatial-temporal travel attributes of driving, charging, and parking. EV users are assumed to be aware of the urban environment like street networks, activity locations distributions in different land use, urban traffic prediction, charging infrastructure locations, etc. Besides, assuming that users make rational decisions based on the information about alternatives in response to dynamic attributes of EV and urban transportation systems. In this context, the integrated urban spatial model provides the opportunity to emulate the EV user's travel behavior in the urban environment, which allows simulating the spatial-temporal attributes of each EV trip. The spatial parameters are OD locations, street segments, and intersections of the trip route, and temporal parameters include departure time from the origin, the times to reach or leave intersection nodes of the trip route, arrival time to destination, parking, or charging time at destination. Therefore, on each trip, EV follows a trip route between OD locations through space as a function of time. Each travel represents three typical behaviors of EVs, namely, driving, parking, and charging. These can be thought of as three states, where an EV traverses among them over time in the electromobility simulation.

In addition to the urban spatial features, the EV technical attributes significantly impact the EV users' travel behavior. The main affecting factors of EVs on the users' travel behavior are the EV energy consumption and the SoC of the EV battery. Hence, it is essential to provide an accurate model of EV to estimate the energy consumption and SoC of EV at each moment of electromobility simulation. To this end, In the next section, the EV is modeled by focusing on its energy consumption components.

4.2.EV Model for Energy Consumption Simulation in Electromobility

In daily mobility, EV consumes energy when traveling through the urban street network according to its technical characteristics and the user driving behavior, and is charged by user decision to avoid becoming stuck with an empty battery. In order to provide a more accurate model, more realistic conditions have been applied to model EV consumption, such as urban traffic, geographic spatial model of the urban street network, an efficiency model, parasitic power, etc. The EV technical specifications, EV driving speed, and streets slopes are required to develop the EV energy consumption model.

4.2.1. EV technical specifications

The required EV specifications to use in the energy consumption model are: curb mass (m_{EV}), EV width (B) and height (H), drag coefficient (C_d) and battery capacity (B_c). In this research, the best-selling EV brands in Brazil 2020 [112] are considered the available EVs in the study area. Table 4.1 shows the selling percentages and attributes of these EVs. In the urban electromobility simulation, an EV brand is assigned randomly to each EV user according to selling percentages, and the corresponding specifications are used in the EV model.

Table 4.1

EV specifications

EV brands	Selling percentage (%)	EV specification				
		Curb weight(kg)	Width (mm)	Height (mm)	Drag coefficient	Battery capacity
AUDI E-TRON	21.3	2490	1935	1629	0.28	71
CHEVROLET BOLT	12.6	1616	1765	1595	0.308	60
NISSAN LEAF	12.3	1558	1791	1560	0.28	40
JAGUAR I-PACE	11.5	2140	1895	1565	0.29	90
BMW i3	9.5	1245	1775	1598	0.29	33.2
RENAULTZ.E	7.5	1530	1829	1801	0.29	33
JAC IEV40	7.3	1460	1750	1560	0.35	40
RENAULT ZOE	3.84	1500	1703	1562	0.29	45
JAC IEV 20	3.38	1340	1685	1570	0.35	41
MERCEDES-BENZ	3.15	2495	1884	1624	0.26	80
BYD ET3	2.2	2420	1772	1875	0.28	50.3
TESLA MODEL 3	1.3	1611	1849	1443	0.23	53
TESLA MODEL Y	1.3	2003	1921	1624	0.23	74
TESLA MODEL X	0.95	2352	1999	1676	0.25	75
PORSCHE	0.6	2140	1966	1379	0.22	71
TESLA MODEL S	0.58	2027	1963	1445	0.24	75
JAC IEV 330P	0.25	2200	1880	1830	0.35	67.2
RENAULT TWIZY	0.23	450	1234	1454	0.64	6.1
BYD E5	0.11	1845	1765	1500	0.28	47
JAC IEV 60	0.11	1665	1782	1656	0.35	63

4.2.2. EV driving speed

In addition to the EV technical attributes, the EV speed has the largest effect on the energy consumption of the EV. The instantaneous speed of EV is used to estimate the instantaneous EV energy consumption of driving on the street network. It is difficult to predict the accurate EV driving speed in the stochastic transportation system with dynamic traffic. Besides, there is no mathematical model for achieving the exact driving speed for an arbitrarily given street at the accuracy needed for the user's driving behavior modeling. In the literature, two methods were mainly utilized to the driving speed of vehicles on the streets, including determining the average speed of street segments according to the segment's traffic and speed limits and stochastically generating driving speeds by driving cycle synthesis model.

In this context, the segment-based energy consumption model based on average speed is developed to predict the required energy for the next trip of the EV. Moreover, to estimate the instantaneous EV driving energy consumption, the EV energy consumption model is developed based on the instantaneous driving speeds generated based on a stochastic driving cycle synthesis model. In the segment-based energy consumption model, the acceleration is assumed to be zero. In contrast, in the instantaneous EV driving energy consumption model, the instantaneous acceleration is calculated based on the instantaneous EV driving speeds.

4.2.3. Street slope

The slope of the part of the street that EV passes through every second may change. However, determining the street slope for each second of EV driving is very difficult and needs high-resolution geospatial data of urban streets. Nevertheless, modeling the street network based on OSM data creates the opportunity to estimate the average slope of each street segment based on the Digital Elevation Model (DEM). The DEM is the 3D representation of continuous elevation data over the Earth's surface. It is represented as a raster that can be expressed as a 2D array so that each pixel has its elevation. Among the various sources of DEM data, the Shuttle Radar Topography Mission (SRTM) [113] is selected that provides the reliable DEM data of the earth. The SRTM void-filled, one arc-second DEM data with a resolution of approximately 30m is extracted for the study area as shown in Figure 4.1.

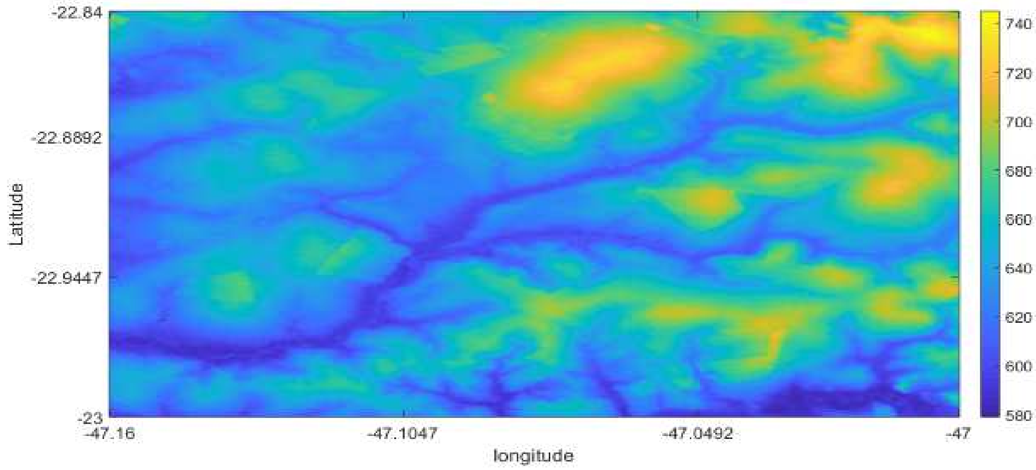


Figure 4.1. DEM raster map of the study area.

SRTM-DEM is a raster map in which each pixel has an individual elevation value that may be the average elevation of the street segment and possible heights (buildings, hills, etc.) beside it. Thus, the slope of each pixel can be the slope of the street segment with the surrounding terrain, which may be higher than the actual street slope. The procedure to calculate the average slope of the urban street segment is described below.

(1) Calculating the slope raster of the study area

SRTM-DEM data are comprised of pixels with individual elevation values. The slope of each pixel is defined as the change in elevation per unit distance along the path of steepest ascent or descent from the pixel to one of its eight immediate neighbors, which can be calculated in two types of units, degrees or percent. The rates of change of the surface in the horizontal (dz/dx) and vertical (dz/dy) directions from the pixel determine the slope that is calculated based on the following equation:

$$slop = \tan^{-1}\left(\sqrt{[dz/dx]^2 + [dz/dy]^2}\right) \times \frac{180}{\pi} \text{(degree)} \tag{4.1}$$

For the elevation raster of the SRTM-DEM data of the study area, the slope raster (in degree) for the study area is shown in Figure 4.2.

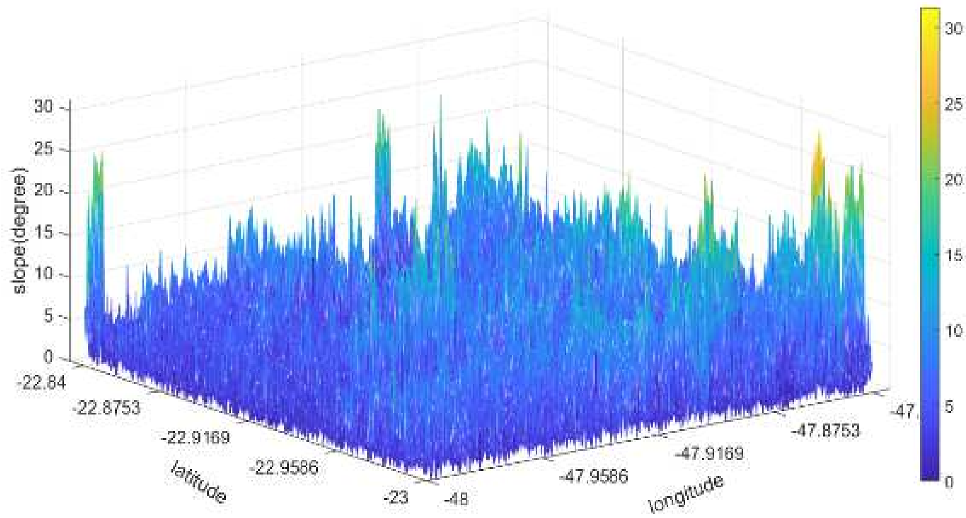


Figure 4.2. The slope of the study area.

(2) Overlapping the street and the slope raster

Since the pixels of the slope raster and street segments are specified by Lat/Long coordinates, street segments are overlaid on pixels to identify their intersections. To accurately determine the intersection of street segments and pixels, each street segment is interpolated and divided into sub-segments with a length of 1m. Then, the intersected pixels for each street segment are determined from overlapping the interpolated street segments and pixels.

(3) Calculating the slope of street segments

The slope value of a street segment is the average slope of all intersecting pixels with that street segment. The slope values of all urban street segments are obtained based on SRTM-DEM data.

4.2.4. Energy consumption model of EV

In this section, a detailed energy consumption model of EV is introduced that includes two main components:

- Tractive effort model with air drags, rolling resistance, acceleration, and hill-climbing components

- Individual efficiencies of powertrain components describe lumped loss model for the mechanical and electric powertrain.

Together, both components provide a reasonably accurate description of the energy consumption of an EV in almost any driving situation. Tractive effort is the force propelling the vehicle forward, transmitted to the ground through the drive wheels.

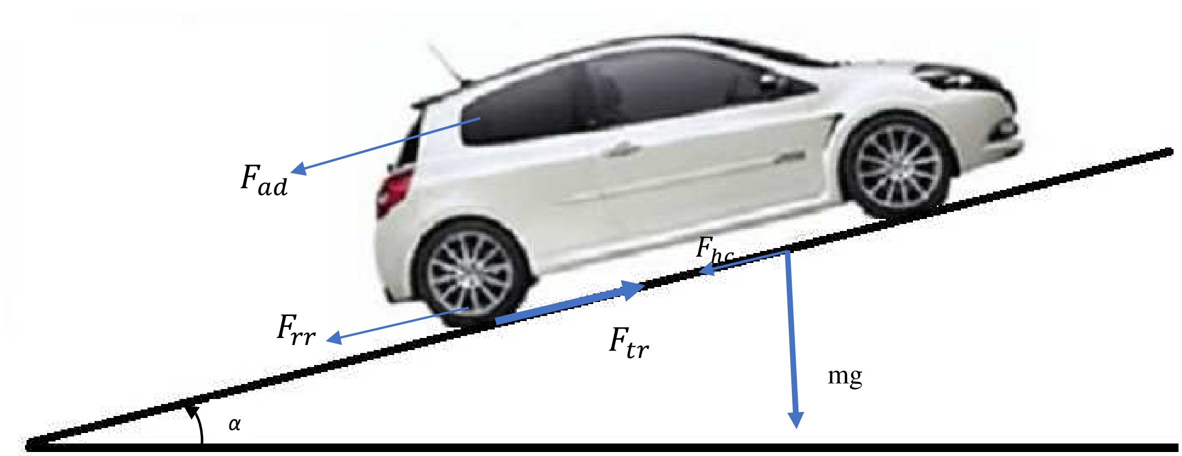


Figure 4.3. The forces acting on an EV move up an inclined road.

According to Figure 4.3, for an EV with mass *m* (sum of curb mass and passengers' mass), that is proceeding at an instantaneous velocity $v(t)$, the instantaneous total tractive effort is described in equation (4.2).

$$F_{tr}(t) = F_{rr}(t) + F_{ad}(t) + F_{hc}(t) + F_{ac}(t) \tag{4.2}$$

The forces are defined as follows.

- **Rolling resistance force (F_{rr})**

$$F_{rr}(t) = f_r mg \tag{4.3}$$

The value of f_r is calculated by following the empirical equation [114], based on the EV attributes.

$$f_r = 0.005 + (\frac{1}{p})(0.01 + 0.0095(0.001v(t))^2) \tag{4.4}$$

Where p is tire pressure considered standard value 30 bar for EVs. g is the gravitational acceleration which is equal to 9.81 m/s^2 .

- **Aerodynamic drag force(F_{ad})**

$$F_{ad}(t) = \frac{1}{2}\rho C_d A_f v(t)^2 \tag{4.5}$$

is the, ρ is the density of air, C_d is the drag coefficient, A_f is the frontal cross-sectional area of EV. The C_d is determined by EV attributes according to Table 4.1. Referring the [115], the A_f (in m^2) for each EV is calculated by the following equation,

$$A_f = -1.23069 + (0.00011m) + (1.304851BH) - (0.05398((BH)^2))$$
(4.6)

Where B is the width of EV and H is the height of EV mentioned in table x for each EV brand.

- **Hill-climbing force** (F_{hc})

$$F_{hc}(t) = mg \sin \alpha (t) \tag{4.7}$$

The hill-climbing force component depends on total EV mass and slope changes along the street segment. $\alpha(t)$ is the slope of the street segment where the EV travels in one second, which is the average slope of the street segment that EV is driving on it at second t.

- **Acceleration force** (F_{ac})

$$F_{ac}(t) = ma(t) \tag{4.8}$$

Where $a(t)$ is the linear acceleration of EV, however, for a more accurate model of acceleration force, the rotational acceleration and linear acceleration should be considered in the model.

To model the angular acceleration force, the axle angular speed of the tire is formulated as v/r (radians per second) which r is the radius of the tire. Then by considering the gear ratio (G) of the system connecting the motor to the axle, the angular acceleration $F_{\omega a}$ is found by equations (4.12). motor angular speed and acceleration are

$$\omega = G\frac{v}{r} \ (rad/s) \tag{4.9}$$

$$\dot{\omega} = G\frac{a}{r} \ (rad/s^2) \tag{4.10}$$

The torque required for this angular acceleration is

$$T = IG\frac{a}{r} \tag{4.11}$$

The force at the wheels needed to provide the angular acceleration is

$$F_{\omega a} = I\frac{G^2}{\eta_{mp} r^2}a \tag{4.12}$$

Where, η_{mp} is the mechanical powertrain efficiency, and I is the moment of inertia. For each EV, an overall fixed gear ratio G is considered between the G_{min} and G_{max} . I is considered constant value 0.025 kgm^2.

Therefore, the total tractive effort of equation (4.2) is rewritten as equation (4.13).

$$F_{tr} = F_{rr} + F_{ad} + F_{hc} + F_{ac} + F_{\omega a} \tag{4.13}$$

To calculate the EV's energy consumption of each second of the driving cycle, the energy flow of a classical EV illustrated in Figure 4.4 is used.

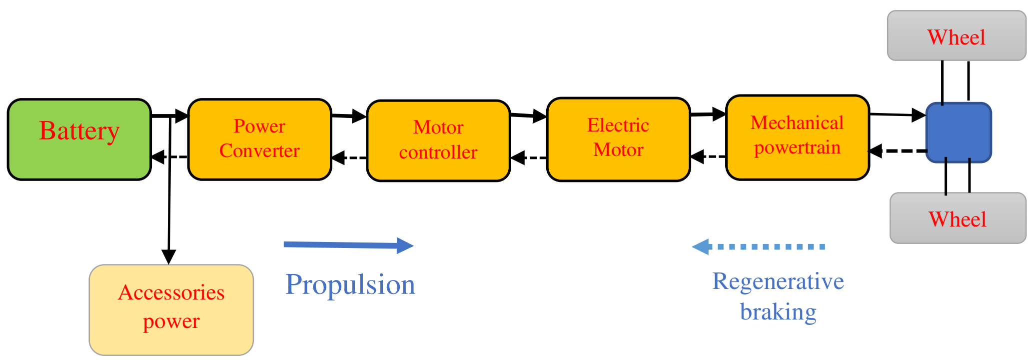


Figure 4.4: Energy flow of EV.

The tractive power consumer at wheels is calculated by equation (4.14).

$$P_{tr}(t) = F_{tr}v(t) \tag{4.14}$$

The energy required to move the EV for one second is the same as the power ($E(t)$=1 × $P_{tr}(t)$). The efficiencies of different EV components are needed to calculate EV's total propulsion power. The efficiencies of battery, power converter, mechanical powertrain are demonstrated by η_{bat} , η_{conv} , η_{mp} , respectively. These efficiencies are described in table 4.2 [116].

Table 4 .2.

EV's efficiencies

	Efficiency (%)	
	Min.	Max.
η_{bat}	93	99
η_{conv}	90	98
η_{mp}	87	93

The efficiencies of the electric motor and its controller are considered together as η_{em} and it is depended on power, torque, and also motor size. A simplified model of electric motor efficiency can be obtained by the following equation.

$$\eta_{em} = \frac{T\omega}{T\omega + k_c T^2 + k_i \omega + k_\omega \omega^3 + C} \tag{4.15}$$

Where, k_c is the copper loss coefficient, k_i is the iron loss coefficient, k_ω is the windage loss coefficient and C represents constant losses that apply at any speed. typical values for these constants for a 100kW high-speed induction motor are $k_c = 0.3$, $k_i = 0.01$, $k_\omega = 5 \times 10^{-6}$, C=600. Therefore, the overall propulsion power balance equation can be written as:

$$(P_{bat}(t) - P_{ac}(t))\eta_{bat}\eta_{conv}\eta_{em}\eta_{mp} = P_{tr}(t) \tag{4.16}$$

In the case of regenerative braking, the power flow is reverse, and by modification of the above equation, it is written as:

$$P_{bat}(t) - P_{ac}(t) = P_{tr}(t)\eta_{bat}\eta_{conv}\eta_{em}\eta_{mp} \tag{4.17}$$

when EV is at propulsion mode where the vehicle is being driven, the output power from EV's battery is

$$P_{bat}(t) = \frac{P_{tr}(t)}{\eta_{conv}\eta_{em}\eta_g} + P_a \tag{4.18}$$

Where P_a is the accessories power (e.g., lights, air conditioning, etc.) are considered in the EV energy consumption model and modeled by Normal PDF (i.e., *N(500w,25)*).

If the motor is being used in regenerative braking mode, then the efficiency (or rather the inefficiency) works in the opposite sense.

In other words, the electrical power from the motor is reduced, and the input power to the battery is:

$$P_{bat}^{in} = \eta_{conv}\eta_{em}\eta_{mp}P_{tr}(t) \tag{4.19}$$

During the driving, based on the instantaneous energy consumption of EV, the battery SoC is updated at each second of driving. The flowchart of energy consumption and SOC calculation for a second time is illustrated in Figure 4.5.

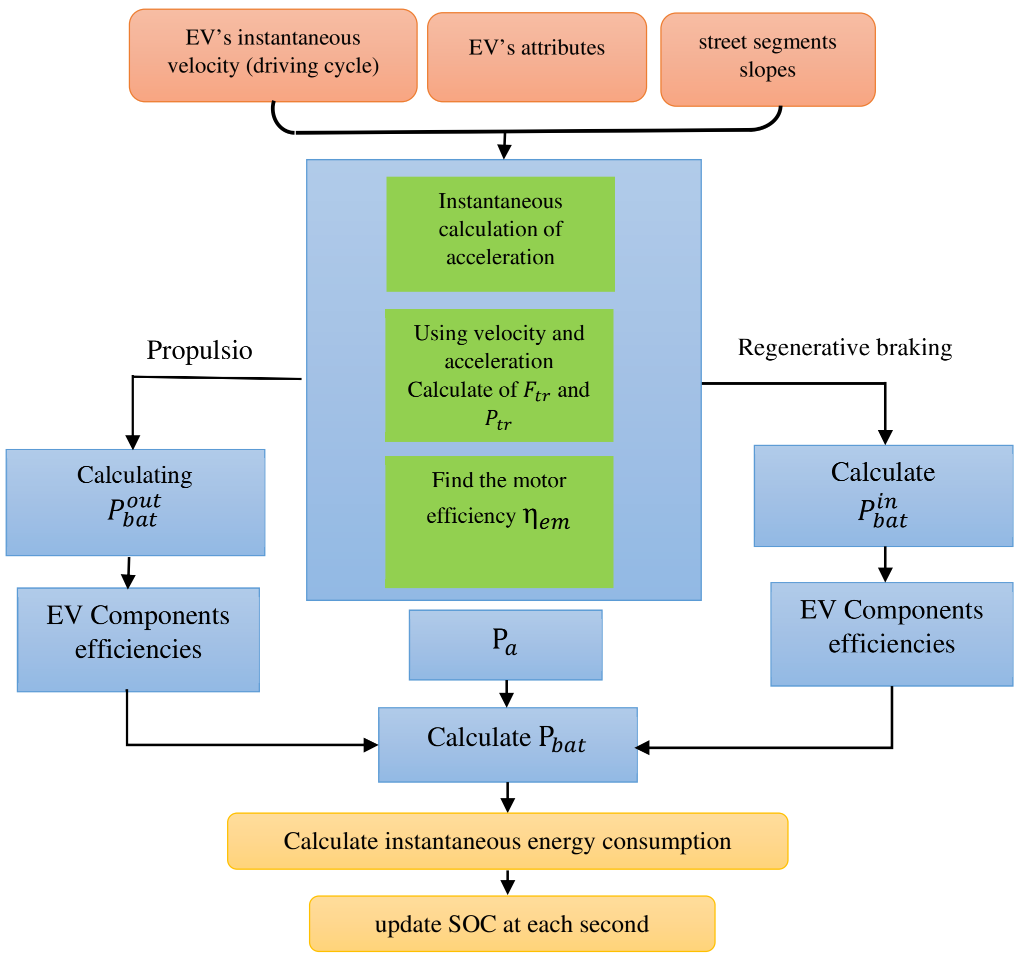


Figure 4.5: Flow chart of instantaneous energy consumption and SOC based on EV's model.

4.3.EV user driving behavior

Besides the technical model of EV, the user's driving behavior significantly influences EV energy consumption in a trip, which is due to the user's decisions on the trip destination and route and driving pattern (e.g., driving speed). In this section, the user's driving behavior in urban electromobility is modeled comprehensively. The EV user driving behavior is modeled into two parts; the decision-making process to predict the trip's parameters and the trip's driving pattern. The decision-making process to determine the trip parameters such as trip purpose, departure time, trip destination, and route. The driving pattern simulates the driving speed, acceleration/deceleration on the decided trip route.

4.3.1. EV user decision-making on the trip parameters

The driving decisions are modeled by assuming that users are sufficiently rational and able to identify all potential alternatives. EV users predict the spatial-temporal characteristics of the trip before departure from the origin. To this end, they determine the travel purpose (activity) and departure time of origin (start time of travel). Then, they choose the trip's destination location, where they perform the activity, and the trip route from origin to the selected destination. The various models of simulating the EV users' driving behavior are described in the following subsections.

4.3.2. EV's user classification

The total number of EVs is determined for a given penetration of EVs in the study area. It is assumed that the users have enough knowledge about places, activities, and urban transport networks at any given time. This spatial-temporal knowledge can be employed to make various spatial-temporal decision tasks such as choosing the destination, departure time, trip route, etc.

Most of the existing works utilized the travel data for all kinds of users and ignored the influence of users' social attributes on their travel behavior, which deteriorates the accuracy of the users' travel and charging demands. In this regard, from the point of user's occupation, the users are classified according to the travel survey data of the study area. In the OD-RMC dataset, the drivers are classified as employed, unemployed, retirees, housewives, and students based on their occupation. Accordingly, in this research, three EV user groups are defined as; employed, unemployed, and students, in which the unemployed group consists of unemployed, retirees, and housewives. In addition, students include students who have a driver's license and are studying at universities.

4.3.3. Departure time

In this paper, EV daily trips are considered home-to-home trips in which the EV departs from home at a specific time, performs a set of activities at different locations, and finally back home. Hence, except for the departure time of the first trip that starts from home, the departure time from an activity location is the sum of the arrival time and the parking time at the location. The first departure time from home is decided by EV users, independent of the urban transportation system and traffic conditions. It largely depends on EV user occupational status, so it is different for the three mentioned user groups. Since there are no specific rules to determine this time, it is modeled probabilistically based on the data extracted from travel survey data to reflect the stochastic nature of the first departure time from home. Figure 4.6 shows the distribution of first departure time from home data extracted from the OD-RMC dataset for three user groups.

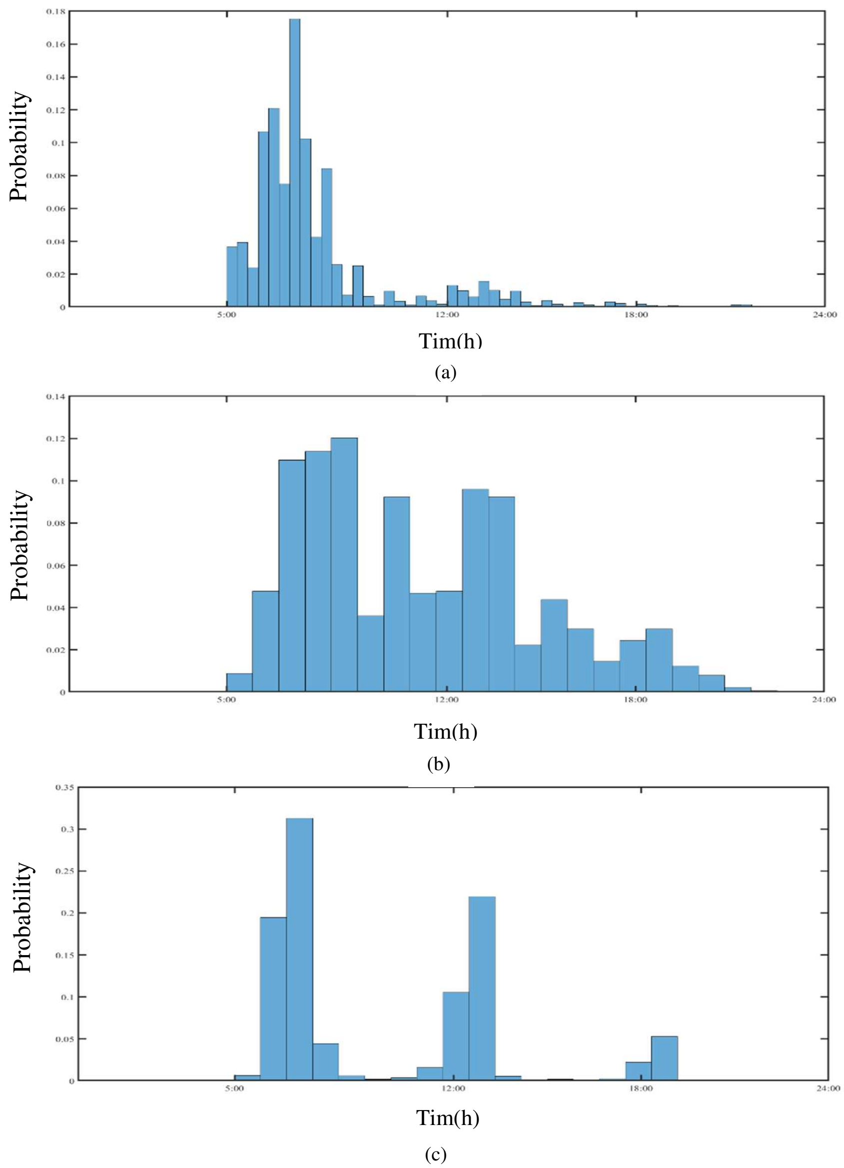


Figure 4.6. Distribution of first departure time from home for drivers; (a) employed, (b) unemployed, (c) students

The first departure time from home is modeled by a PDF for each EV user group. The Generalized Extreme Value (GEV) as the best-fitted PDF on the data is selected to model each EV user group's first departure time.

4.3.4. Stochastic trip purpose prediction

Daily EV travels include two or more trips with different purposes. The purpose of each trip represents the activity that will be performed at the destination location. To simulate EV daily trips in a multi-purpose framework in real-world conditions, the empirical EV's travel data can be used to model the realistic EV user travel behavior.

Since nowadays EVs are not yet widely popular in the urban transportation system, it is difficult to obtain a large number of EV travel statistics (especially in developing countries like Brazil), so it is assumed that EVs have the same travel patterns as conventional vehicles and the travel characteristics of EVs can be simulated based on travel survey dataset of fuel vehicles. Therefore, conventional cars' travel survey data of the study area is used to model the trip purpose prediction for each user's trip of the daily itinerary.

In some existing studies, a complete activity schedule for a whole day is extracted from travel data and assigned to each EV user, consisting of a sequence of activities with the starting time, ending time, etc. However, in these studies, it is ignored that arrival time to each activity depends on driving time, which is highly affected by urban street topology and urban traffic.

Thus, extracting all travel attributes from travel data is not realistic enough because the spatial characteristics of the urban street networks and dynamic traffic are not considered. To overcome this problem and represent the stochastic nature of trip purpose decisions by EV users, the trip activity(purpose) is generated trip-by-trip stochastically at the departure time of each destination location by taking into account the influence of traffic condition of the street network and users' driving behavior on arrival time to destination.

The trip purpose prediction model is developed based on the Markov chain concept, assuming that the trip purpose of the forthcoming trip depends on the origin's departure time and activity type. In order to predict stochastically the purpose of daily trips that represent real-world travel conditions and differentiate the trips by time, the Transition Probability Matrices (TPM) are calculated based on the frequencies of transferring between different purposes collected from the OD-MRC at one-hour intervals.

The trip purposes defined in OD-MRC are home (H), Work (W), Education (E), Shopping (S), Meals(lunch) (M), Health (H), Recreation (R), Personal matters (P), and Others (O). In the daily itinerary, home is divided into three purposes: starting the trip from home (H_0), short stay at home during the daily trips (H_1) and end of daily trips at home (H_2). Therefore, by considering the 24-hour day and the eleven trip purposes (H_0, H_1, H_2, W, E, S, M, H, R, and O), 24 hourly TPMs with square size 11×11 are generated for each user group. For instance, the TPMs for hours 7:00-8:00 and 17:00-18:00 for three user groups are shown in Figure 4.7.

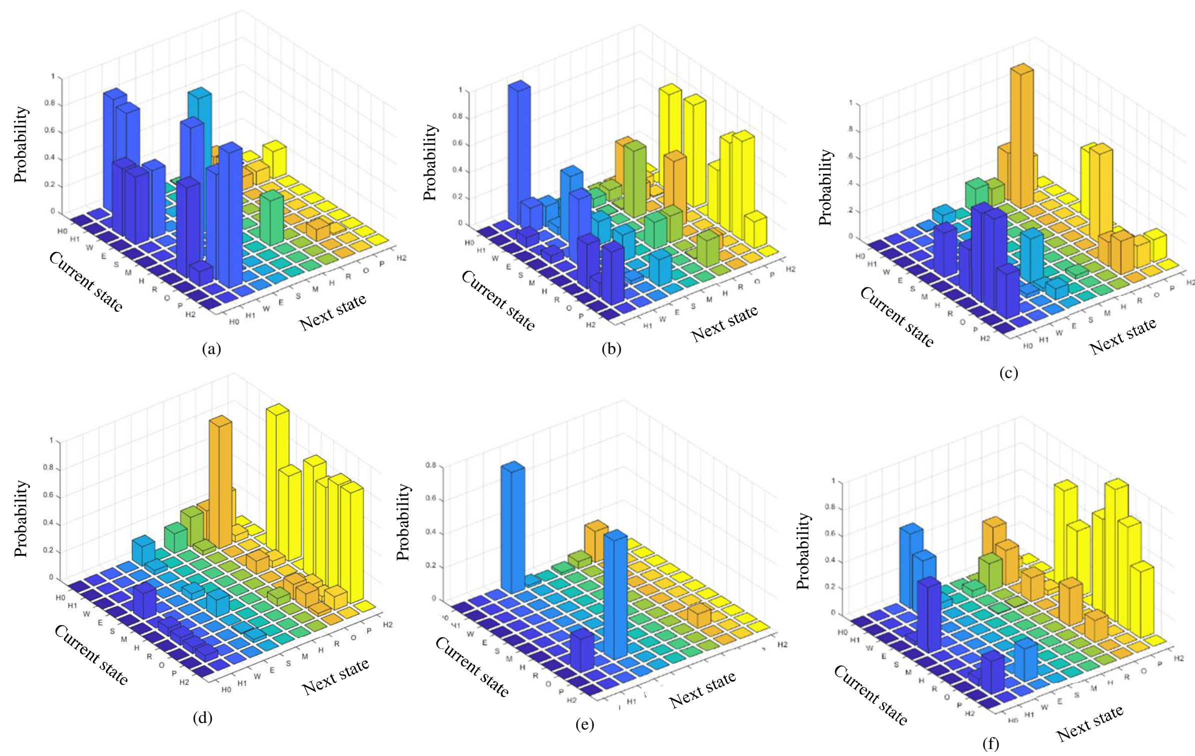


Figure 4.7: (a) TPM at 8'ocolock of employed, (b) TPM at 18'ocolock of employed, (c) TPM at 8'ocolock of unemployed, (d) TPM at 18'ocolock of unemployed, (e) TPM at 8'ocolock of student, (f) TPM at 18'ocolock of student

In urban electromobility simulation, the trip purpose is predicted stochastically for each EV trip according to the TPM corresponding to the hour of departing and the EV user group. To this end, the row of the TPM respective origin activity type is identified, then the row's accumulative probabilities are compared with a random number drawn from *U (0,1)* to determine the trip purpose.

4.3.5. Modeling the destination location choice and trip route choice

The EV users' decisions on the destination location and trip route between origin and destination locations significantly impact EV travel and charging demands in the urban electromobility simulation. Integrating the urban street network and land use provides a spatial framework to simulate the EV user's behavior in selecting the destination and route for each trip.

The daily travels of EV users are made to perform a set of activities at different locations. To simulate the EV user's destination choice behavior, two activity types are considered as activities at fixed locations and non-fixed locations. Regarding the activities defined as trip purposes in the previous section, home, work, and education are activities with fixed locations. On the other hand, shopping, meal, health, recreation, personal matters, and others are non-fixed locations. The proposed urban electromobility simulation requires the exact activity locations with their own Lat/Longs. In the absence of this data in the study area, the potential activity locations are generated synthetically in the respective land-uses blocks.

4.3.5.1.Synthetic activity locations in urban land-uses

To synthesize potential activity locations, two location points are considered; home points and non-home points. Each non-home point is regarded as a potential location for non-home activities like work, shopping, etc. Due to the fact that activity locations are situated in parallel to the streets, home points are specified in parallel to residential streets in the land-uses with habitability like residential, mixed zones, and city center land-uses. On the other hand, non-home points (e.g., workplaces, shops, etc.) are determined parallel to tertiary, secondary, and primary streets in land-uses blocks adjacent to these streets. To this end, hypothetical lines are considered in parallel to the OSM streets with a short distance (i.e., 5 meters), and the location points are generated on these lines with certain distances between two consecutive points: for homes, a random distance is extracted from the uniform distribution *U (20-50),* but for non-home points, a random distance is extracted from *U (50-150).* Figure 4.8 shows the synthetic home points and non-home points in the land-uses of a sample part of the study area.

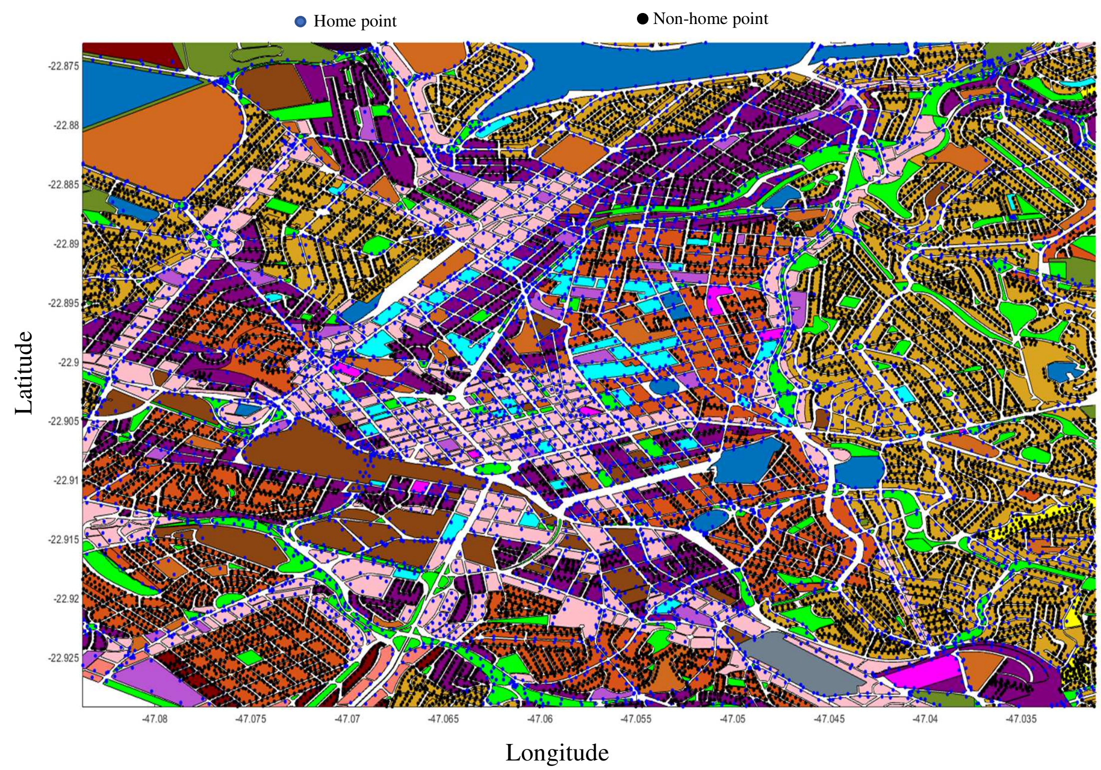


Figure 4.8. Synthetic home points and non-home points.

Destinations for activities with fixed locations are not chosen on a trip-by-trip basis, and they remain fixed over a long period. As such, during the EV mobility simulation, no destination choice is made for such activities. Instead, for each EV user, the activities with fixed locations are assigned in the setup phase of modeling and simulation regarding the EV user type.

- **Home locations**

Since EV users belong to households and have home-to-home daily trips in the electromobility simulation, a home location should be assigned to each of them. The home locations are at the land uses with residential possibilities, i.e., residential zones, mixed zones, and the city center area. Due to the price of the EV, it is assumed that high-income households are more likely to have an EV. Based on households' income in the different areas of Campinas extracted from the city's census data [117], the study area is divided into three groups: high, medium, and low income. The EVs are randomly assigned to residential land use in the high, medium, and low-income regions with 60%, 30%, and 10%, respectively.

- **Workplace locations**

The workplaces are assigned to the employed EV user types regarding their work type. In this regard, a work type is given to each employed EV user based on the work type distribution of the employees extracted from city economic indicators [118] adapted from the city's census data shown in table 4.3. Furthermore, for each work type, potential land uses are identified. A land-use from potential land uses is assigned to an EV user based on the spatial attributes of work trips for each work type extracted from the OD-MRC dataset. Since the OD-MRC dataset was collected at the TAZ level, the TAZ respective to work type is first identified. Then a land-use block corresponding to the work type is selected in the specified TAZ.

Table 4.3
work type distribution of study area

Work type	Percentage (%)
Services	37.2
Commercial	24.4
Industrial	15.2
Education	7.3
Administrations	6.8
Health and social services	5
Construction	3.4
Arts, culture, sports, and recreation	0.7

Therefore, to assign a workplace to an EV user, firstly, a work type is randomly picked out from the work type distribution (Table 4.3). Secondly, a TAZ is stochastically assigned to the EV user according to the percentage of work trip destinations respective work type at TAZs. Finally, the land-use blocks related to the user's work type in selected TAZ are identified, and a land-use from the available land-uses is randomly assigned to the EV user. Since the Lat/Long of workplace location is required to simulate the EV mobility, a non-home point in the selected land use is randomly selected as the workplace of the EV user.

- **Education locations**

The education land uses containing universities and colleges are identified as potential land uses for students who can own EVs. Then, the education location for each student is randomly selected from non-home points in the identified education land uses.

For the trips ending at the fixed destination locations, the EV users only decide on the trip route from origin to the preset destination locations. On the contrary, for trips to the non-fixed destination locations, users need to determine the trip's destination location and route, which are chosen simultaneously due to their interdependency.

4.3.5.2.Optimal-energy trip route choice for fixed-location

Once the EV trip is toward the destination with a fixed location, the user selects the route between the origin and the assigned fixed destination location. Unlike conventional trip routing methods, which determine the trip route as the shortest or fastest route between activity locations, this research develops a route planning model specifically for EV users that prefer to choose the trip route with minimum EV energy consumption. To this end, the realistic EV user behavior in finding a minimum-energy route is modeled in the dynamic and stochastic urban transportation networks that the streets' traffic varies dynamically over the day. In this context, it is assumed that the daily traffic conditions of urban streets are provided for EV users, who can predict the minimum-energy trip route by estimating the EV energy consumption of driving based on their EV technical attributes, traffic conditions, and topology of urban streets.

In the microscopic simulation of EV driving on the urban street network, the instantaneous EV energy consumption can be calculated based on the second-by-second driving speed and acceleration/deceleration. However, in the route planning model based on EV driving microscopic simulation on the urban street network graph, the acceleration/deceleration of transition between adjacent edges for edges of the graph with two or more incoming edges arises a significant issue in the EV speed driving and energy consumption modeling, because the first-second speed of EV on a segment with two or more incoming edges cannot be determined uniquely. Consequently, the transient speed and energy consumption are not unique.

To use microscopic driving simulation in predicting trip routes between OD locations, one option could be to find all possible routes between OD locations to uniquely determine the transient speed and energy consumption. However, determining all paths between a pair of OD locations on the large-scale urban street graph is very time-consuming and impractical. In this regard, route choice set generation can reduce the computational time. Still, generation route choice without empirical data of EV user's behavior or generating random route choice sets is not realistic and creates unrealistic or unfeasible routes. Furthermore, changing the graph structure may help find the unique acceleration/deceleration transition between adjacent edges in small graphs, but due to the large size urban street network graph in this research, changing the graph structure to use the microscopic simulation of EV driving is very difficult and impossible.

The macroscopic modeling of trip route choice was used for conventional vehicles to find shortest or fastest routes, which are not always the most energy-optimal routing, can be developed to find optimal route choice models of EVs. In this context, an energy-optimal routing model is developed based on the macroscopic model of EV energy consumption, which takes as inputs the mean EV velocity, mean driving time, and mean road grade of street segments to estimate the EV energy consumption on the urban street network and find the minimum-energy trip route. By taking into account the EV technical characteristics, topography, and dynamic traffic conditions of the street network, the macroscopic routing model can provide a reasonable model of the EV user's route choice behavior on the large-scale street network graph with short computational time.

In the EV energy consumption macroscopic model, the street segment's energy consumption is proportional to the segment's mean EV velocity and mean EV driving time. Hence, in the stochastic and dynamic urban transportation system, EV users prefer to choose the streets without traffic congestion that driving time and consequently energy consumption is small. In congested streets, although the average speed is low, the energy consumption is high due to the extensive driving time.

4.3.5.2.1. Estimation of the segment's average driving speed and driving time

The EV driving speed on each street segment is affected by the segment's traffic condition and street type, which determine the average speed and speed limit, respectively. In this regard, the Speed Performance Index (SPI) introduced in [119] as the ratio between average driving speed and maximum permissible speed on a street segment for different traffic conditions is used to estimate the average EV driving speed on a street segment. The SPI values for the different traffic conditions are shown in Table 4.4.

Table4.4

The traffic levels and the speed performance index.

Traffic level	SPI	Traffic condition
1	[0, 0.25]	Traffic jam
2	(0.25, 0.5]	Heavy traffic
3	(0.5, 0.75]	Moderate traffic
4	(0.75, 1)	Smooth traffic
5	1	No traffic

The maximum driving speed in different street types are adapted from the speed limits of the study are by assuming that the driver may exceed the speed limit of the street as 10 to 15 percent of maximum speed, the maximum speed in km/h for OSM street types of the study area are determined as shown in Table 4.5.

Table 4.5

The maximum speed of urban streets

Street type	Motorway	Trunk	Primary	Secondary	Tertiary	Residential	Especial	Motorway-link	Trunk-link	Primary-link	Secondary-link	Tertiary-link
V_{max}	110	90	70	60	50	40	30	50	50	40	30	30

The aforementioned values of V_{max} are used to estimate the average EV driving speed on the street segments. For this purpose, first, the traffic condition of the street segment is determined based on the urban traffic prediction model by considering the time-step and the driving time in the day. Then an SPI value is extracted randomly from the SPI range presented in table 4.4 corresponding to the street's traffic condition. Finally, the average EV driving speed on the street segment is calculated by the following equation:

$$V_{avg} = r_{SPI}.V_{max} \tag{4.20}$$

In the traffic jam (Traffic level 1), the minimum velocity of EV is set to 5 km/h.

The average driving time on each street segment is calculated based on the V_{avg} and the length of the street segment that is calculated by the Haversine formula using the Lat/Long coordinates of both nodes of the street segment.

4.3.5.2.2. Segment-based EV energy consumption

The average EV energy consumption on a street segment is calculated based on the segment's average values of driving speed, driving time, and street slope. Regarding the described EV model, the segment-based EV energy consumption model is obtained by assuming acceleration $a(t)$=0 and replacing the instantaneous speed $v(t)$ with v, which is the average EV driving speed on the segment. Then, the average mechanical power consumption at wheels on the segment is calculated by equation (4.21).

$$P_m = F_{tr}v = \left(f_r mg + \frac{1}{2}\rho C_d A_f v^2 + mg\sin\alpha_s\right)v \tag{4.21}$$

With zero acceleration/deceleration, the regenerative power will also be zero, and the power draw of the battery is;

$$P_{bat} = \frac{P_m}{\eta_{bat}\eta_{conv}\,\eta_{em}\,\eta_{mp}} + P_a \tag{4.22}$$

by considering the length of the segment l_s and the driving time on the segment $t_s = \frac{l_s}{v}$, the total consumed energy of the EV's battery on i^{th} segment E_s^i is calculated as below.

$$E_s^i = P_{bat}.t_s \tag{4.23}$$

4.3.5.2.3. Minimum-energy dynamic route choice model

An energy-optimal dynamic route choice model is created using a dynamic traffic prediction model, segment-based EV energy consumption model, and a routing algorithm. In the proposed route choice model, the traffic model predicts the dynamic traffic condition of the street segments at each time step of traffic simulation over the day.

At each time step, the average driving speeds and driving times on all street segments are estimated according to the segment's street types and traffic conditions. Next, the EV energy consumptions on street segments are calculated based on the segment-based energy consumption model regarding their average EV driving speed, average driving time, and average segment slope. Finally, a routing algorithm (i.e., the Dijkstra algorithm) is used to find the energy-optimal trip route between OD locations on the weighted street network graph, in which the edges' weights are the estimated EV energy consumption of driving on these edges. This process is repeated at each time step in EV driving prediction on the street network. At the departure time of O location, the optimal trip route is found, EV driving is simulated segment-by-segment on the predicted trip route, at the beginning of each time step the trip route is updated, the route updating is repeated until EV arrives at the D location.

Therefore, the dynamic route choice model predicts the trip route choice behavior of the EV users by pre-trip route planning and en-route replanning according to the dynamic predicted traffic condition of street segments.

Pre-trip route planning is simulated the EV users' behavior at the departure time to find the optimal route between the OD locations. En-route replanning simulates the EV users' behavior during the trip that updates the EV's trip route according to the updated street traffic states at each time step and the new calculated travel cost of street segments. The procedure of finding the optimal trip route between the OD locations of each EV trip based on the proposed dynamic trip route choice model is described as follows:

(1) Since the OD locations are not on the street network graph (they are located parallel to the streets), each of them should be connected to the street network graph with a street segment. To this end, two straight lines from the O and D locations to the nearest nodes of the graph are established, named as departure segment and destination segment, respectively.

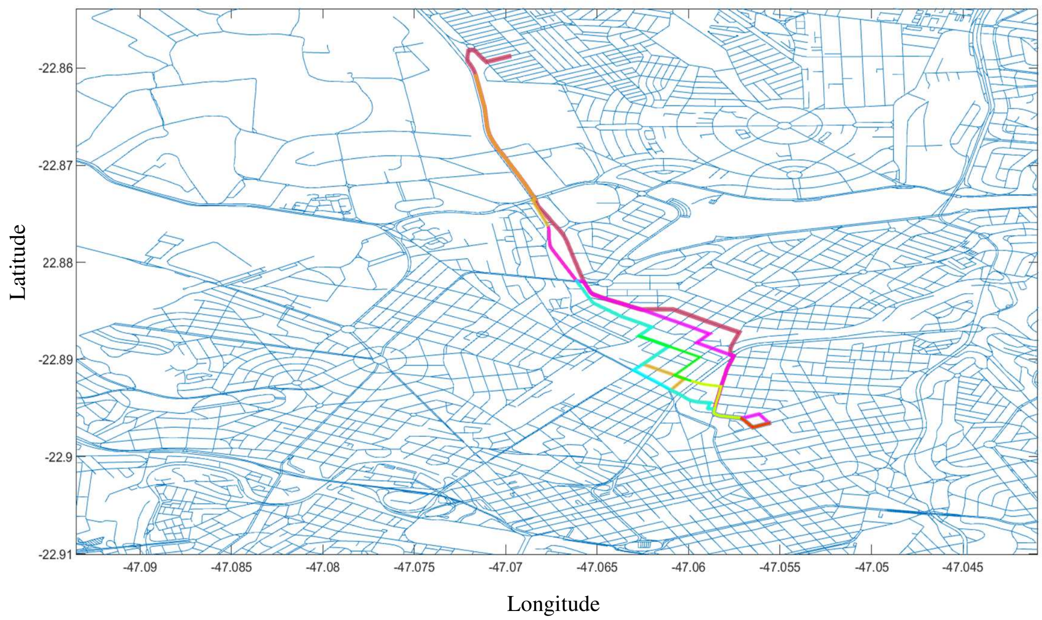
(2) At the departure time of the O location, the pre-trip route planning predicts the initial trip route between the OD locations on the weighted street network graph using the Dijkstra algorithm, which the weighs are the driving energy consumption of street segments estimated by segment-based energy consumption model regarding the traffic conditions at the time-step corresponding to the departure time. The initial trip route starts from the departure segment, contains the street segments with the minimum energy that connects the departure segment to the destination segment, and ends at the destination location.

(3) While EV driving along the trip route is simulated segment-by-segment, the possibility of en-route replanning is checked at the end node of segments by considering driving time, arriving time at the end node of segments, and the time-step change. If the time-step has changed when the EV reaches the end node of a segment, the route is updated by the Dijkstra algorithm from the node to the D location according to the new energy weights of the street graph.

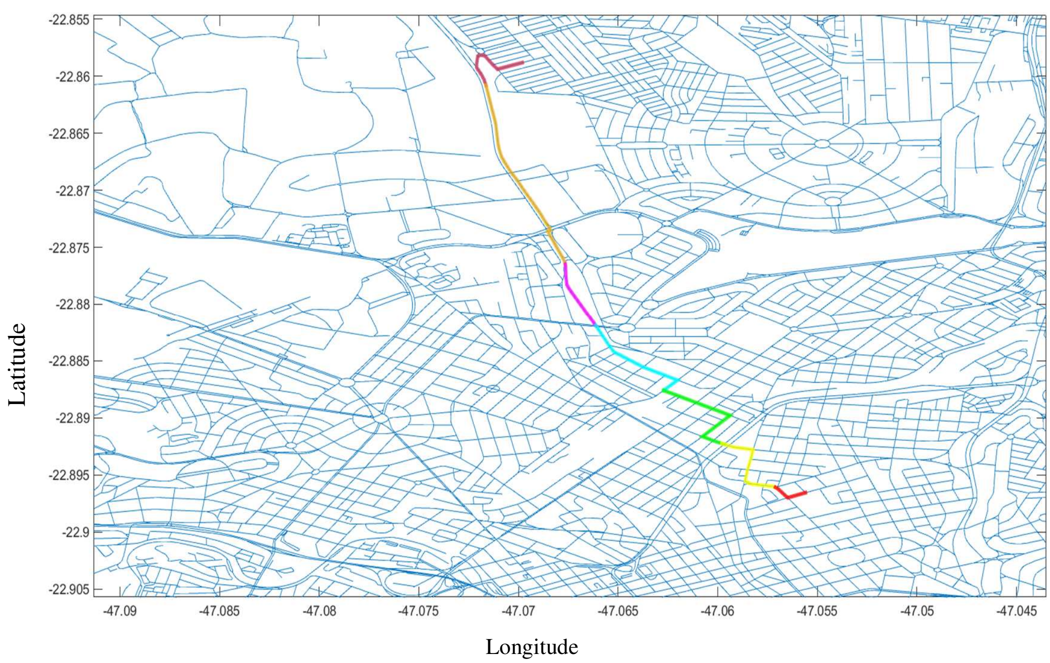
(4) Step 3 is continued until EV driving prediction simulation is over, or in other words, the EV reaches the D location at the end of the destination segment.

In a nutshell, the EV user behavior in predicting a trip's trip route with a fixed destination location is modeled by the energy-optimal dynamic route choice model based on macroscopic simulation of EV energy consumption model and urban traffic simulation. In this context, according to the trip's starting time (or departure time from the O location), the first time-step number of traffic simulations is determined. At the departure time, the initial trip route between OD locations is found (pre-trip route planning) by the Dijkstra algorithm on a weighted street network graph, in which the weights are the EV energy consumption on each graph edge (street segment). Then, the EV driving on the initial trip route is simulated segment-by-segment.

By taking into account the departure time and driving time on each segment, when the time-step of traffic simulation is changed, the traffic conditions of street segments and energy consumption on segments are changed, thus, the previously determined trip route is updated (en-route replanning) to find the new trip route from the current position of EV to D location based on new weights of graph edges. The en-route replanning is performed at the beginning of each time-step until the EV reaches the D location. Therefore, the user predicts the trip route by choosing the minimum-energy route between OD locations while refusing to choose the traffic-congested street segments that driving time and energy consumption on them are high. For a pair of arbitrary OD locations, the proposed model to find the minimum energy route by pre-trip route planning and en-route replanning following the dynamic urban traffic is demonstrated in Figure 4.9, in which figure 4.9 (a) illustrates the dynamic routing with six en-route replannings and (b) shows the final route between OD locations.



(a)



(b)

Figure 4.9. The dynamic routing between two sample OD locations. (a) pre route replanning and en-route (b) final trip route.

4.3.5.3.Simultaneous Destination and Route Choice Modeling for non-fixed locations

Unlike fixed locations, non-fixed locations are changed trip-by-trip, and a point from the synthetic non-home points in a land-use block respective to trip purpose should be selected as the destination location. Due to the interdependency of destination choice and route choice, a model is developed to simulate the EV user behavior in selecting the destination and trip route for non-fixed locations simultaneously. The destination choice models were typically developed based on travel survey data. Since this data is generally collected at the TAZ level, the destination choice models were usually created at the TAZ level where a TAZ or a random point in a TAZ is selected as the destination location. However, the actual location of an activity can be better represented by a type of land use instead of a TAZ, which is an aggregation of several land uses.

In this research, the destination choice model is developed at the land-use level that selects a land-use block as the destination land use and picks out a random non-home point in the chosen land use as the destination location of the trip. To this end, the simultaneous destination and route choice model generates a choice set consisting of potential land-uses destinations corresponding to trip purpose. Then, it calculates the choice probability of each land-use block in the choice set based on the travel cost (energy and time) from O location to land-use blocks in the choice set. Finally, based on the calculated choice probabilities, a land-use block is selected stochastically, and a point is randomly extracted from the non-home points in the destination land-use as the destination location of the trip. It is worth noting that since there might be many land-use blocks respective to the trip activity of a trip, the same connected land-use blocks are considered as aggregated land-use. In this case, the aggregated land use is a polygon consisting of the land-use blocks.

4.3.5.3.1. Choice set generation

For each trip to a non-fixed destination location, a choice set consisting of land-uses with potential locations corresponding to the trip's purpose is generated to prevent selecting irrelevant land use for the trip. For this purpose, based on the land uses characteristics, the possible destination land-use blocks from non-residential land-use blocks corresponding to the trip purpose (activity) are selected as the choice set. Furthermore, there are non-home points in some residential land-uses that can be potential destinations for some trip purposes like shopping, meal, personal matters, and Others. In this regard, it is assumed that the residential land-uses with none-home points can be potential land-uses for EV users living near these land-uses. As such, for home-based trips (i.e., the trips that are started from home) to the mentioned non-fixed location, in addition to the possible non-residential land-use blocks corresponding to the trip purpose, the residential land-uses with none-home points with a distance of less than 2km from the EV user's home are also included in the choice set.

4.3.5.3.2. Determining the attractiveness of land uses by the Fuzzy system

The possibility of choosing a land-use block by an EV user depends on the attractiveness of land use from the user's point of view. In this context, considering the EV users' preference and their logical decision-making on choosing the trip destination and route with the minimum driving energy consumption and time, the proposed simultaneous trip destination and route choice model assumes that the attractiveness of a land-use from the EV user's perspective depends on the following three main variables.

(1) The EV driving energy consumption of traveling from the origin location to potential land-use destinations.
(2) The travel time from the origin location to potential land-use destinations.
(3) The number of trips corresponding the trip purpose to the destination land use.

Significant data and an extensive model calibration process are needed to model the actual relationships between the attractiveness as a dependent variable and the aforementioned independent variables. Thus, modeling these relationships is impossible due to the shortage of travel data at the land-use level, as the travel survey data is typically collected at the TAZ level. However, these relationships can be constructed with fuzzy logic using logical rules, in which the calibration is neither necessary nor challenging.

Therefore, the three variables mentioned earlier are considered inputs of a Fuzzy system to estimate the choice probabilities of potential land-uses in the choice set. In this regard, for each trip with tip purpose corresponding non-fixed location activity, the simultaneous destination, and route choice model, firstly, find the choice set of potential land-uses destination corresponding to trip purpose, then the values of three fuzzy inputs are estimated for the potential trips from the O location to the center of land-uses in the choice set. Thirdly, the fuzzy output determines the choice probabilities of each potential land-use destination. Finally, a land-use is selected stochastically according to choices probabilities as destination land-use, and the trip route is the minimum-energy route from the O location to the selected land-use that is already simulated as the fuzzy input in the second step.

- **Fuzzy input1: EV driving energy consumption to the land-uses in the choice set**

According to the EV users' preferences, the simultaneous trip destination and route choice model aims to find a destination location for each trip consuming minimum energy. Thus, although there are many trip routes between the origin location and center of a land use, the minimum energy consumption route is selected as the trip route between the origin location to each land-use block in the choice set. As such, the values of energy consumption of the minimum-energy trip routes from the origin to the centers of land-uses blocks in the choice set are specified as the first input of the Fuzzy system. The land-use block with the lowest trip's energy consumption has the highest choice probability among the land-use blocks in the choice set.

In order to obtain the energy consumption of traveling from the origin location to the center of the land-use blocks of the choice set, since the OD locations of the trips are known, the already described energy-optimal dynamic route choice model described is used to find the minimum-energy trip routes. As an example, for a trip with leisure purpose from a sample origin location and the 27 land use blocks in the corresponding choice set, the minimum-energy routes between the origin location and the centers of land use blocks in the choice set are shown in Figure 4.10.

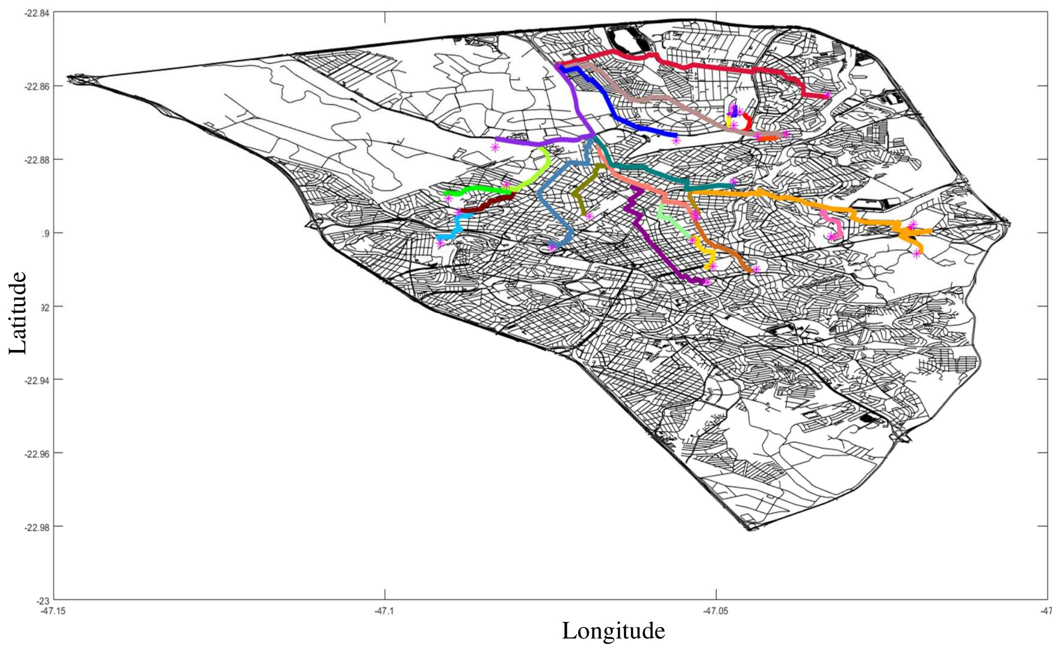


Figure 4.10. Trip routes from origin to land-uses in the choice set for a sample of simultaneous destination and route choices.

The energy consumption of the trip (in KWh) to each land-use block is the sum of energy consumptions of driving on the route's segments, which is the first input of the fuzzy system to determine the choice probability of the land-use block.

- **Fuzzy input2: EV driving time to the land-uses in the choice set**

In addition to the energy consumption, the driving time of traveling from the origin location to the center of a land-use block affects the EV user's decision to choose the land-use as the trip destination. Thus, the trip's driving time between the origin location to the center of a land-use block in the choice set is considered the second fuzzy input to determine the choice probability of the land use and is the sum of the driving time on the segments of the minimum-energy route found by the Energy-optimal dynamic route choice model.

- **Fuzzy input3: number of trips to the land-uses in the choice set**

For a trip purpose (activity), the number of trips made with that purpose to a land-use indicates the attractiveness of the land use for that trip purpose. The historical travel data of the study area can be used to determine the trip numbers by assuming that the pattern of travels in the study area is maintained. Given that the travel data of the study area was collected at the TAZ level, not at the land-use level, the number of trips to the corresponding TAZ of the land-uses is considered to determine the land-use attractiveness. Moreover, to consider the effect of time of the day on the number of trips, the hourly number of trips to the TAZs is taken into account. The number of trips to the TAZs of the study area with a one-hour interval for the mentioned trip purposes corresponds to non-fixed activity locations are extracted from the OD-RMC.

Therefore, for each land-use in the choice set, the corresponding TAZ is specified, and the hourly number of trips to the TAZ corresponding to the trip purpose and the hour of travel starting time (departure time) is used as the third input of the fuzzy system.

The Fuzzy system works in three steps; First, all input values are fuzzified into fuzzy membership functions. One of the main solutions for assigning membership functions to Fuzzy variables is intuition. Second, all applicable rules are executed in a rule-based platform to compute the fuzzy output functions. The fuzzy rules are defined as the conditional statement (IF-THEN), which sets the relationship between the input and output variables regarding the logical decisions of users. Third, the fuzzy output functions are de-fuzzified to obtain crisp output values using the centroid defuzzification method.

In the simultaneous trip destination and route choice model, the Fuzzy system is developed to determine the relative attractiveness of land-uses in the choice set based on the mentioned inputs. In other words, a land-use with the lowest driving energy consumption and driving time and the greatest number of trips to its TAZ has the highest attractiveness among the land-uses in the choice set from the EV user's point of view. Hence, to set the values of the membership functions of inputs, different percentile values (i.e., 25th, 50th, and 75th percentile values) of the maximum input values of alternatives are considered. As such, the values of each input are normalized to generate the number between 0 to 1, and the three fuzzy triangular membership functions with three linguistic variables, low, medium, and high, are used to describe the mentioned three fuzzy inputs. The fuzzy outputs are the attractiveness of land-uses in the choice set ranging from 0 to 1, which is described by four linguistic variables low, medium-low, medium, medium-high, and high. Figure 4.11 shows the membership functions of inputs and output of the fuzzy system.

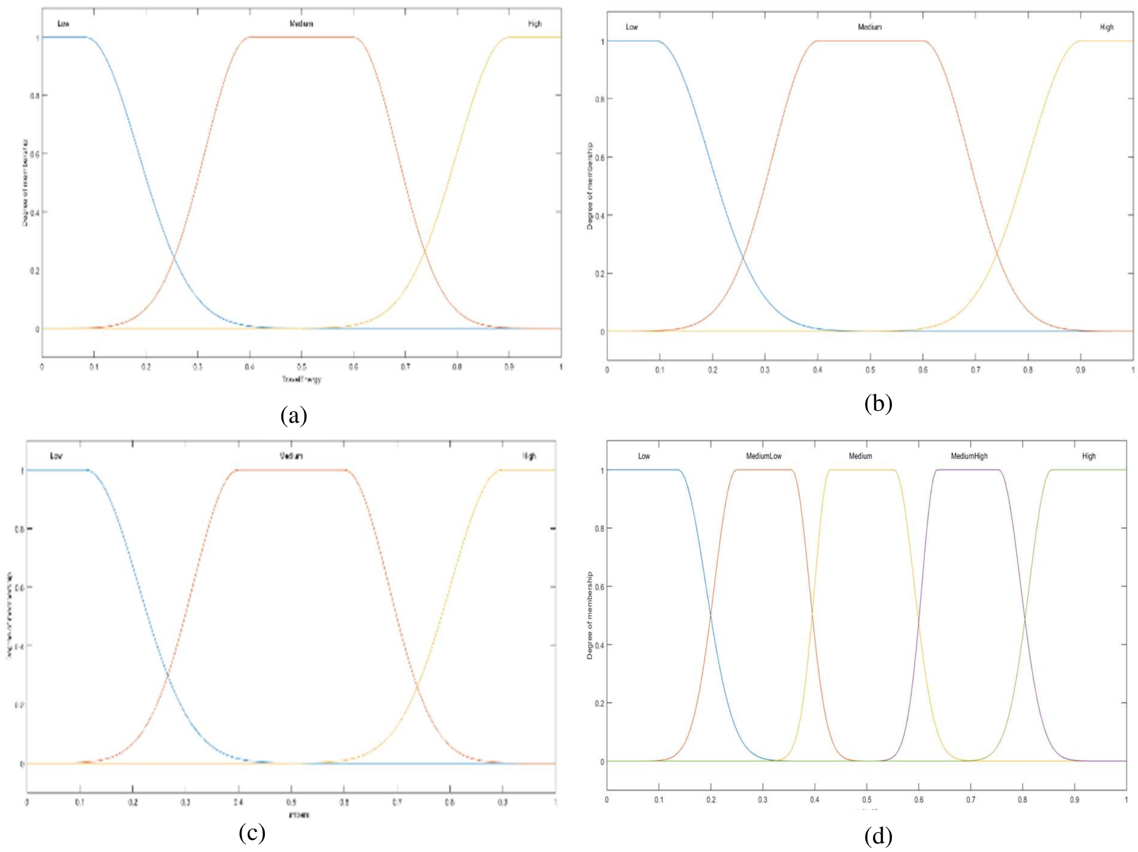


Figure 4.11. Membership functions;(a) energy of trip route, (b) driving time of trip route, (c) trip numbers, (d) output

4.3.5.3.3. Choice probabilities of land-uses in the choice set

Based on the attractiveness of land-uses obtained by the Fuzzy system, the choice probabilities of the land-uses are calculated from the following equation.

$$p_i^k = \frac{e^{\mu A_i}}{\sum_{j \epsilon U} e^{\mu A_j}} \tag{4.24}$$

Where p_i^k is the probability of *i-th* land-use corresponding to the trip purpose k in the choice set, A_i is the attractiveness of *i-th* land-use obtained by the fuzzy system, and μ is a scale parameter. As the choice set may have many alternatives, the differences in the probabilities of high and less attractive options can be very small. As such, a scale factor μ is imposed to inflate the most attractive opportunities and simultaneously penalize the least attractive options.

A value of μ provides different outcomes for attractiveness. In this study, we considered different values of μ and found that a higher value inflates the probabilities of the attractive options while penalizing the least attractive options. However, in this study μ = 20 seems to provide slightly better predictions than others.

To choose a destination land-use stochastically based on the calculated choice probabilities, a tempting approach would be to choose the land-use with the maximum probability. Still, this strategy would have the effect of choosing only the dominant alternative, and less frequent alternatives would be eliminated entirely. Clearly, this is not a realistic choice model because a few EV users can decide a little illogic decision.

In order to address this problem, an alternative can be selected by sampling a random number from the uniform distribution in the range 0 to 1(U (0,1)) and comparing this random draw to the cumulative probabilities of the alternatives. Whichever alternative the sampled random number falls within is the alternative that is selected as the chosen one.

Since the exact destination location point is required in electromobility simulation, a destination location is randomly selected from synthetic non-home points in selected land use.

Moreover, the trip route is the minimum energy route from the origin location to the center of selected land use, which is completed then from the equivalent node of the graph to the selected non-home point in the chosen land-use destination.

The flowchart of the simultaneous destination and trip route choice model is illustrated in Figure 4.12.

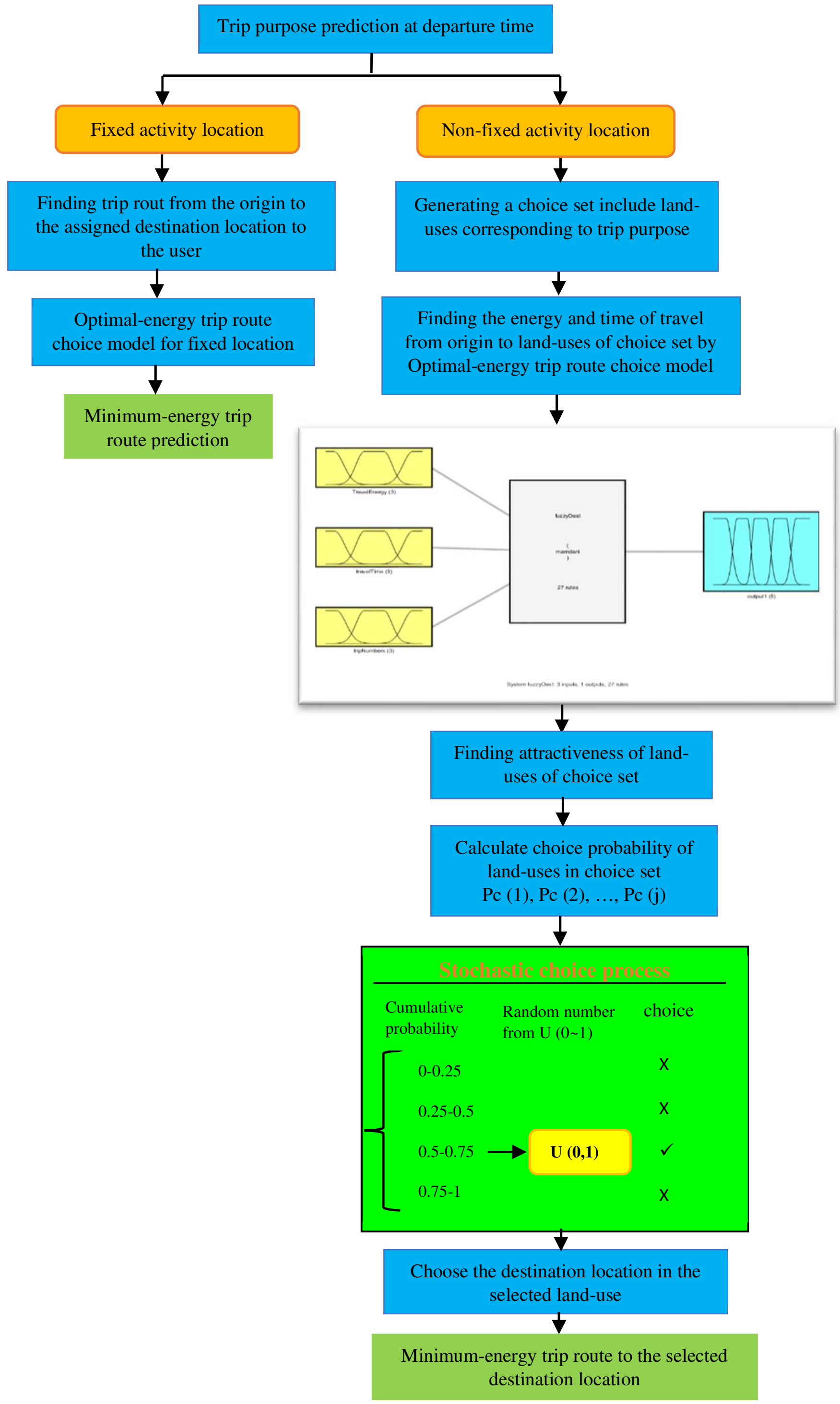


Figure 4.12. Flowchart of simultaneous modeling of destination and trip route choices.

4.3.6. Driving pattern modeling

As mentioned before, the user driving behavior is modeled in two steps. In the first step, the trip purpose, departure time, destination location, and trip route are predicted. In the second step, the driving pattern (i.e., driving speed, acceleration/deceleration) is modeled to simulate the EV driving on the predicted trip route. There is no mathematical model for achieving the realistic EV driving speed at the accuracy needed to model the users' driving patterns in the urban electromobility simulation. In the literature, the vehicle driving speed profile is modeled with a driving cycle, which is defined as a series of data points representing the speed of a vehicle versus time.

The standard driving cycles were used in a few studies as the driving speed of EVs, while standard driving cycles cannot display realistic driving conditions because the standard cycles were recorded under specific conditions and cannot represent real-world driving conditions.

A driving cycle is a speed-time profile designed to represent a real-world driving pattern. The relationship of speed-time at any time in the driving process is uncertain, so actually driving cycle should be a random process. Due to the stochastic nature of EV driving speed in the transportation system, stochastic driving cycles can represent the realistic driving speed of vehicles. Driving Cycles are used for many purposes, such as traffic engineering purposes, estimation of emission inventories, and estimation of fuel consumption. For the estimation of fuel consumption and emission inventories, vehicles are tested using chassis dynamometers with respect to a given driving cycle. While various driving cycle generation methods have been presented in previous studies, they have all centered around the concept of constructing a single statistically representative cycle for a region based on measured data. Opposite these studies, in this research, the objective of driving cycle generation is to synthesize the driving speed profile for each trip.

Thus, for each EV trip, a Trip-Specific Stochastic Driving cycle (TSSDC) is generated with a one-second resolution time from origin to the selected destination of the trip on the predicted trip route. To this end, the Markov Chain (MC) is used to generate TSSDC in the urban electromobility simulation. MC generates the driving speeds based on Transition Matrix Probability (TPM), representing the transfer probability between different speed levels. The general idea of the MC is to predict the probability of a transition into a particular state of the system. In an n-order MC, the transition probability depends on the last n previous states.

Hence, it is unnecessary to regard the whole chain of prior states. An MC in which only the current state is considered to predict the probability of the following state is called an MC of the first order, which is used in this study for stochastic driving cycle generation.

Based on this idea, it is possible to create a TPM that includes all of the possible transitions between every possible state of the recorded driving data. Each state s_i contains one value for velocity. Each transition is assigned to a probability that leads to transition probabilities p_{ij} for each pair of states s_i, s_j. Each row in the TPM represents the transition probabilities from the state s_i in the first column to the following states s_{i+1} in the subsequent columns. Therefore, the sum of each row in the TPM equals one. The MC begins with an initial state, and at each second, a choosing mechanism determines the next state stochastically based on states' probabilities in the TPM. To this end, a random number U (0,1) is picked out and compared with the cumulative probabilities of the TPM's row corresponding to the current state to choose the next state, in which a state with the highest probability is usually chosen, while it is possible to select another state. The procedure is repeated until the MC has reached the desired length. However, a sizeable real-world dataset of driving speed is needed to generate the required TPMs. Therefore, in the absence of the driving speed of EVs, the collected driving speed of conventional vehicles can be used to synthetic driving speed profiles. In this context, the large dataset of driving data provided by the National Renewable Energy Laboratory (NREL) is used to generate TPMs. Although the driving speeds on the streets are stochastic, traffic conditions and the type of street affect the users' driving patterns. The users adjust the driving speed of EVs on each street segment in accordance with the speed limit and the congestion level of the street segment. Since the speed limit depends on the type of street and the congestion level of the street determined by street traffic condition, the trip's driving cycles should be stochastically generated according to the street's type and traffic condition. Whereas the street type and traffic condition parameters are not considered in the driving speed recording in the NREL dataset, as expressed in [120], the characteristics that describe driving under different street types and traffic conditions can be assumed to classify driving speed data. The street type of a street segment determines the speed limit, and segment traffic conditions identify the segment's average driving speed. Hence, the average and maximum driving speeds can be considered two indicators to classify driving data according to traffic and street type. In this context, according to the four SPI values illustrated Table 4.4corresponding to the traffic conditions, and seven unique V_{max} for street types speed limits mentioned in Table 4.5, the 28 classes are specified to classify the driving speed data for different combinations of traffic conditions and street types.

Table 4.6 demonstrates the classes specification for 28 classes of traffic-street type combinations.

Table 4.6

Traffic class specifications

class	Street type	traffic	Avg.speed fragments(km/h)	$V_{max}$of fragment(km/h)
1	motorway	Traffic jam	$5 < V_{avg} \leq 27.5$	27.5
2	motorway	Heavy traffic	$27.5 < V_{avg} \leq 55$	55
3	motorway	Moderate traffic	$55 < V_{avg} \leq 82.5$	82.5
4	motorway	Free flow	$82.5 < V_{avg} \leq 110$	110
5	trunk	Traffic jam	$5 < V_{avg} \leq 22.5$	22.5
6	trunk	Heavy traffic	$22.5 < V_{avg} \leq 45$	45
7	trunk	Moderate traffic	$45 < V_{avg} \leq 67.5$	67.5
8	trunk	Free flow	$67.5 < V_{avg} < 90$	90
9	primary	Traffic jam	$5 < V_{avg} \leq 17.5$	17.5
10	primary	Heavy traffic	$17.5 < V_{avg} \leq 35$	35
11	primary	Moderate traffic	$35 < V_{avg} \leq 52.5$	52.5
12	primary	Free flow	$52.5 < V_{avg} \leq 70$	70
13	secondary	Traffic jam	$5 < V_{avg} \leq 15$	15
14	secondary	Heavy traffic	$15 < V_{avg} \leq 30$	30
15	secondary	Moderate traffic	$30 < V_{avg} \leq 45$	45
16	secondary	Free flow	$45 < V_{avg} < 60$	60
17	Tertiary, motorway-link, trunk-link	Traffic jam	$5 < V_{avg} < 12.5$	12.5

18	Tertiary, motorway-link	Heavy traffic	12.5< V_{avg}<25	25
19	Tertiary, motorway-link, trunk-link	Moderate traffic	25< V_{avg}< 37.5	37.5
20	Tertiary, motorway-link, trunk-link	Free flow	37.5< V_{avg}<50	50
21	Residential, primary-link	Traffic jam	5< V_{avg}<10	10
22	Residential, primary-link	Heavy traffic	10< V_{avg}<20	20
23	Residential, primary-link	Moderate traffic	20< V_{avg}<30	30
24	Residential, primary-link	Free flow	30< V_{avg}<40	
25	Especial, secondary-link, tertiary-link	Traffic jam	5< V_{avg}<7.5	7.5
26	Especial, secondary-link, tertiary-link	Heavy traffic	7.5< V_{avg}<15	15
27	Especial, secondary-link, tertiary-link	Moderate traffic	15< V_{avg}<22.5	22.5
28	Especial, secondary-link, tertiary-link	Free flow	22.5< V_{avg}<30	30

As mentioned before, the objective is to develop a model to synthesize driving cycles for possible combinations of street type and traffic conditions (e.g., the 28 classes as mentioned earlier) to generate EV driving speed in each trip. For this purpose, the real-world driving speed data should be assigned in the classes. To classify driving speed data, similar to [121], the driving speed data of NREL are divided into kinematic fragments that each fragment includes an idle phase followed by a driving phase. Figure 4.13 shows the kinematic sequence fragmentation for a sample trip of the NREL driving speed dataset.

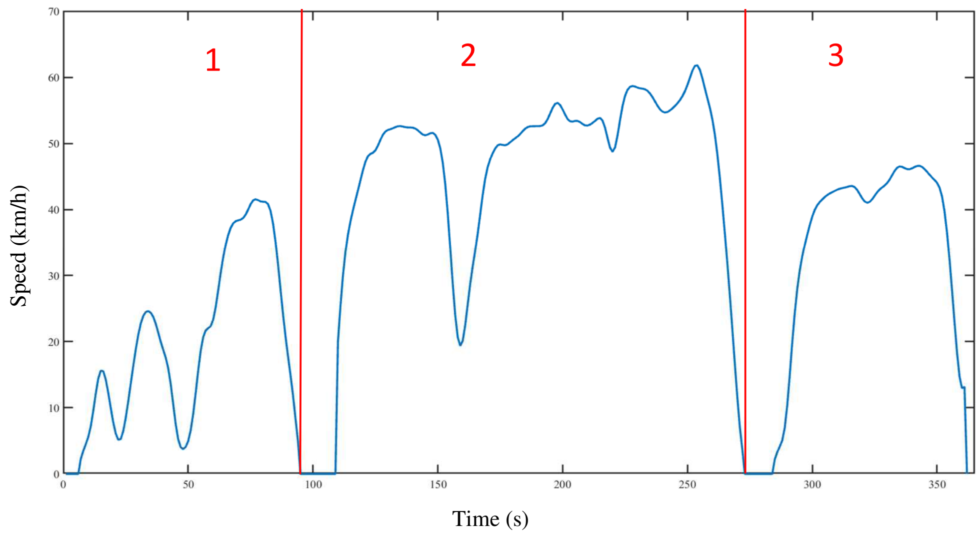


Figure 4.13. Kinematic fragments of a sample trip.

The extracted kinematic sequences are examined to remove abnormal sequences so that the sequences with a maximum speed of more than 120km/h, acceleration more than 4m/s^2, deceleration less than -4m/s^2, idle time of more than 180 seconds and running time smaller than 30 seconds are removed. Each kinematic fragment is a part of a trip representing the driving speed profile on a street segment under a specific street type and traffic condition. As such, the kinematic fragments can reflect the driving under a particular pair of street types and traffic conditions. Thus, the kinematic fragments are assigned to classes regarding each class's average and maximum speeds (Table 4.5). To this end, each fragment's average and maximum speed are determined. Then, kinematic fragments are assigned to classes according to their average and maximum speed and each class's average speed range and maximum speed. It is worth noting that a fragment may be assigned to several classes, which is not an issue because the objective is not to generate a unique driving cycle.

After assigning kinematic fragments to classes, a TPM is constructed for each class. The TPM of each class is constructed based on transferring probabilities between different speed levels in the fragments of the class. The speed bins with a constant bin width of 1 km/h are considered as states. For each class, the number of states is equal to v_{max}, which v_{max} is the maximum permissible speed of the class. Thus, the speed values of each kinematic sequence, which are with one-second resolution, are discretized into speed bins, with a constant bin width of 1 km/h, so that the *v*(t)∈ [0, 1] km/h are in the first velocity state s_1, all velocities *v*(t)∈ [1, 2] m/s are in the second state s_2, and so on. Thus, each kinematic sequence is defined as

$$v_{ks} = \{s_1, s_2, s_3, \ldots, s_n\} = \{[0, . . ,1], [1, . . ,2], \ldots, [v_{max} - 1, . . , v_{max}]\}$$
(4.25)

Finally, based on transferring probabilities between states in all kinematic fragments in a class, its square matrix TPM with size v_{max} * v_{max} is created. Figure 4.14 shows the TPM of class 20 with $v_{max} = 50$.

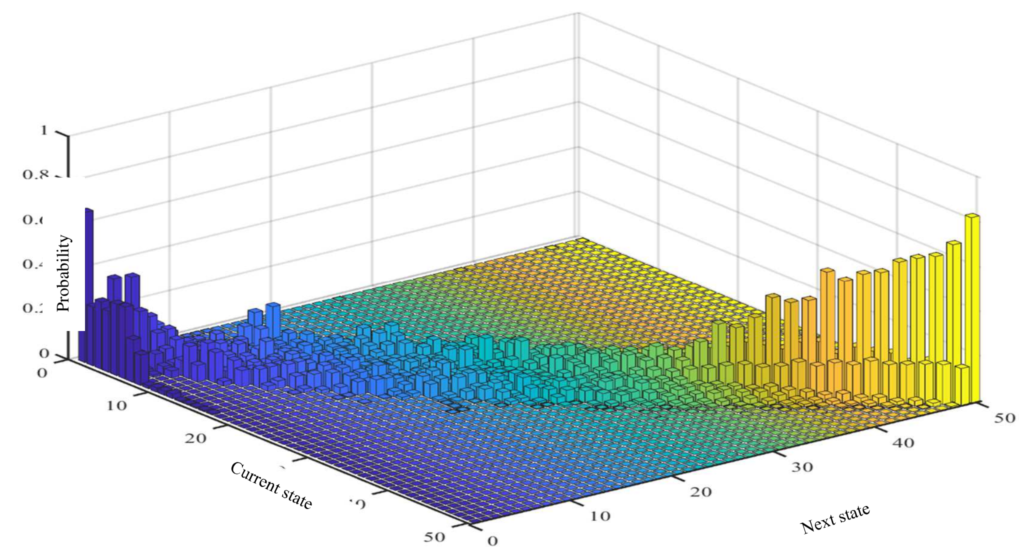


Figure 4.14. Speed TPM of class 20.

4.3.6.1.Synthesis stochastic driving speed profile of a street segment

The MC generates the second-by-second driving speed of each street segment based on the segment's corresponding TPM and initial state s_0. The procedure of generating a stochastic driving speed profile for a segment with the known street type, daily traffic condition predictions, length(l_s) is described as follows.

- **Determining the segment's TPM**

The segment's TPM is selected from the generated 28 TPMs according to the segment's class, determined based on the segment's street type and traffic condition. The street type of a segment is known and is fixed during simulation, but its traffic condition is changed over the day. The traffic prediction model determines the daily traffic of urban street segments with the two-minute time-step that the segments' traffic state is considered fixed within each time step. The daily traffic of each segment includes 740 traffic states, in which the time-step number for determining the segment's traffic state for EV driving is selected based on the arrival time of EV at the segment. The arrival time is the sum of departure time from the O location (starting time of the trip) and driving time from the O location until the beginning of the segment. For example, suppose departure time from an O location is 9:00 hours and EV driving time to an arbitrary segment is three minutes. So, the arrival time will be 9:03(543 in minutes), so the time step number to determine the traffic state of the segment is 272(ceil (543/2)). Accordingly, the segment's class is specified based on segment traffic state and street type according to Table 4.6. The segment's TPM is selected from the classes' TPMs.

- **Specifying the initial state s_0 for street segment**

To generate the driving speed profile of the segment, in addition to the segment's TPM, the MC needs the s_0 that is determined based on the initial speed v_0 . For the first street segment of the trip route the $v_0 = 0$ and s_0=1, because the driving starts from the O location at zero speed.

For other segments of the trip route, the transition from the previous segment to the segment is determined according to the previous segment's last-second speed and *Vmax* of the segment. If the previous segment's last-second speed is less than *Vmax* of the segment, the v_0 is considered the last-second speed of the previous segment, and the corresponding state is determined. Otherwise, the previous segment's last-second speed cannot be considered as the v_0 for the segment because there isn't a row in the TPM corresponding to the s_0 corresponding to this v_0. For example, suppose the previous segment's last-second speed is 50 km/h, and the maximum speed of the segment is 40 km/h, so the segment'TPM, which is a square matrix 40*40 (s=1,2,..40), doesn't have a row corresponding to 50 km/h to generate driving speed for the first-second speed of the segment. In this case, a few seconds deceleration modal with constant deceleration called slow-down is added to decrease the speed from the last-second speed of the previous segment to the first speed less than Vmax of the segment. The constant deceleration for slow-down is determined as the maximum deceleration corresponding to the previous segment's last-second speed, determined based on the acceleration-speed distribution of driving data as shown in Figure 4.15.

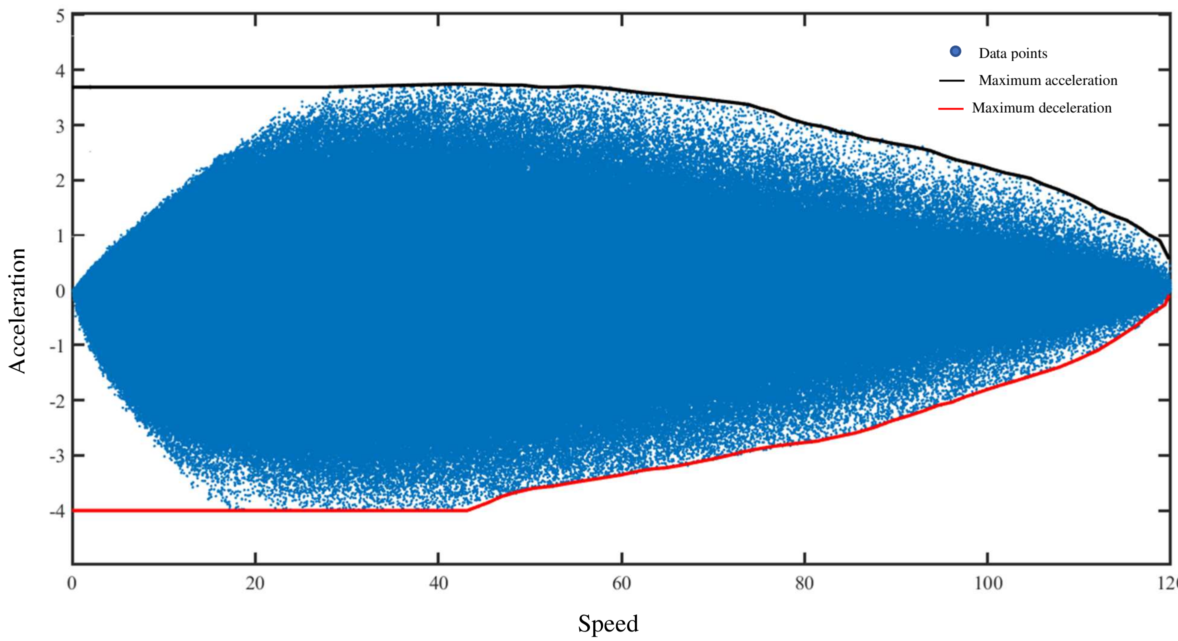


Figure 4.15. Distribution of speed-acceleration data.

- Generating driving speed profile of street segment by MC

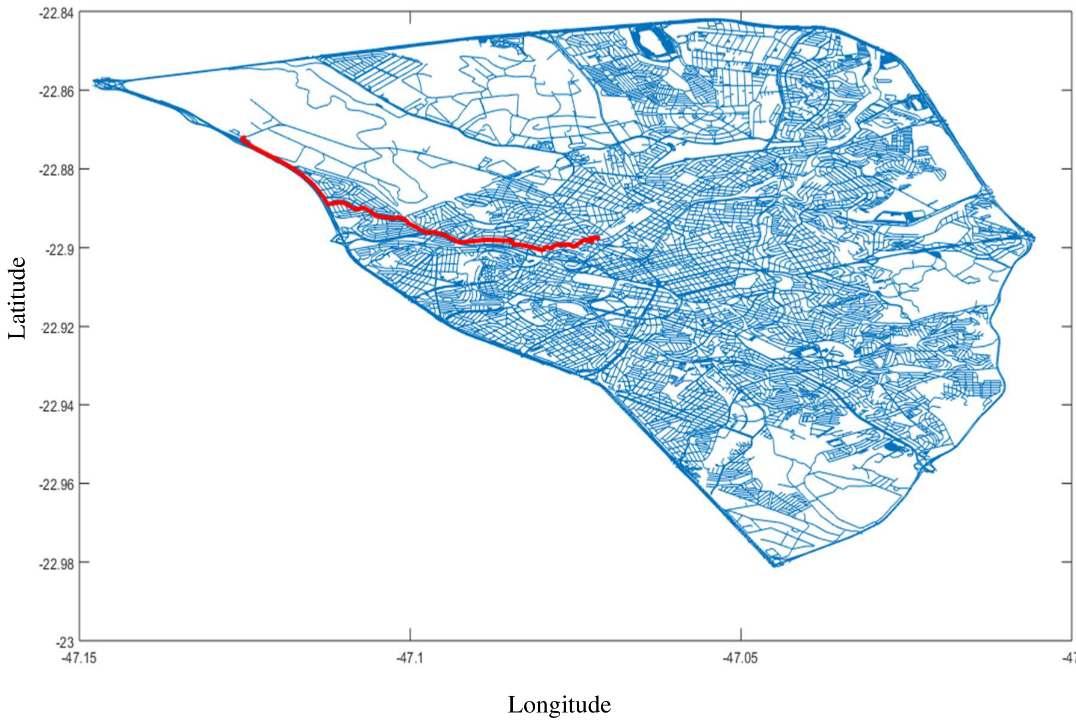
After determining the initial state and TPM for the street segment, MC generates the second-by-second speed of EV driving on the segment based on the TPM and the speed of the previous second. Moreover, the acceleration/deceleration, travel distance, and energy consumption are calculated each second. This process is continued until EV reaches the end of the segment.

4.3.6.2.Trip-Specific Stochastic Driving Cycle (TSSDC)

For an EV trip, the predicted trip route consists of n_s street segments, which according to their IDs, attributes include street type, length, and daily traffic predictions are extracted from the urban street network information. The stochastic driving speed profiles of the route's segments are generated by the MC according to the previous section, and then they are put together to generate the TSSDC. The procedure of the TSSDC synthesis is summarized below.

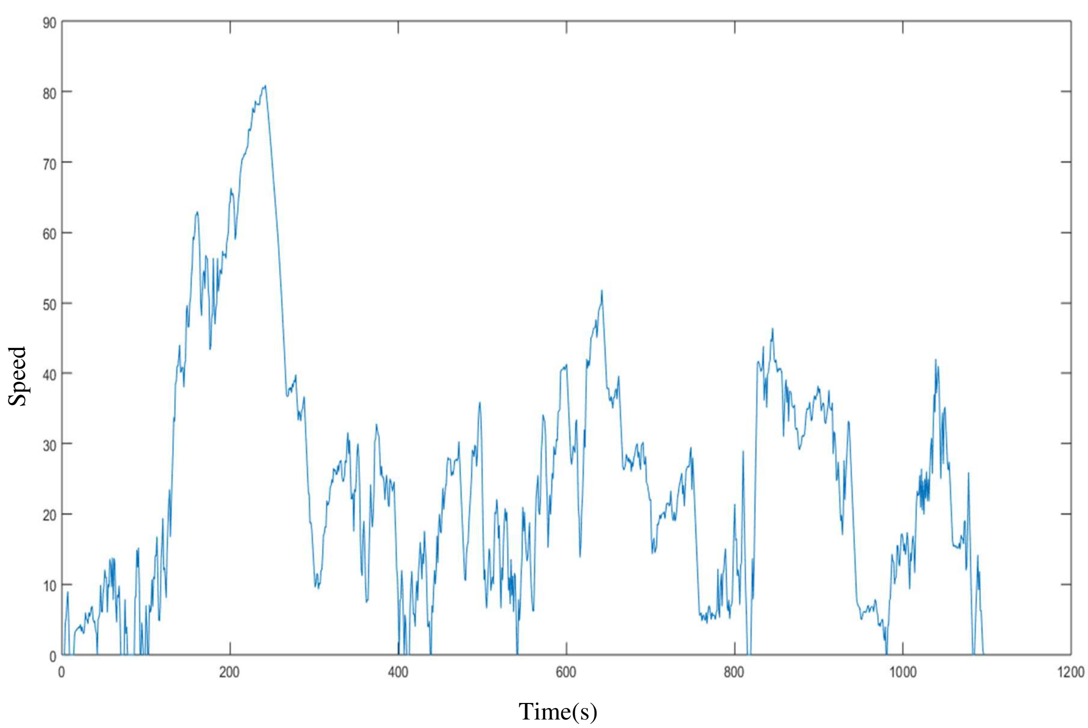
(1) According to the IDs of n_s street segments of the trip route, the required information of route's segments are extracted.
(2) Set the sequence number of rout's segments; N=1, 2, …, n_s.
(3) EV driving starts from the O location at zero initial speed.
(4) MC generates the second-by-second driving speed profile of each segment.
(5) The acceleration/deceleration, travel distance, and energy consumption are calculated each second.
(6) According to instantaneous SoC calculation of EV on the segment, the SoC of EV at the end of the segment is considered to assess the possibility of en-route charging by the EV user (i.e., whether SoC is less than SoC critical). If en-route charging is the case, the EV user finds the nearest FCS to charge the EV. To simulate the user behavior in FCS selection, the shortest routes on the street network graph from the end node of the segment to FCS candidates are determined by the Dijkstra algorithm. Then the nearest FCS is selected, and the shortest route to the selected FCS is considered the new trip route. The information of the new trip route is extracted and go to step 3.
(7) If en-route charging is not the case and $N < n_s$, *N*= *N*+*1,* and go to step 3.
(8) If $N = n_s$, the EV reached the D location, and a slow-down from the last speed of the last segment to zero (i.e., EV reaches zero speed at the D location.) is added to the driving speed profile of the last segment.
(9) The driving speed profiles of segments are combined to generate the TSSDC.
(10) Based on departure time at the O location and driving times on segments, the arrival time at the D location is calculated.
(11) According to departure SoC at O location, the instantaneous EV energy consumption and SOC updating at each second of driving, the driving SoC profile, and arrival SoC at the D location are obtained.

For a sample EV trip, the trip route, TSSDC, and SoC profile of an EV trip are illustrated in Figure 4.16.



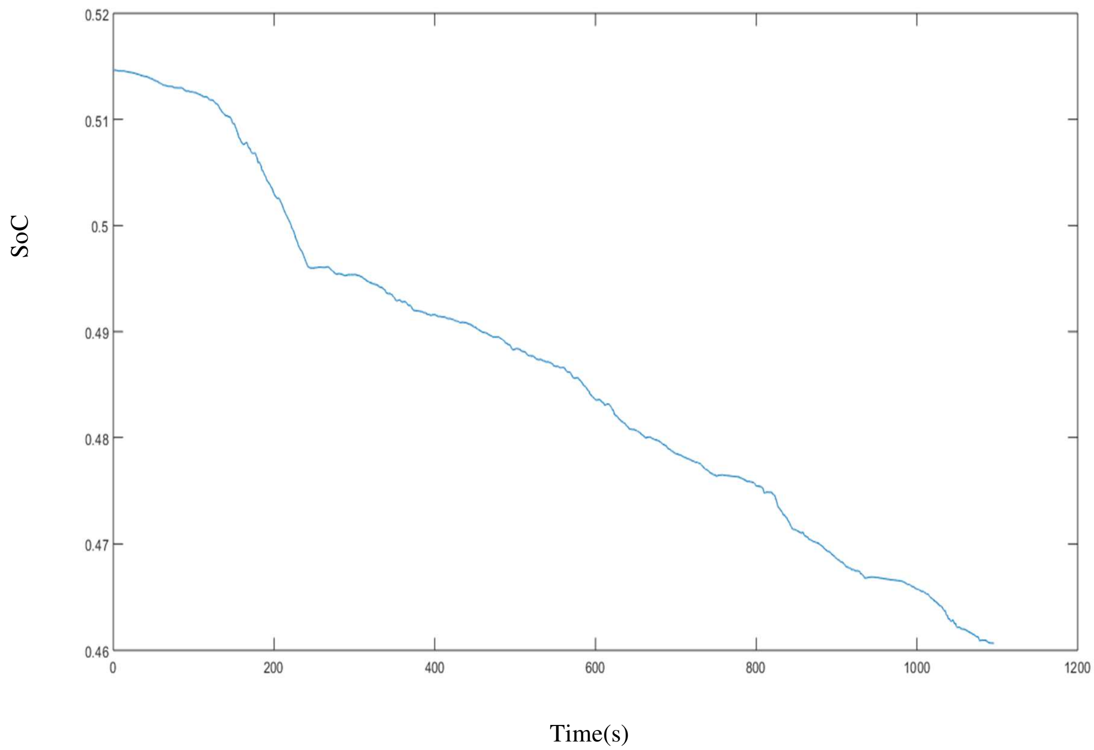
-22.84
-22.86
-22.88
-22.9
-22.92
-22.94
-22.96
-22.98
-23
-47.15
-47.1
-47.05
-47
Latitude
Longitude

(a)



90
80
70
60
50
40
30
20
10
0
0
200
400
600
800
1000
1200
Speed
Time(s)

(b)



(c)

Figure4.16. Driving pattern of a sample EV trip: (a) trip route, (b) TSSDC, (c) SoC profile.

The flowchart of generating the TSSDC for an EV trip is demonstrated in figure 4.17.

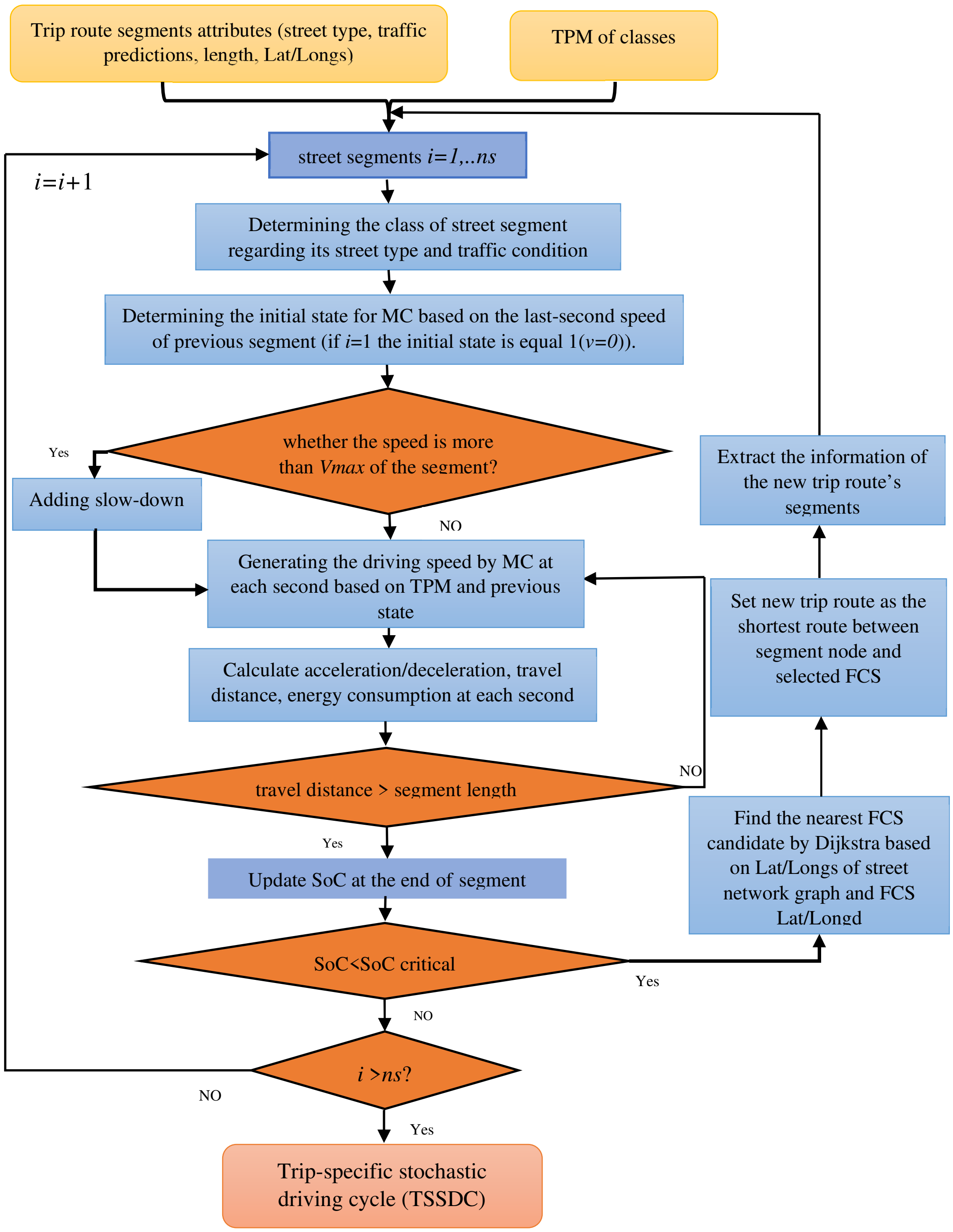


Figure 4.17. Flowchart of the TSSDC generation.

4.4.EV user's charging behavior

In the electromobility simulation, the charging behavior of the EV user is interpreted as their decision-making at a given charging opportunity, which determines their tendency to charge. Furthermore, EV users who decide to charge also make decisions on the charging mode and start time of the charging process.

In most literature, charging behavior is often modeled based on simple rules that initiate charging when certain SoC thresholds are reached. However, these methods are not suited to the realistic model of charging behavior because they do not consider that in the real world, users are aware of their mobility behavior and environment (street topology, traffic, etc.) and can estimate the amount of energy to meet their subsequent travel demands. Moreover, EV users prefer to integrate charging into their daily activities, especially in primary activities (home, work), which is more comfortable.

The previous models that in contrast to real-life charging behavior, in which users might decide to charge in anticipation of their impending energy consumption, using threshold- and feasibility-based behaviors assume that users blindly use their vehicles until charging becomes unavoidable, leads to inaccurate prediction of EV charging demand in different location of the urban area. Therefore, to provide a realistic model of users' charging behavior in a realistic simulation of the urban electromobility, it is essential to consider all influencing parameters on users' decision-making.

4.4.1. EV user classification based on access to charging location

In the daily itinerary, the EV users travel between different activity locations that can be classified as home, workplace, and public locations. It is not realistic to assume that every user can charge at each activity location. All homes in the urban area cannot be equipped with a charging pile due to the shortage of budget and space. Besides, the charging facilities are partially provided at workplaces, such as government agencies, large offices, companies, manufacturing, etc. However, contrary to the home and workplace, it is assumed that all agents have access to slow and fast charging at public destination locations, which include the EV parking lot at different activity types (e.g., shopping malls, recreation amenities, restaurants, etc.), FCS, public EV parking lots, etc.

Therefore, according to the access of the charging locations (i.e., home, work, and public), EV users can be classified into four types as follows.

(1) Home-based users

(2) Work-based users

(3) Home and work-based users

(4) Public-based users

The home-based users consist of the employed, unemployed, and student user types that have charger piles at their homes. Work-based users only include the employed user type with access to charging facilities at their workplaces. Home and work-based users consist of employed users who have chargers at their homes and workplaces. Public-based users include users that only have access to charging facilities at public locations.

It is worth noting that all EV users have access to charging facilities at public charging, that is, home-based, work-based, and home and work-based users, in addition to their private charging at home or workplace, can charge EV at each public location. Moreover, it is assumed that public locations have enough charger piles to charge all incoming EVs at these locations.

Charging network coverage can be represented by the probability that a charger is available at an activity location type. Two probabilities are assumed for users who live in single-family houses and multiple families for access to charging facilities at homes. For workplaces, according to the work type of user, the probabilities of availability of charging facilities at workplaces are assumed. Besides, it is assumed that there are enough charging infrastructures in the land-uses to meet the charging demand of EVs with the destination at public locations (travel activities at S, R, H, R, P, and O). Each public location in different land-uses has enough charging piles to charge incoming EVs.

4.4.2. Influencing factors on EV users charging decision

To achieve accurate predictions of urban charging demand for transportation electrification planning, besides the models of the actual urban street network, urban traffic pattern, and EV user driving behavior, the realistic charging behavior of EV users, must be modeled by taking into account the main effective parameters. However, most existing studies reduce charging behavior to a fixed and often overly simplistic set of rules, which trigger the charging process at a fixed SoC threshold at a fixed charging opportunity (only at home or workplace) a particular hour of the day. While in the daily urban trips, EVs can be charged at different locations and times of the day under EV user preference that is influenced by technical and mental factors. Contrary the most of the existing models that assumed users blindly use their EVs until charging becomes unavoidable, in real-life charging behavior, users are aware of their mobility behavior as a whole, and they are capable of estimating the amount of energy they will need until the next destination regarding the urban traffic predictions and EV energy consumption estimation.

Therefore, the charging decision of EV users can be affected by technical considerations, behavioral patterns, mental models, price, and personal preferences. In this regard, in this research, the impact of the SoC level of EV at the moment of decision, required energy for the next trip, user range anxiety, convenience in charging are considered in the EV user charging behavior modeling.

4.4.2.1.SoC level of EV's battery

SoC of EV as an indicator can help EV users decide whether to charge or not. In this regard, the prediction of the SoC for the forthcoming trip and estimation of instantaneous SoC during driving enable users to decide the charging at destination location and en-route emergency charging. As described in the EV users' driving behavior modeling, users predict the trip route and required energy for the next trip at the destination location. Accordingly, they can decide to charge EV at the destination location based on the available SoC and required SoC for the next trip. Furthermore, the TSSDC generating and instantaneous SoC calculation on the predicted trip route described in the EV driving pattern modeling help users to make decisions on en-route charging.

Upon arrival at a destination with a charging opportunity, the user decides to charge EV at the current destination if the arrival SoC is less than the needed SoC for the next trip. Thus, predicting the required energy for the next trip facilitates the user's decision to charge EV at each activity location. To this end, based on the arrival time and parking time at a destination, the departure time of the destination is calculated. The purpose of the next trip is determined based on departure time and hourly TPM corresponding to the user type. The required SoC for the next trip is predicted based on the optimal-energy trip route choice and segment-based EV energy consumption models regarding the EV technical features, street network topology, and traffic conditions.

As described before, since the prediction of instantaneous EV driving speed and energy consumption predictions for the next trip is complicated on the large urban street network, the destination location and route of the next trip are determined based on the segment-based optimal-energy trip route model, in which respect to the next trip fixed or non-fixed destination location, the optimal-energy route found by the optimal trip route choice model or simultaneous destination and route choice model for the non-fixed destination location. As such, the user decides to charge EV at the destination location if the arrival SoC is insufficient to support the next trip. However, despite having enough energy for the next trip, it is still possible that the user tends to charge EV at this destination, which can be caused by their range anxiety and preferences of charging at locations more comfortably.

4.4.2.2.EV user's Range Anxiety

Range anxiety has a strong influence on charging behavior that refers to the psychological state of the users who are trying to avoid a low SoC to prevent the psychological stress associated with the possibility of an empty battery. The range anxiety parameter is difficult to quantify as it is determined with the users' thoughts. To quantify the range anxiety of users, the anxiety SoC (SoC^{anx}) is defined as the minimum SoC preference of a user, which is the SoC level that EV must be charged before the battery's SoC reaches it. As such, for each user, a specific SoC^{anx} is considered so that EV user prefers to charge EV before the battery's SoC reaches SoC^{anx} even if EV has enough energy to meet the next trip. According to this, users prefer to keep the SoC of EV's battery more than SoC^{anx} before starting a new trip. The SoC level at the beginning of EV charging presented by [122] is considered to determine the SoC^{anx} of EV users that they do not allow EV's SoC to fall below this SoC level by charging at destination before departure from the destination. Accordingly, the SoC^{anx} is represented by a normal distribution with μ= to 0.466 and σ=0.179, which this PDF is truncated from the lower and upper tails to 0.2 and 0.8, respectively.

4.4.2.3.Convenience in EV charging

Charging convenience refers to EV users' preference to integrate charging into their daily activities. Hence, if the charger is available at the activity location, users take advantage of the dwell time to charge their EVs with slow charging without interfering with their travel plans. In this regard, the charging at home and workplaces are more comfortable than in other locations to users who access charging facilities at these locations. As a result, home-based users prefer nighttime charging at home to public charging to take advantage of low-price charging costs.

4.4.3. Charging strategies

Regarding charging's influencing factors and users' preferences, the following charging strategies are used to model the users' charging behavior.

4.4.3.1.Obligatory charging

Obligatory charging is developed based on the users' range anxiety concept and the required energy for the next trip. In this context, obligatory charging is invoked when the battery's SoC is insufficient to meet the user's range anxiety and required energy for the next EV trip. Two obligatory charging are considered; obligatory charging at destination and en-route obligatory charging.

- **Obligatory charging at destination location**

At any destination location with charging opportunity if the arrival SoC (SoC^{ar}) of EV less than the sum of required SoC for the next trip ($SoC^{n.t}$) and SoC^{anx} , EV must be charged immediately.

- **En-route obligatory charging**

According to the instantaneous driving speed of TSSDC on the chosen trip route, the instantaneous acceleration/deceleration, travel distance, and energy consumption are calculated. Based on instantaneous energy consumption, the SoC of EV is updated at each instant. As such, whenever the SoC is less than the critical SoC (SoC_{cr}), the obligatory en-route charging is invoked. At this moment, the user accepts a detour to charge EV at the nearest FCS, and after fully charging the EV, continues the trip to reach the planned destination location. The SoC_{cr} is considered as 25%, which is widely assumed in the literature. It is worth noting that, although for a trip, at the arrival of the origin of the trip, the required energy of the trip is estimated and charging decision is made, there is the possibility that the actual EV energy consumption based on instantaneous driving speed is more than estimated required energy based on segment-based energy consumption. Thus, it is possible that during driving the SoC of EV reaches the critical SoC, and EV needs to emergency en-route charging.

4.4.3.2.Convenient Charging

In contrast the obligatory charging, convenient charging is decided by EV users while the SoC^{ar} at the destination is still sufficient to meet the required energy for the next trip, but the EV user prefers to charge the EV at the destination location. The user’s decision for this charging strategy is mainly influenced by the destination type (home or workplace), the amount of SoC^{ar}, and parking time at the destination. For users with charging facilities at home and work, the convenient charging is the nighttime charging at home and daytime charging at the workplace so that these users’ preferences are the convenient charge at home and work regardless of the required energy for the next trip and range anxiety, to take advantage of parking time to charge EV as much as possible. Public charging is not convenient for EVs who have charging facilities at home or work, and the preference of these users is postponement charging to home and workplace. On the other hand, for users who only have access to public charging facilities, it is assumed that there is no priority between public locations. The public-based users' decision for convenient charging at public destinations can be affected by the current SoC level of EV's battery, parking time, distance to the next destination.

4.4.3.3.Charging delay

It is assumed that the Time of Use (TOU) electricity tariff motivates EV users to delay charging to the low-price off-peak hours if they have enough parking time at the destination location. Regarding the TOU electricity price in the study area, delayed charging is considered only for home charging, so the EV user who arrives home early (before 23:00 hours) delay EV charging to 23:00 hours to take advantage of the low-price energy from 23:00 to 6:00 hours.

4.4.4. EV user's decision-making on the charging mode

The charging mode is mainly divided into slow and fast charging modes. Slow charging is available at the home, workplace, parking lots at different activity locations (e.g., shopping, recreation, etc.), and public parking lots. Fast charging is mainly available at the FCS in the urban area.

It is assumed that for slow charging at workplaces and public locations, the EV user leaves the EV in the charging location and goes to the activity location to perform the activity. Then, at the end of activity time, the user takes EV from the charging location. In this case, the slow charging facility is usually located at the activity location or near it within a reasonable walking distance (e.g., maximum 300 meters).

However, contrary to slow charging, fast charging time is short, and the user cannot leave the EV at FCS. Therefore, it is assumed that a user with fast charging demand at an activity location, at the end of the activity and before starting the next trip, goes to the nearest FCS to charge EV. Moreover, it assumed that the user who goes to FCS prefers to charge EV fully and then continues the trip to the next destination. In this case, the trip route is updated from the FCS location to the already predicted destination at the departure time of the activity location. Given that homes and workplaces are only equipped with slow charging, the user does not make the charging mode decision whenever they decide to charge at them. Contrary, the user needs to choose the charging mode for charging EVs at public destinations.

Basically, the users prefer to choose slow charging to integrate charging with their activities. Nonetheless, the fast charging mode will be selected if the parking time is very short (e.g., less than 30 minutes) or if slow charging within the parking time cannot meet their minimum expected SoC (SoC_{min}^{exp}), which is calculated as follows:

$$SoC_{min}^{exp} = (SoC_{n.t} + SoC^{anx}) - SoC^{arr} \quad (4.26)$$

Therefore, if equation (4.27) is satisfied or if t_p is less than 30 minutes, the user chooses to charge the EV by fast-charging power. Otherwise, the slow charging mode is used.

$$\frac{P_{slow} t_p}{B_c} + SoC^{arr} < SoC_{min}^{exp} \quad (4.27)$$

Where P_{slow} is the slow charging power and B_c is the battery capacity.

When the charging decision has been made, and the user has chosen the charging mode, EV's charging demand and charging time are calculated. For slow charging mode, the maximum charging time equals parking time (activity duration), and EV can be fully charged during parking time if the required time to full charge is less than parking time. Otherwise, the charging demand is the amount of energy that EV can receive during parking, which is calculated according to the equation (4.28). For fast charging at FCS, the EV will be fully charged, and the charging time is the required time for fully charging regarding the charging power rate and battery capacity, as shown in equation (4.29).

$$\text{Slow charging: } \begin{cases} \frac{P_s t_p}{B_c} + SoC^{arr} > SoC_{min}^{exp} \\ t_{fch_s} = \frac{(SoC_{max} - SoC^{arr}) B_c}{\eta_s P_s} \\ t_{ch_s} = \begin{cases} t_{fch_s} & t_{fch_s} \leq t_p \\ t_p & t_{fch\_s} \geq t_p \end{cases} \\ D_s = \begin{cases} P_s t_{fch_s} & t_{fch_s} \leq t_p \\ P_s t_p & t_{fch_s} \geq t_p \end{cases} \end{cases} \quad (4.28)$$

$$\text{Fast charging:}\begin{cases} \frac{\eta_s P_{slow} t_p}{B_c} + SoC^{ar} < SoC_{min}^{exp} \\ t_{fch_f} = \frac{(SoC_{max} - SoC^{ar})B_c}{\eta_f P_{fast}} \\ D_f = P_f t_{fch\_f} \end{cases} \tag{4.29}$$

Where *P* is the charging power rate, η is the charging efficiency, t_{fch} is the full charging time, and *D* is the charging demand. The subscriptions *s* and *f* refer to slow and fast charging mode, respectively.

At the departure time of the destination location, the departure SoC of EV (SoC^d) is updated based on the equation (4.30) and equation (4.31) for slow and fast charging, respectively.

$$SoC^d = SoC^{ar} + (D_s/B_c) \tag{4.30}$$

$$SoC^d = SoC^{ar} + \left(\frac{D_f}{B_c}\right) = SoC_{max} \tag{4.31}$$

Therefore, regarding those above four charging strategies and two charging modes, the charging behaviors of four EV user types are modeled as follows.

4.4.5. Charging behavior of home-based users

These EV users have the possibility to charge their EVs at home and public locations. Regarding convenience charging, their preferences are nighttime charging at home. Moreover, they delay the charge to lower energy price time regarding arrival and parking times at home. In this regard, based on arrival time and the departure from home at next day, the parking time at home is calculated. Then, the possibility of delay charging time to 23:00 hours is evaluated. If the user's arrival time to home is after 23:00 hours, the EV is connected to the charger immediately upon arriving home. If the arrival time is before 23:00 hours, regarding the SoC^{ar}, it is assessed whether EV can be charged fully at the low-price time after 23:00. If it is the case, the charging start time is delayed to 23 hours. Otherwise, the charging is started before 23 hours, and a charging start time is selected that EV will be fully charged so that the maximum low-price time from 23:00 – 6:00 is used to charge EV.

Once the home-based EV users are at public locations, if the EV needs obligatory charging, the EV must be charged immediately. Otherwise, the user postpones charging until they reach home to take advantage of nighttime charging at home. In fact, for these users, the probability of public charging is very low due to frequent nighttime charging at home.

4.4.6. Charging behavior of home and workplace-based users

Although these users have access to all charging alternatives (home, work, and public), they prefer to convenient charge at home and the workplace even if the EV doesn't need charging. As such, upon arriving at the workplace, EV is connected to charge immediately, and EV is charged while the user is working at the workplace. The home charging behavior of these users is the same as home-based users mentioned in the previous section. These users choose public charging only for obligatory charging, otherwise, they postpone charging to home and workplaces. For these users, the probability of public charging is very low because of frequentative charging at the home and workplace.

4.4.7. Charging behavior of work-based users

These users only have access to charging facilities at their workplaces. The preference of these users is charging at the workplace during working time. If obligatory charging is the case at the public destinations, EV will be charged immediately. Otherwise, the charging is postponed.

These users charge their EVs at workplaces regardless of the SoC level and range anxiety and tend to full charge EV.

4.4.8. Charging behavior of public-based users

This group consists of users who only can charge EVs at public charging locations in the urban area. It is assumed that there is no priority between different public charging locations for these users, and they tend to select the most convenient charging location. In this regrade, if there is no need for obligatory charging at the public activity location, the convenient charging is stochastically determined based on the charging probability estimated via the Fuzzy system according to the affecting factors. The main affecting parameters on the charging decision of these EV users are the SoC level of EV's battery, parking time, distance to the next destination. Since these EVs have enough energy to support the next trip (i.e., obligatory charging is not the case), the users are not concerned about the following travel distance. Hence, the charging decision is mainly affected by the SoC level and parking time.

Explicit mathematical expressions cannot express the influence of these parameters on users' charging decisions. Due to the lack of actual charging behavior data of EV users, there is no basis to determine specific formulas or assumptions to determine the users' decisions. Moreover, modeling the charging behavior by assuming that the charging takes place at a particular time or is based on a specific formula is not realistic. To overcome this drawback, the probability of EV charging is determined based on a Fuzzy inference system by taking into account the influential factors on the charging decision of EV users, which can lead to a realistic model of the charging decision of users. The Fuzzy system consists of four principal components: fuzzification, a rule base, inference logic, and defuzzification. First, the numerical inputs are applied to the fuzzification block, and the fuzzification interface converts numerical inputs into fuzzy variables. Finally, the defuzzification interface changes the Fuzzy variables back into the numerical output. For both inputs and the output, fuzzification is achieved utilizing membership functions, determined primarily based on the choice of shape and the number of fuzzy signals. Inputs to the fuzzification block include two variables for each EV: SoC level at arriving at the destination location and the parking duration. The output is the charging probability for EV at the destination location. For both inputs and the output, fuzzification is achieved through membership functions, determined primarily based on the choice of shape and the number of fuzzy variables. Gaussian shapes are chosen for the inputs and outputs after several trials and practices.

Two fuzzy inputs are converted into different linguistic variables through the proposed fuzzy inference system, which is Mamdani fuzzy inference system. The SoC amount of battery is a significant parameter to EV's driver deciding charging at the destination location, which is defined in the range of [0~1]. The Gaussian membership function with five linguistic terms as Low (L), MediumLow (ML), Medium (M), MediumHigh (MH), and High (H) are defined for SoC. The maximum parking duration is assumed as 12hourss (720min) according to the OD-RMC dataset. Parking time is described by five linguistic variables as; Very Short (VS), Short (S), Medium (M), Long (L), and Very Long (VLD). The output of the fuzzy system as a decision variable is charging probability which is defined in the range of [0~1]. Its membership functions are gaussian with five linguistic variables: Low (L), MediumLow (ML), Medium (M), MediumHigh (MH), and High (H). Finally, the fuzzy system is coupled by stochastic sampling to determine the charging decision (charging or not charging) according to the obtained charging probabilities. The stochastic charging decision model based on the Fuzzy system is shown in Figure 4.18.

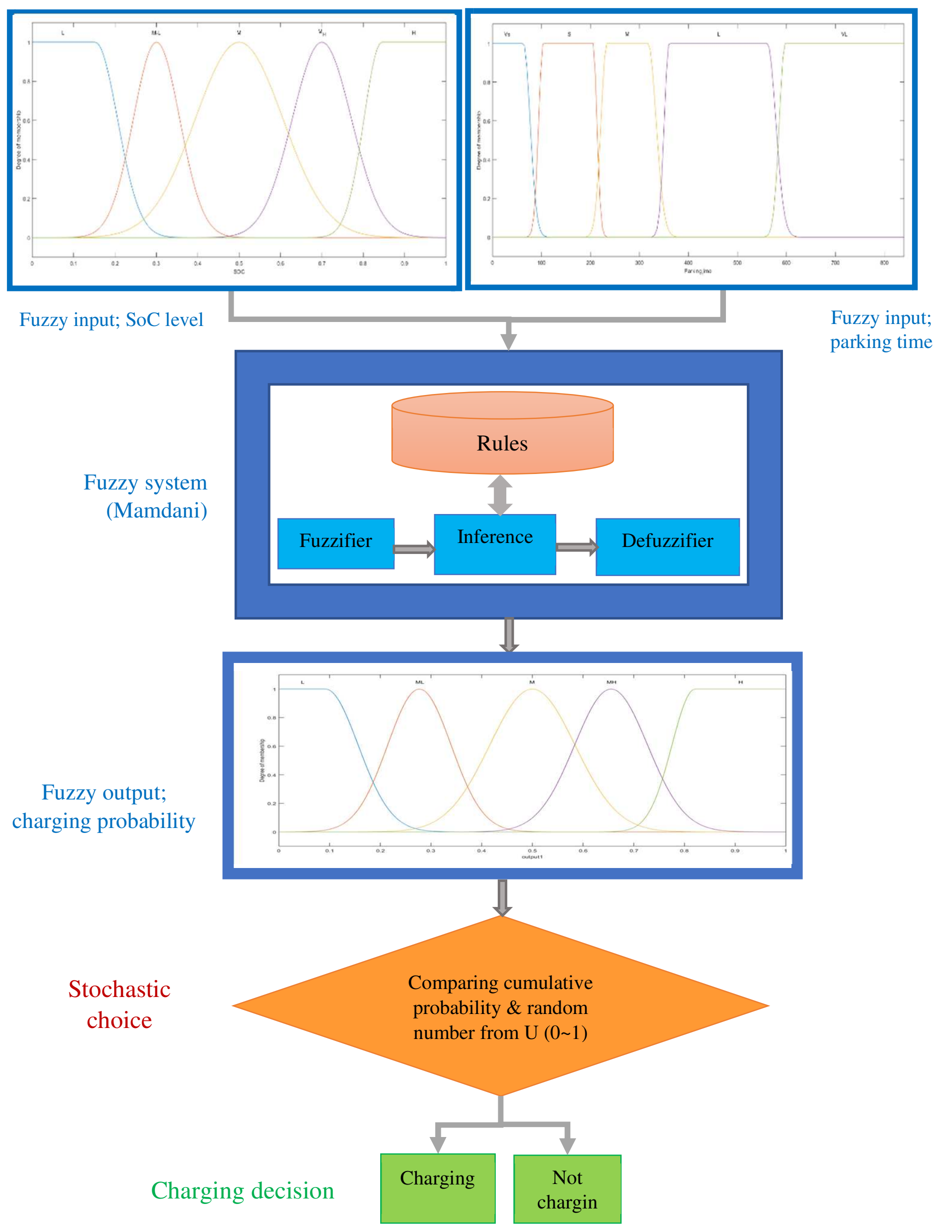


Figure 4.18. Flowchart of Fuzzy charging decision process.

Therefore, the charging behavior of EV users is modeled regarding the influencing factors on user decisions, EV user charging opportunity access, different charging strategies, and two slow/fast charging modes. Figure 4.19 shows the flowchart of EV users charging behaviors in the urban electromobility simulation.

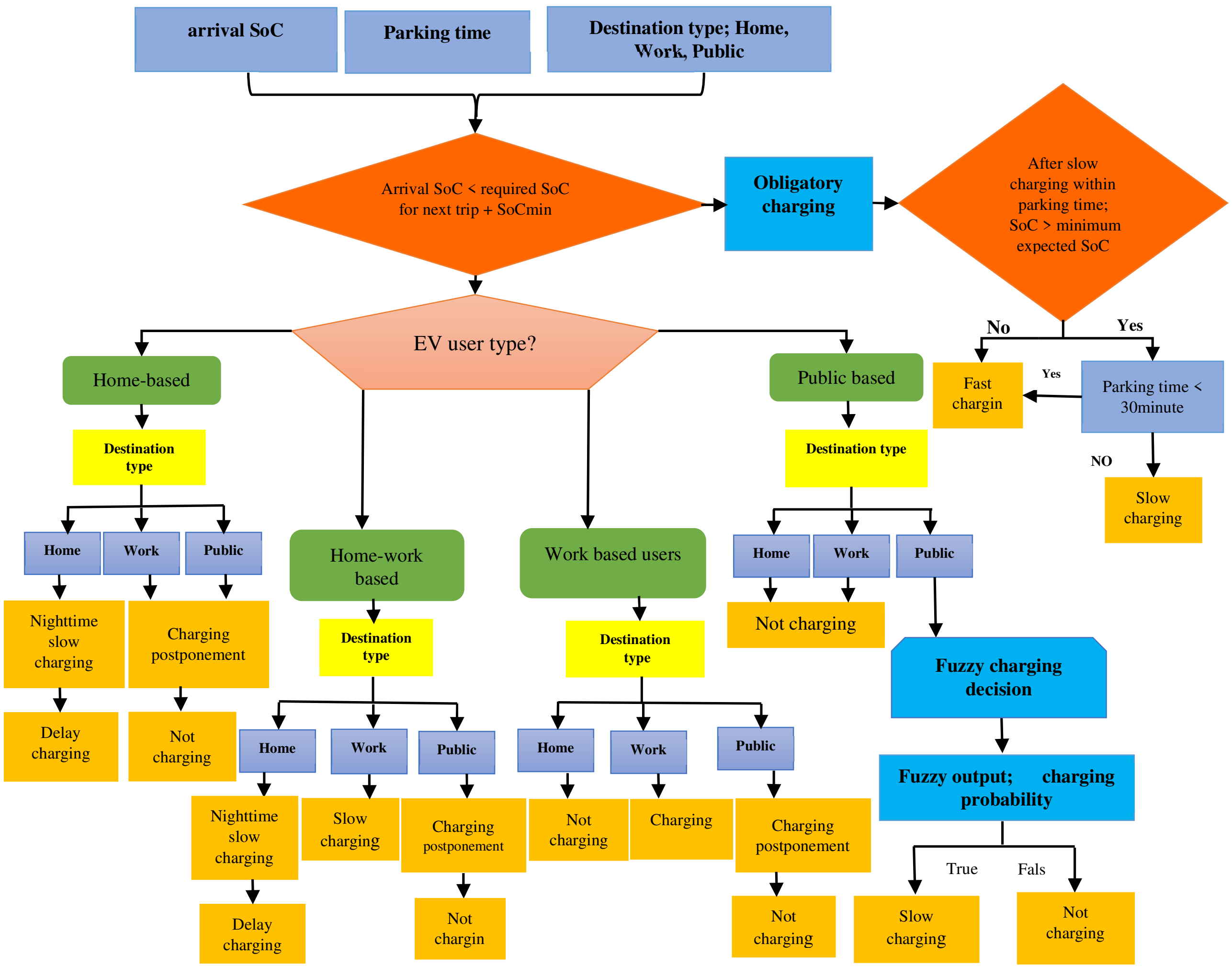


Figure 4.19. Flowchart of EV user charging behavior in the urban electromobility simulation.

4.5.EV users' parking behavior modeling

The EVs are parked at the destination location for a specific parking time decided by the EV user. The parking times at different activity types, which are independent of the urban street network and traffic pattern, are modeled by PDFs calibrated by dwelling times at different destination types extracted from the OD-MRC dataset. In addition to the destination type, it is assumed that parking times vary with the time of the day. In other words, the parking time at a destination depends on the destination type and arrival time to the destination. The average dwell time at the shopping destination extracted from the OD-MRC dataset is shown in Figure 4.20. For example, the EV that arrives at four in the morning at 8:00 will stay on average 56 minutes, and other that arrives at 20:00 will park on average 100 minutes.

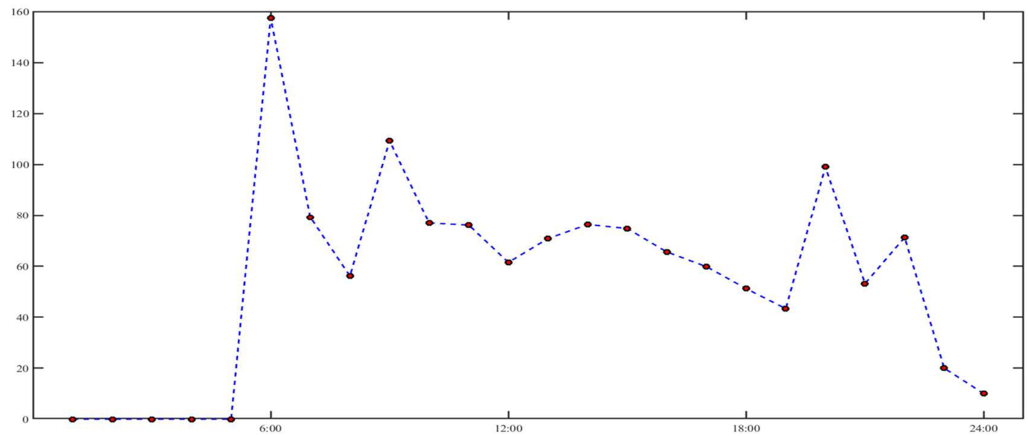


Figure 4.20. The hourly average dwell time for trips with shopping purposes.

Thus, by considering one-hour intervals for the destination types (H1, W, E, S, M, H, R, P, O), 24 PDFs are modeled based on the dwell time data at the destination type (activity locations) extracted from the travel dataset. These PDFs include Uniform, Normal, Lognormal, Loglogistic, Gamma, Weibull, Nakatomi, and Generalized extreme value.

The parking time at H2(ending at home purpose) is considered the period between the ending time at home and the departure time on the next day. It is worth noting that the PDFs are truncated from low tail to five minutes to prevent the generation zero or negative random number as parking time. In other words, the minimum parking time at the destinations is assumed to be five minutes.

Chapter 5

5. Forecasting spatial-temporal charging demands and charging infrastructure planning

5.1.Introduction

Energy consumption of EV driving in the transportation system is eventually translated into spatial-temporal charging demand in the urban area. Each EV trip is simulated based on EVs' driving and charging behaviors in the EV-transport-land use-energy integration to determine the charging demand of the EV over the trip. Since each EV user performs several travels in a day, the daily travels of EV are simulated in a multi-purpose multi-location context in the integrated framework of EV-transportation-land use-energy to predict the daily charging demand of EV. Accordingly, the spatial-temporal urban charging power demand distributions are obtained by simulating the daily travels of all EVs in the urban area. Moreover, forecasting spatial-temporal EV charging energy demand distributions provides an opportunity for slow/fast charging infrastructure planning in the urban area.

In the urban area, the slow charging demand is spatially divided into home charging, workplace charging, and public charging, while the fast charging demands are considered the demands at FCSs. The home and work dedicated chargers meet slow charging demands at home and workplaces. Hence, the charging infrastructure planning model is not applied to home and work charging demand. Instead, the public slow charging demands are satisfied locally by the slow charging piles located at the urban land-uses, in which the number of charging piles at each land use is determined by the charging infrastructure planning model. In contrast, the fast-changing demands are met by the FCSs built at the urban street network, which are optimally planned based on the fast-charging demand prediction and urban street network structures. In this research, the urban street network constructed based on OSM data and traffic prediction model make it possible to identify street segments with heavy daily traffic as street candidates to locate the FCSs by considering the spatial-temporal urban fast charging demand power prediction.

In this chapter, the forecasting model of spatial-temporal charging demand distribution is developed based on the driving and charging behavior of EV users modeled in the previous chapter. Then, the slow and fast charging infrastructure planning models are used for planning urban charging infrastructures based on predicted spatial-temporal charging demand distributions.

5.2.EV trip charging demand

According to the driving, charging/ parking behaviors of the EV user, each EV trip is modeled temporally and spatially in the EV-transportation-land use-energy integrated framework. In this regard, an EV trip between two activity locations is described as follows.

Before departure from the current activity location (origin) to the next activity location (destination), the EV user decides the departure time, travel purpose (next activity type), destination location, and trip route from origin to destination. The departure time of each activity location except the first departure time from home is the sum of arrival time and parking time at the activity location. The first departure time from home is stochastically extracted from the PDF corresponding to the EV user type.

To simulate the stochastic nature of EV users' trips, the travel activity type (trip purpose) is predicted stochastically based on the Markov chain concept according to the hourly TPM corresponding to user type and the departure time. The destination location corresponding to the trip purpose can be a fixed activity location or a non-fixed activity location. In the case of fixed activity location, the destination location is already assigned to the EV user, and the destination choice is not made, and only the trip route and estimation of required energy of trip are determined based on the segment-based optimal energy trip route choice model of fixed locations. For non-fixed activity location, the EV user decides the destination location and trip route based on simultaneous destination and route choice model as well as estimate the required energy for the trip.

At departure time, the EV driving is started from zero velocity, and the second-by-second driving speed of the EV on the chosen trip route to the selected destination location is generated based on the TSSDC model. Accordingly, the instantaneous acceleration/deceleration, travel distance, energy consumption, battery SoC are calculated at each second. During the driving, the user monitors the instantaneous SoC. If SoC falls below the critical SoC, the user decides obligatory en-route charging, otherwise continue trip until reach destination location. If the en-route charging is the case, the user finds the nearest FCS to charge EV, assuming that the EV user knows the FCS locations. To this end, the travel distances from the fast demand point to all FCs candidates are calculated using the Haversine formula based on the Lat/Longs of demand point, FCS locations, and shortest paths found by the Dijkstra algorithm on the street network graph. Then, the FCS with the minimum distance is selected, and EV travel to the selected FCS on the shortest path is modeled by the TSSDC model to generate the instantaneous driving speed regarding the path segment street types and their traffics. At FCS, the EV is fully charged and then continues the trip to the already selected destination by finding the new trip route from FCS to the destination location based on the optimal energy route choice model of the fixed destination. The TSSDC model again generates the instantaneous driving speed, and accordingly, the instantaneous acceleration/deceleration, driving distance, energy consumption, SoC are calculated at each second. This process continues until EV arrives at the destination location and the trip is over. As such, the driving behavior of the trip is modeled, and the driving trajectory is recorded. Upon arriving at the destination location, the user decides whether charge at the destination location or not. If the user doesn't decide to charge, the EV is parked at a non-EVPL for a parking time equal to the activity duration decided by the user. In this case, the parking trajectory is recorded.

If the decision is to charge, the user also determines the charging mode. If the user decides to slow charging, EV is charged at an EVPL that is at the destination location or a public EVPL in the destination land-use block within the acceptable walking distance to the destination location. The EV will be charged during the activity duration while the user performs his/her activity. After finishing the activity, the user takes EV from the EVPL to make a new trip. If the user decides the fast charging mode, the EV is parked at a non-EVPL, and after finishing the activity and before starting a new trip, the user finds the nearest FCS and goes to the selected FCS to charge EV. After full charging EV at FCS, the next trip attributes (purpose, destination location, and route) are decided at the departure time of the FCS.

Therefore, an EV trip includes the driving and charging, or parking afterward is simulated based on EV user driving, charging, and parking behaviors in the integration framework of EV-transportation-land use-energy. The detailed spatial-temporal characteristics of each EV trip are recorded to determine where and where EV is charged. The spatial attributes include the Lat/Longs of OD locations, street intersections of the trip route, slow charging location, or FCS location. The temporal characteristics include the departure time from the origin location, arrival time at the destination location, and times to reach or leave the street intersections, charging start time, and charging time. Moreover, the instantaneous energy consumption during driving, SoC profile of trip, charging demand of each trip are also recorded. Figure 5.1 shows the simulation flowchart of an EV trip.

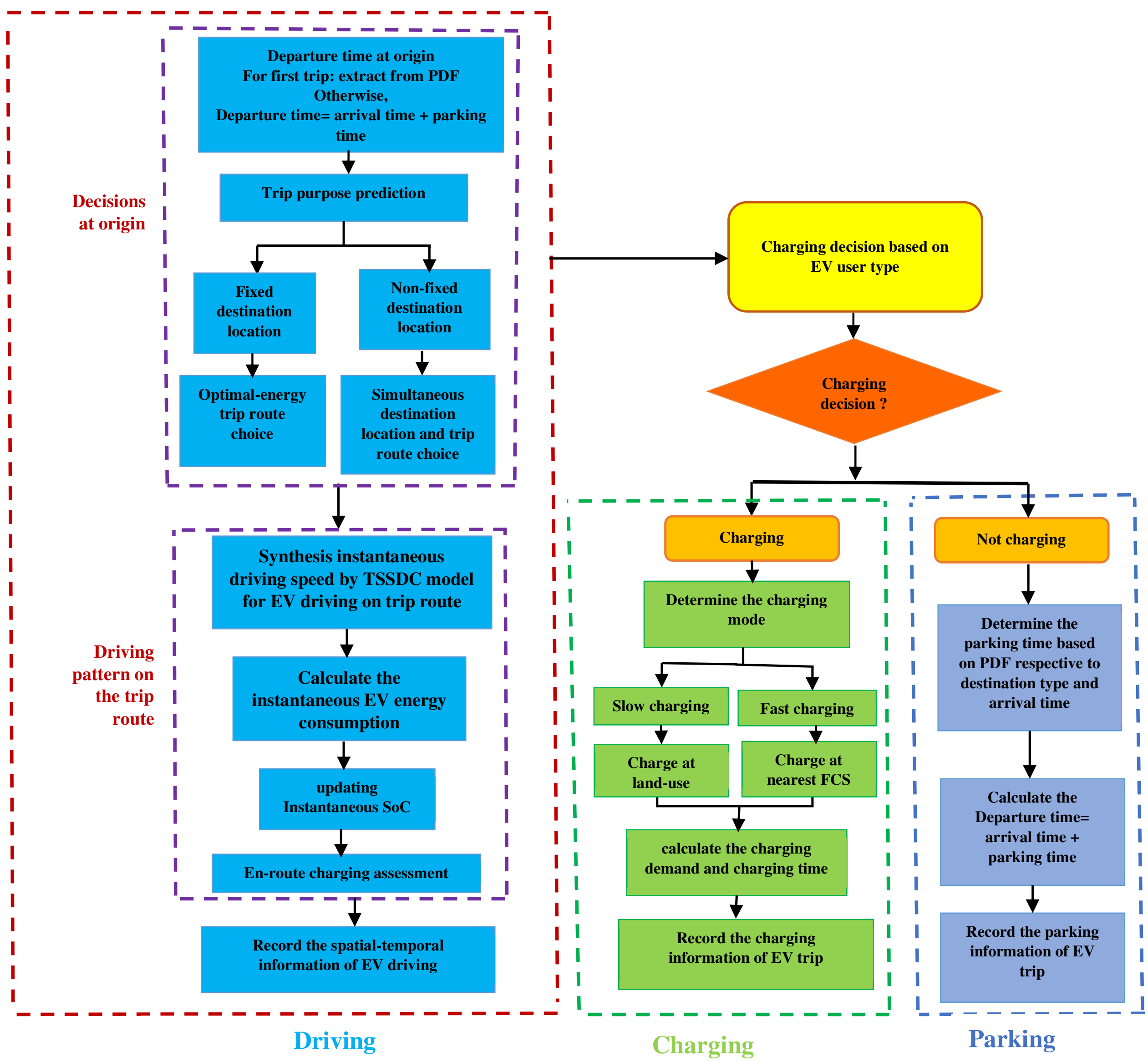


Figure 5.1. The flowchart of an EV trip modeling in the urban electromobility simulation.

5.3.EV daily charging demand

The charging power demand at each charging location of the urban area is the sum of the charging demands of the EVs parked at the location. To predict the daily charging power demand profile of a charging location, it is required to estimate the arrival time, parking time, and the possible charging demand of EVs that may select the location as their destinations. As such, the simulation of daily EV trips makes it is possible to predict the spatial-temporal urban charging demand of the urban area.

The daily trips of EVs between activity locations of different urban land-use must be modeled in detail to predict the spatial-temporal EV charging power demands. Whiles some previous studies without considering the dynamic EV mobility estimate charging demand at charging stations by assuming the arrival flow of EVs at charging stations with probability distribution functions like Poisson.

Besides, many studies modeled EV mobility by simple trip chains that the EV trips characteristics like driving time and driving distance are modeled based on extracted data from travel survey data. In these studies, the street network attributes, traffic flow, EV energy consumption model are totally ignored. Hence, the predicted charging demand in these studies cannot be accurate enough.

Moreover, proposed models in these studies are not applicable for urban charging demand because of ignoring the urban street network, urban traffic, the multi-locations pattern of urban mobility, etc. Therefore, it is essential to consider both the urban area's actual street network and travel data to model EV mobility in a study area. In the urban electromobility simulation in this research, the daily travels of EVs are modeled in a multi-purposes and multi-locations framework to determine the possibility of EVs charging at different locations of the urban area. In other words, the EV mobility on the urban street network is translated to EV charging demand at private and public locations in the urban area. EV daily trips are considered home-to-home trips in which the EV user departs from home at a specific time of the day, performs several activities in different locations, and finally returns home.

Contrary to the existing studies that assigned a daily travel chain with predetermined spatial-temporal attributes, in this study, the activity types (trip purpose) of EV daily trips are predicted trip by trip, considering the EV user type, stochastic nature of trips, and the effect of day time.

To this end, the daily travel data of the study area is used that include spatial-temporal data of daily travels for different groups of drivers.

For each trip at the departure time of origin, the trip purpose is predicted based on the hourly TPM corresponding to the user type and time of day and the origin's activity type. This process is implemented for each EV trip so that it starts from home, continues at several activity locations, and finishes once the trip purpose is end trip at home. Between the start trip at home and end trip at home, EV users have one or more travel determined stochastically by TPM corresponding to the EV user type (i.e., employed, unemployed, and student).

Therefore, contrary to the existing studies, the EV user daily trips are modeled stochastically in the study area by considering all affecting parameters like street network topology, streets traffic, EV energy consumption, etc. In this context, EV mobility in the urban area is modeled in detail on the basis of interactions between EV users, transportation system, land use, and energy system. As such, the achieved spatial-temporal charging demand is more accurate from the previous studies. However, with the increasing diffusion of EVs in the urban area in the near future and using real-world data of EV mobility, the accuracy of the proposed model in EV charging demand prediction can be improved. The process of daily trips generation for an EV user is shown in the flowchart of Figure 5.2.

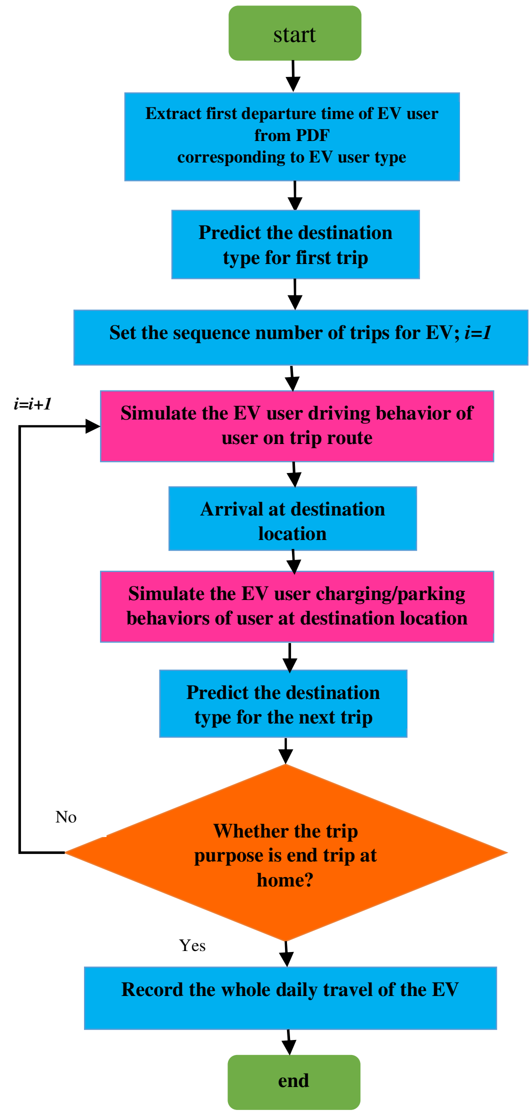


Figure 5.2. EV Daily trips modeling in urban electromobility simulation

For an arbitrary EV, the daily travel trajectory for a home-to-home tour includes four trips in the study area on the street network grape illustrated in the following Figure 5.3.

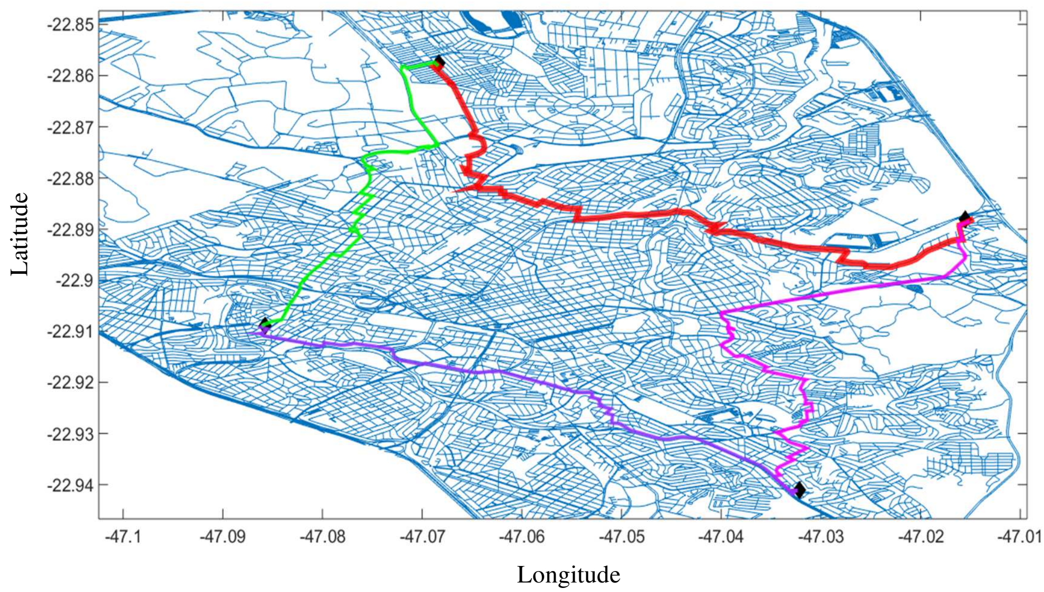


Figure 5.3. A sample daily travel trajectory in the study area.

5.4.Forecasting the Spatial-temporal urban charging power demands

In the urban electromobility simulation, from the perspective of EV, the EV consumes energy while driving on the street network, and it is possible that during daily travels, EV user decides to charge EV at any location of the urban area and any time of day.

From the perspective of charging locations, they are equipped with several chargers that provide energy for charging the incoming EVs. They are mainly divided into slow and fast charging stations, in which the slow charging stations are selected by EV users who have relatively long dwell time at their activity locations. The slow charging facilities are located at or near the user's activity locations in different urban land-uses to meet the local charging demands. On the contrary, FCSs are usually located on high-traffic streets to serve EVs with emergency charges or ones that do not have enough time to charge by slow charging. The energy that each charging location draws from the power grid or renewable energies depends on the demand of incoming EVs to the charging locations.

Therefore, to predict the spatial-temporal charging power demand distribution of the urban area, it is essential to model the EV daily trips accurately to find out that when and where EV users decide to charge their EVs. The charging infrastructures are the interface between urban energy and transportation systems by providing the required energy for EV charging. The daily travels of EVs are modeled based on the proposed models in this research based on the interactions of EV users by the urban environment.

As described in the previous chapter, each EV travel that includes the driving and charging/parking afterward is spatially-temporally is modeled according to EV user's driving and charging/parking behaviors based on EV user interactions with the integration of transportation-land use-energy. As such, the location and time of possibly charging of EV trip are predicted.

Furthermore, by modeling each trip of EV daily trips, the daily charging demands of the EV at the private and public locations of the urban area are predicted. By predicting the time and location of daily demands of all EVs in the study area, the spatial-temporal distributions of daily charging power of different charging locations in the urban area are predicted. The forecasting procedure of spatial-temporal urban charging power distributions based on EVs' daily charging demand is summarized below.

(1) For the first EV trip, which starts from home, a departure time is decided randomly from the PDF of the first departure time from home corresponding to the EV user type (e.g., employed, unemployed, and student).
(2) The trip purpose of the first trip is obtained stochastically from hourly TPM corresponding to the hour of departure from home and EV user type.
(3) The travel trajectory includes the driving, charging/parking, and SoC profile of the trip are simulated.
(4) For the second and further trips, the departure time is calculated as the sum of arrival time and parking time at the destination location. The next trip purpose is determined stochastically based on corresponding hourly TPM regarding departure time and the activity type of trip's origin.
(5) If the trip purpose is "end trip," the current trip will be the last one the travel trajectory for the last trip is simulated, and the daily travel of the EV is over. Otherwise, the daily travel of the EV will continue, and the process will be repeated from step (3).
(6) The daily travel trajectory of the EV is obtained by combining the simulated travel trajectories of daily trips based on steps (1)-(5), which can consist of one or several trips with different purposes.

(7) For a number of EVs (N_{EV}) in the study area, the steps (1)-(6) are repeated N_{EV} times to obtain daily travel trajectories and daily SoC profile of all EVs in the study area.

(8) The daily spatial-temporal charging power demand distributions of slow charging at each land-use block and fast-charging power at each FCS candidate are obtained based on the incoming EV charging demands. The total charging load $P_l(t)$ at time t for a location type *l* is calculated by the following equation:

$$P_l(t) = \sum_{m=1}^{M} p_l \tag{31}$$

Where *M* is the number of EVs that are charged simultaneously at time *t* at location *l*, p_l is the charging power rate of the charging piles at location l

The flowchart of spatial-temporal charging load demand prediction is shown in Figure. 5.4.

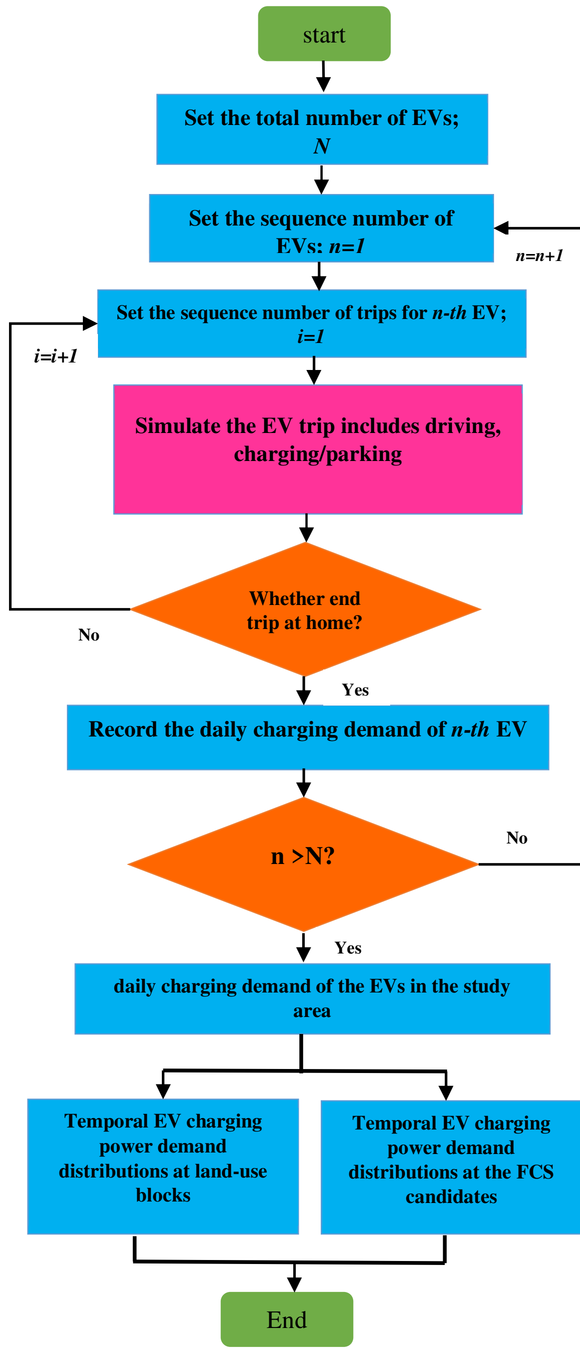


Figure 5.4. Flowchart of spatial-temporal charging load demand prediction.

5.5.Slow charging infrastructure planning

The slow charging demand is classified as home charging demand, work charging demand, and public charging demand. The home charging demand is mainly slow nighttime charging demand met by dedicated home charging piles. The work charging demands are mostly slow daytime charging demands that are satisfied by charging facilities designated for employees at workplaces. As such, it is not required to plan charging infrastructures for the home and work charging demands.

The public charging demands include the demands at activity locations in urban-land uses that are the destination of the trips with purposes including education, shopping, meal, health, recreation, personal matters, and others. The slow charging demands can be satisfied locally by slow charging piles located at EVPLs in the activity locations (e.g., shopping malls, trading centers, restaurants, universities, hospitals, recreation areas, etc.) or public EVPLs (like conventional public parking lots).

For a trip that ends at a public location, the EV user chooses a land-use as the trip destination and subsequently an activity location in the land use. Upon arriving at the activity location, the EV user decides whether to charge EV at the current destination location. If the user chooses slow charging mode, EV has slow public charging that can be satisfied by the EVPL in the land use. In this case, the user leaves the EV at EVPL, goes to the activity location, and returns to get the EV after completing the activity. In this regard, the EVPL may be located at the activity location, or the user chooses the nearest EVPL with a short walking distance (maximum 300meter). As a result, in the urban area, the locations of charging facilities should be dense enough to avoid wasting time and energy. Therefore, considering the walking distance to the nearest EVPL in the locating problem is compatible with the assumption that each land-use is equipped with enough charging stations to meet the EVs charging demand.

In this research, the public slow charging infrastructure planning is performed at the land-use level. Instead of determining the exact locations for EVPLs at land-use blocks, it is assumed that there are enough EVPLs at each land use that EV can be charged at the destination location, by ignoring the modeling walking distance between the destination location and the nearest

EVPL. As such, the public charging infrastructure planning model determines the charging piles' number at the land-use block based on the spatial-temporal public slow charging demand of the land use and considering the parameters like charging demand time, charging power, parking time, the number of EVs that are charged simultaneously.

5.6.Fast charging infrastructure planning

FCSs are planned according to the distribution of the spatial-temporal public fast charging demands distributions and the structure of the urban street network. FCSs planning aims to determine the site and size of FCSs at the street network to satisfy the fast charging demand of EVs. The FCS planning problems are often based on multi-objective optimization methods (with the objective like coverage rate of charging services maximization, minimizing the total construction cost, minimizing waiting time, etc.), which lead to taxing computational efforts for the large urban transportation system. Moreover, several studies have shown that the charging station placement problem is an NP-hard problem. Thus, the literature proposed that finding an optimal solution at the scale of the urban transportation system requires heuristic methods, which can obtain good solutions in a reasonable calculation time. The heuristic approaches should be developed according to the optimization criterion, urban transportation system attributes, and EV user preferences. This study proposes an evolutionary heuristic method for FCS planning in the urban transportation-land use integrated system based on the following objectives;

- Minimizing the detour distance between fast demand point and FCS.
- Maximizing the service area of FCSs.
- Maximizing the assigned EVs number to FCSs.

With the following constraints;

- Detour distance for each EV is less than the predefined maximum distance (d_t^{max}).
- Each EV is assigned to one and only one FCS.
- Travel distance between demand point to FCS is calculated according to geographic characteristics of the street network.
- Considering the minimum number of daily assigned EVs to FCSs
- Determining the upper and lower limits of chargers in an FCS.

The proposed evolutionary heuristic algorithm is implemented in three steps. In the first step, the FCS candidate's locations are determined in the urban area. In the second step that executed during the electromobility simulation, each EV with fast charging demand is assigned to the nearest FCS candidate so that their distance is less than d_t^{max}. Finally, the third step that is performed after obtaining the temporal charging demand distribution in each candidate is a refinement process to merge the candidates to more favorable overlapping candidates. The d_t^{max} is considered 1.5 km in this thesis to prevent the overload or idle in the FCSs.

Step 1: FCSs candidate locations

In the urban area, the FCSs are placed along the urban street network to be able also to meet the en-route fast charging demands. In this regard, the street segments with a large amount of daily traffic are appropriate to locate the FCSs. Therefore, according to the street network constructed based on OSM data and the traffic prediction model developed based on the GMTL data, the arterial street segments with two or more one-way lanes have more than one hour of heavy traffic (traffic jam condition) during the day are considered as candidates street segments. As such, the candidate segments are the motorway, trunk, primary, and secondary street segments that have heavy daily traffic. Furthermore, to specify the geographic coordinate of FCS candidate's locations, since the lengths of the extracted street segments are not too long, the segments' midpoints are determined, and FCSs candidates' points are specified next to midpoints with Lat/Long coordinates.

Step2: assigning EV with fast charging demand to the nearest FCS candidate

During the electromobility simulation, once the EV has fast charging demand, the Lat/Longs of demand point and the demand time are recorded, and EV is assigned to an FCS candidate. Regarding the first objective of planning, EV users' choice about where to charge is dictated by the proximity between the fast demand point and the FCSs candidate locations, which minimizes travel costs. Thus, the EV is assigned to the nearest FCS candidate so that the travel distance is less than d_t^{max}. To this end, the trip routes from the fast demand point to all FCSs candidates are determined by the Dijkstra algorithm on the street network graph, based on the Lat/Longs of demand point, FCS candidates, and street network. Then, route distances are calculated by the Haversine formula, and the EV is assigned to the nearest FCS candidate. For assigning EVs to FCSs, it is assumed that the capacity of each FCS is large enough to serve all the EVs that arrived at the station.

Step3: Reallocation step

To achieve the second and third planning objectives, some refinements are performed under the following conditions to assess the possible reallocation of the EV to another FCS and combine the FCS to obtain the minimum number of FCSs that meet the urban fast-charging demands.

- **The economic aspects of the FCS planning**

The first optimization objective only considers the distance criteria to assign EVs to FCS candidates. Still, it does not consider the economic objective in the planning. It is reasonable to understand that an FCS candidate with very few allocated EVs numbers is not economic. Thus, to ensure there is no deployed FCSs with very low charging demand, the FCS candidates having the allocated EVs number less than the defined minimum number (i.e., <15 in a day) are eliminated, and their assigned EVs are reallocated to other FCS candidate so that the detour distance from fast demand point to the new FCS is not more than d_t^{max} .

- **FCS capacity**

In the assignment step, it is assumed that FCS candidates have an infinite capacity to serve all incoming EVs without considering waiting time. Since such a design is unrealistic and impractical, it is essential to determine the optimal size of the FCSs considering both technical and economic objectives. By imposing finite capacity, the service level is then defined based on the waiting times of the users at each FCs. Accordingly, the number of required chargers for each FCS is affected by the arrival flows of the EVs at the FCS. Therefore, regarding the arrival time of EVs to each FCS, the optimal size of the FCS is selected based on a trade-off between the waiting time and the number of active simultaneous chargers. Based on the determined number of chargers at the FCS, once the number of assigned EVs exceeds FCS capacity, the additional EVs are transferred to other FCSs according to the allocation mechanism.

Therefore, the proposed evolutionary heuristic algorithm aims to determine the minimum number of FCSs in the urban area to meet the fast charging demand, considering the EV user convenience and the economic benefits of FCSs.

Chapter6

6. Simulation Results and Analysis

6.1.Introduction

This chapter provides numerical simulation and analysis to describe the proposed models of urban electromobility simulation in the integration framework of EV user-transportation-land use-energy. To this end, the number of EVs in the study area is determined for a given EV penetration percentage. Then for each EV, the daily travels on a typical weekday are simulated based on proposed models to predict the spatial-temporal charging demand of the EV. Accordingly, the spatial-temporal urban charging demands are determined at homes, workplaces, and public locations. Finally, the required slow and fast charging facilities to meet the urban charging demand are specified based on the proposed model in the previous chapter.

6.2. Simulation parameter settings at the simulation setup

At the setup phase of simulation, the values of the simulation parameters are set regarding the socio-demographic characteristics of the study area extracted from the city's census data, EV technical attributes, etc. The specific values of the simulation parameters are set as follows:

1) EV's number

The number of EVs in the study area is determined based on the vehicle's number of the city of Campinas, which is based on the latest data (October 2021) of the city's vehicle fleet provided by the Brazilian Ministry of infrastructure [123], the number of private cars in Campinas is 620063, and regarding the city area 795.667km^2, the car per area ratio (car/km^2) is 779.3. Hence, for the study area with an area of 116.525 $km^2$and the EV penetration level that due to the computational burden is considered 20%, the EV's number is set to 18162 ($N_{EV} = 18162$).

2) EV's technical attributes

In the urban electromobility simulation, the technical characteristics of EVs are required. The actual EV attributes of different existing brands should be used to obtain the realistic model of EV. To this end, according to the selling percentage of EV brands in Brazil mentioned in Table 4.1, an EV brand is randomly assigned to each EV, and corresponding technical specifications of the brand are used in the simulations.

3) Fixed activity locations of EV users

The fixed activity locations (home, work, and education) are assigned corresponding to the user's occupation status. A user type is randomly assigned to each EV according to assumed distributions of EV user groups (employed, unemployed, student). Since the private EVs are considered in this research, and each user belongs to a household, a home location with a specific Lat/Long is randomly assigned to each EV user from the determined home location point in residential land uses. Furthermore, a workplace location with a particular Lat/Long is also given to employed users according to their users' work types allocated based on work type distributions of the study area. Similarly, an education location(university or college) with predetermined Lat/Long is assigned to each student for his/her regular education activity. It is necessary to mention, besides the regular education, each EV of all user groups may have irregular education, which for these users, the education location is assigned during the simulation as fixed activity location.

4) Initial SoC of EVs

For each EV in the study area, an initial SoC is assigned as the amount of EV battery's SoC at the starting time of the daily itinerary, that is the SoC at the first departer time of the home. It is assumed that the initial SoC of EVs obeys the Normal PDF, $N(0.5,0.1)$ [124], which is truncated to a lower and upper bound regarding the EV user type defined based on user access to charging facilities, as shown in Table 6.1.

Table 6.1.
Initial SoC of EVs

EV user's type	PDF of Initial SoC	Lower tail of truncation	Upper tail of truncation
Home-based	$N(0.5,0.1)$	0.5	0.9
Work-based	$N(0.5,0.1)$	0.4	0.8
Home and work based	$N(0.5,0.1)$	0.5	0.9
Public-based	$N(0.5,0.1)$	0.35	0.6

5) Probability of availability of charging facilities at homes and workplaces

In the electromobility simulation, it is assumed that all homes and workplaces are not equipped with charging facilities. The probabilities that an agent who lives in a single-family house and multiple families has the charging pile at homes are assumed 80% and 70%, respectively. The probabilities of charging facilities' availability at workplaces are assumed according to the work type of users that are shown in Table 6.2.

Table 6.2.
Probabilities of charging facilities availability at workplaces

Work type	Probabilities
Services	0.4
Commercial	0.6
Industrial	1
Education	0.7
Administrations	0.8
Health and social services	0.7
Construction	1
Arts,culture,sports, and recreation	0.5

6) Charging power rate at charging locations

Three types of charging power levels are considered: Level 1 (3.3 kW output), Level 2 (up to 14.4 kW output but typically 6.7 kW), and Level 3 (up to 240 kW output but typically45kW). The slow charging power in homes is assumed to be 3.3 kW, while it is considered 6.7 kW in other locations. The fast-charging power rate in FCSs is set to 45 kW. Moreover, the charging efficiencies of charging piles are assumed to be a random number between 0.8 and 0.9. The maximum SoC that EV can be charged through slow and fast charging facilities are set to 0.8 and 0.9, respectively.

The electromobility simulations are performed for the assumed number of EVs in the study area based on the above simulation parameters. The recorded daily travel information and SoC profile of EVs are used to determine the spatial-temporal distribution of charging power demand in the study area. Figure 6.1 shows the distribution of the daily trips number of EVs in the electromobility simulation. Moreover, the daily SoC profiles of sample 25 EVs are shown in figure 6.2.

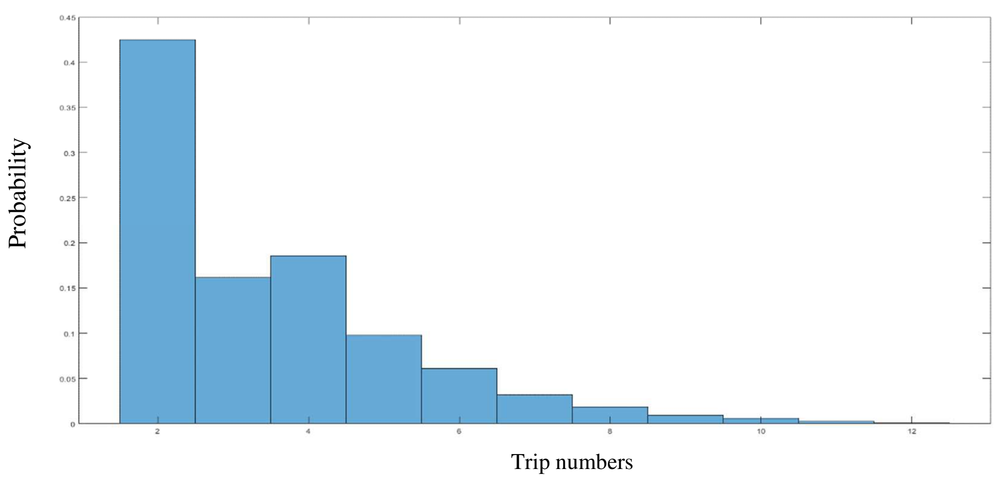


Figure 6.1. Distribution of the number of trips for simulated EV daily trips.

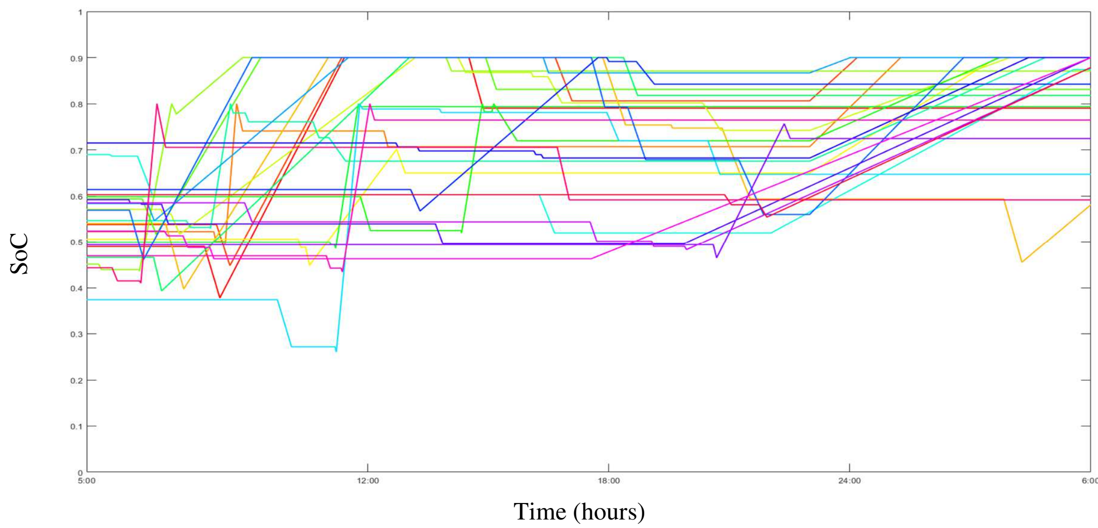


Figure 6.2. Daily SoC profile of 25 sample EVs.

6.3.Total EV charging power demands of the study area

The total slow and fast-charging power demands are 439445 kWh and 67352 kWh, respectively. Figure 6.3 shows the total slow and fast charging power demand profile of the day with a one-minute resolution.

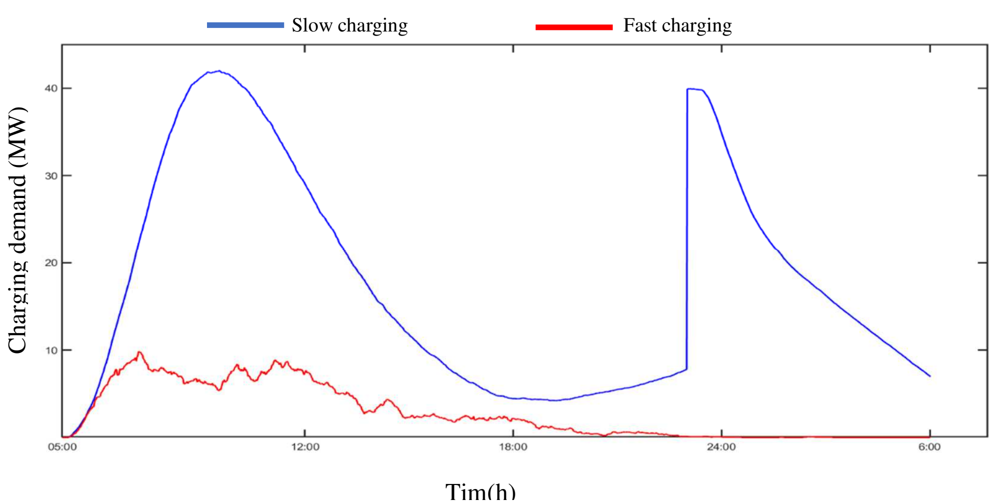


Figure 6.3. Total slow and fast charging power demand of the study area.

From the simulation of daily trips of EVs in the study area, the total charging load at home, work, and public are 32.89%, 43.17, 23.94%, respectively. For home charging, 98.6% of total demand is slow charging, and 1.4% is fast. At work, 98.65 % and 1.35% of total charging are for slow and fast charging demand, respectively. At public locations, 48.84% of total demand is slow charging, and 51.16% is fast.

The total slow and fast charging power demand profiles of the study area at home, work, and public, for a typical weekday from 5:00 to 6:00 of the next day, are illustrated in Figure 6.4. The public charging demand is the sum of the charging demand at destinations, including education, shopping, meal(lunch), health, recreation, personal matters, and others.

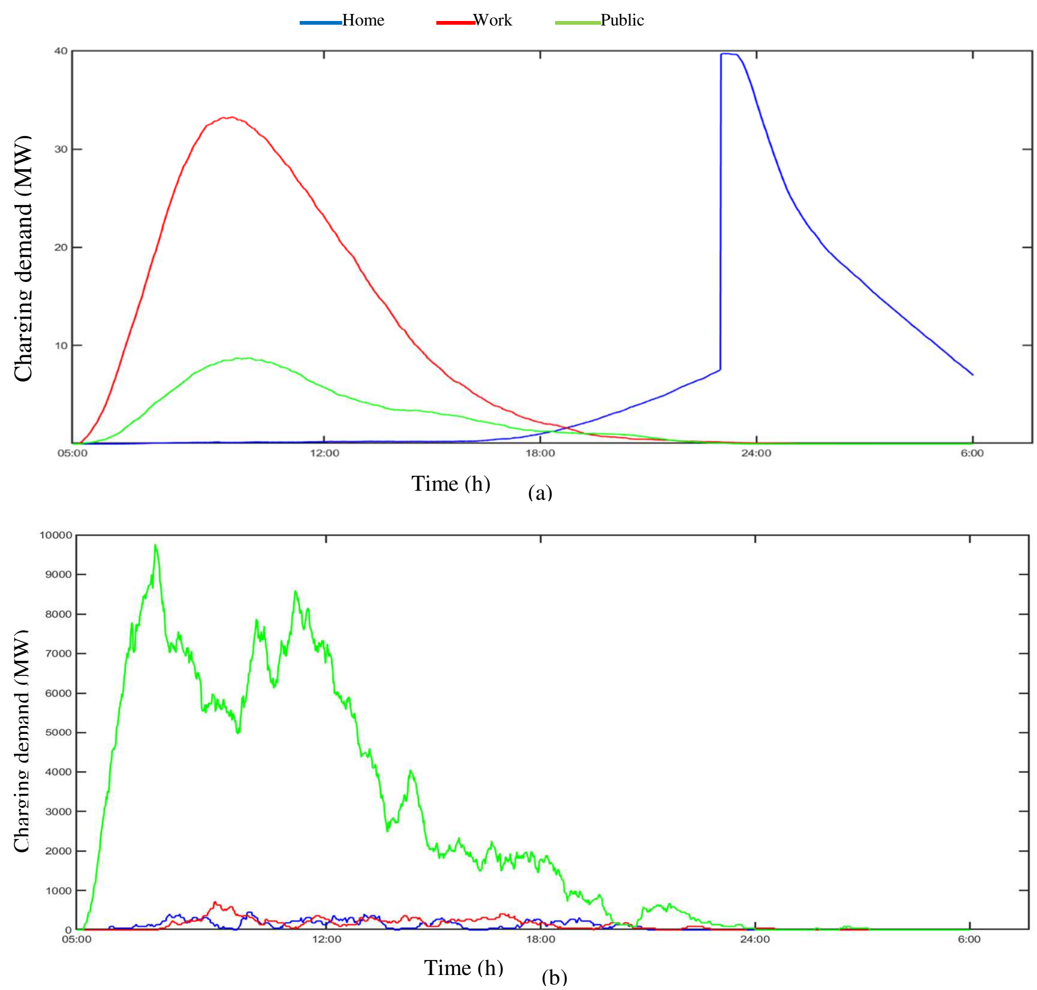


Figure 6.4. The total slow (a) and fast (b) charging power demand profiles of the study area at home, work, and public.

As can be seen from this figure, the slow charging demand mainly includes morning charging at work and nighttime charging at home. Fast charging demands are usually in the morning to midday times.

6.4.Daily charging power demands at different charging destination

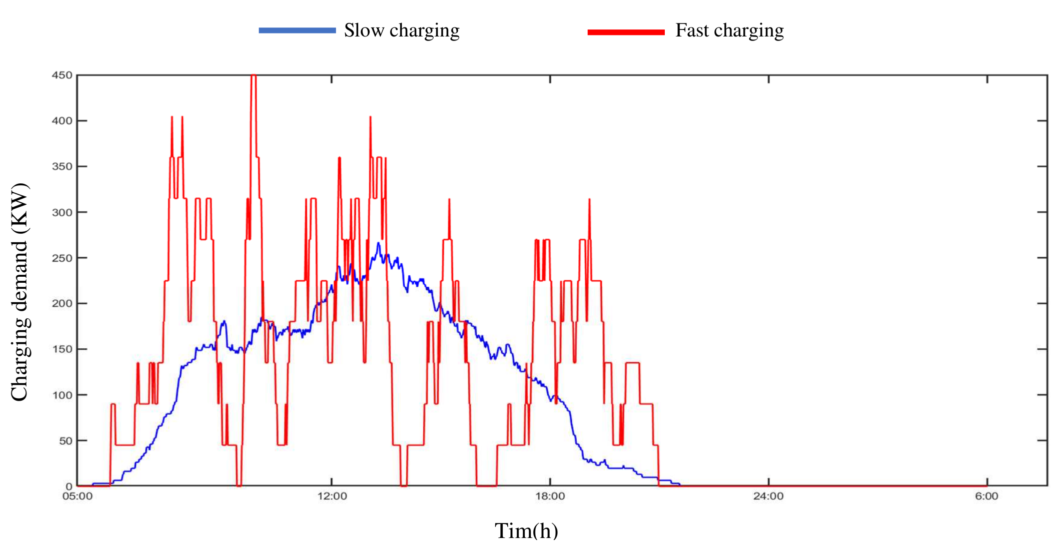
The daily charging demand amounts of slow and fast charging modes at the different destination types in the study area are illustrated in Table 6.3.

Table6.3

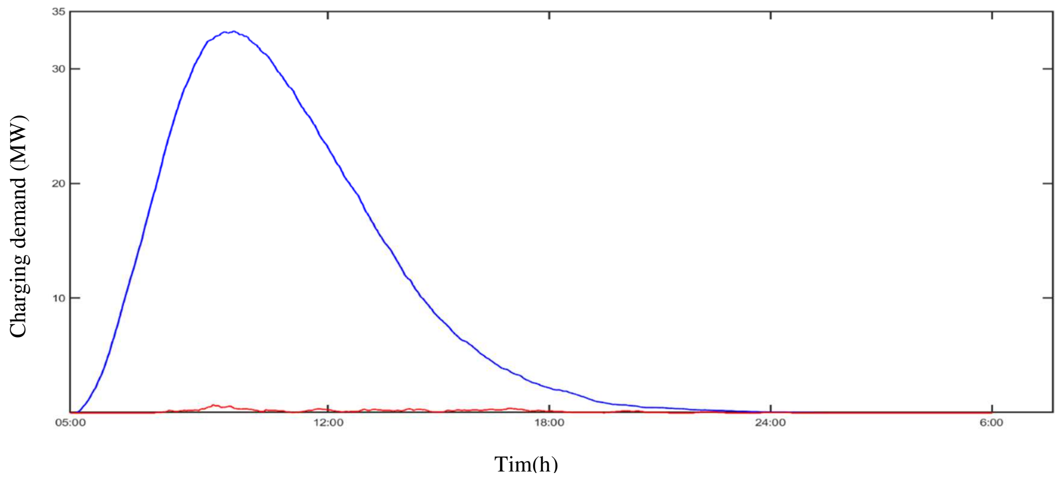
Daily charging demand in different destination types

destination type	Home (H1)	Home (H2)	Work	Public						
				Education	Shopping	Meal	Health	Recreation	Personal	Others
Slow charging demand (kwh)	2005	162332	215858.8	24185	3975.4	396.7	6637.4	6818	11319	5917.3
Fast charging demand (KWh)	2339.3	-	2952	1120.5	6945.8	402	5526.8	2540.3	9557.3	35968

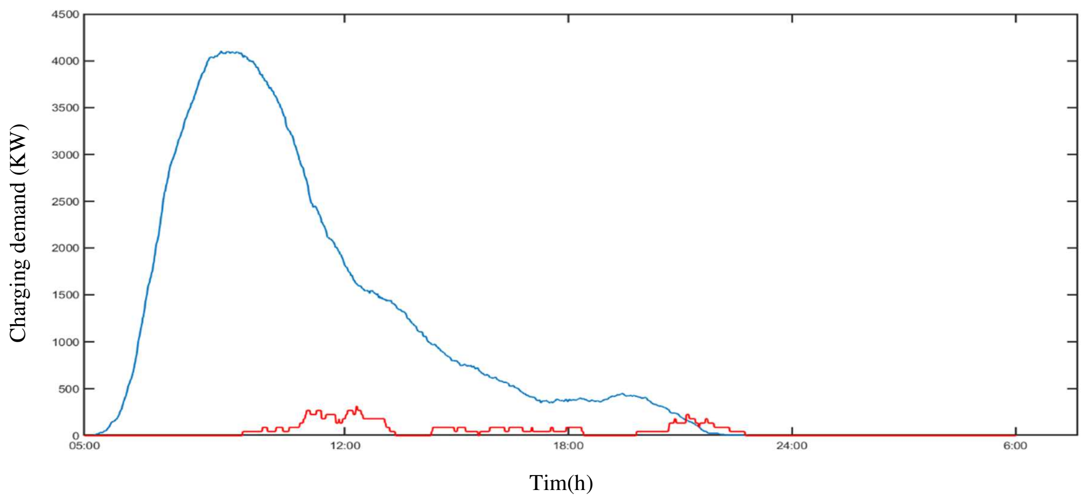
Figure 6.5(a) to 6.5 (i) shows the daily charging power profiles of slow and fast charging demand per minute from 5:00 to 6:00 the next day for different destination types.



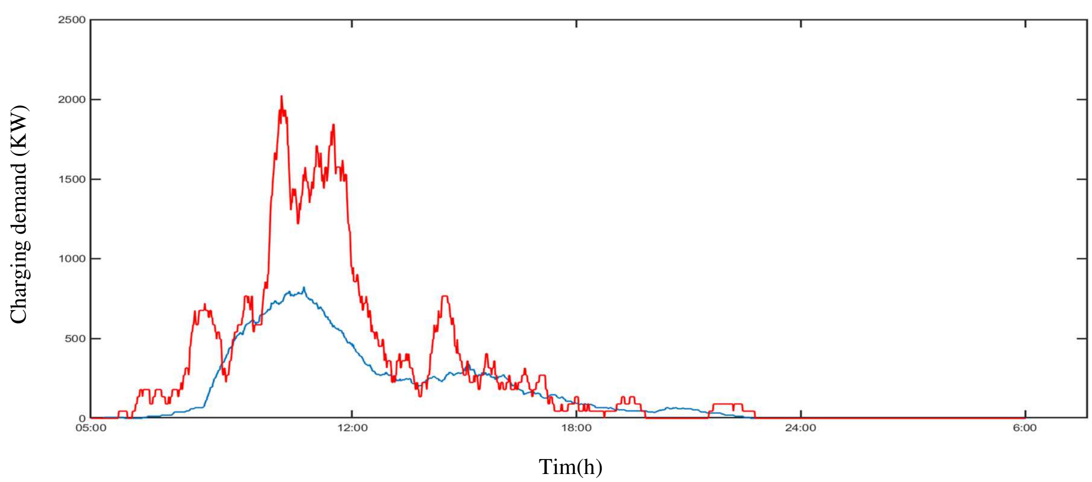
(a)


Charging demand (MW)
35
30
20
10
05:00
12:00
18:00
24:00
6:00
Tim(h)

(b)

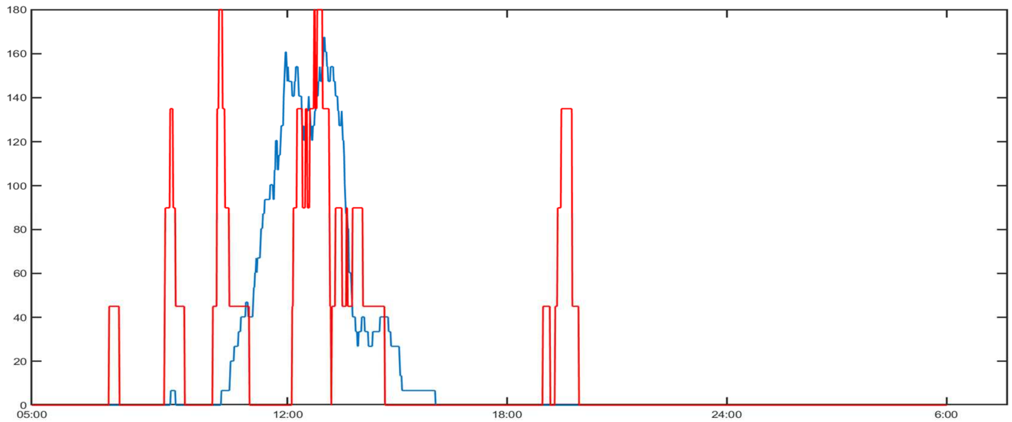

Charging demand (KW)
4500
4000
3500
3000
2500
2000
1500
1000
500
0
05:00
12:00
18:00
24:00
6:00
Tim(h)

(c)


Charging demand (KW)
2500
2000
1500
1000
500
0
05:00
12:00
18:00
24:00
6:00
Tim(h)

(d)

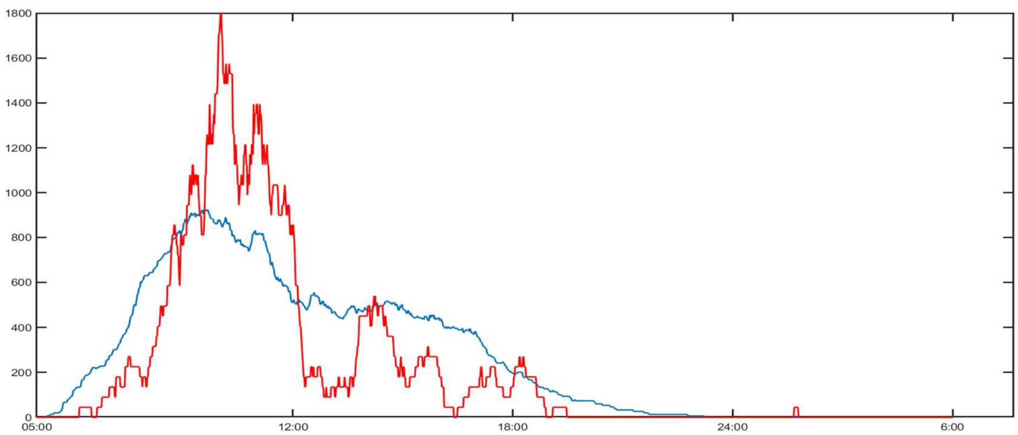
Charging demand (KW)



Tim(h)

(e)

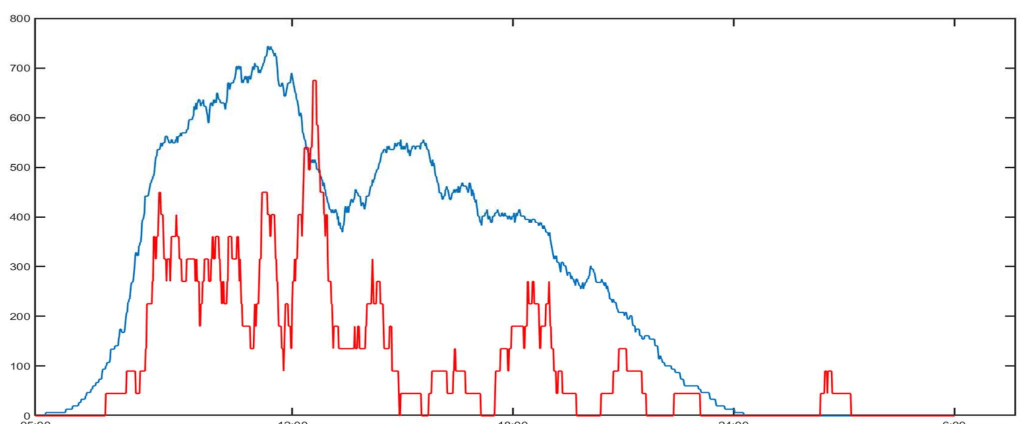
Charging demand (KW)



Tim(h)

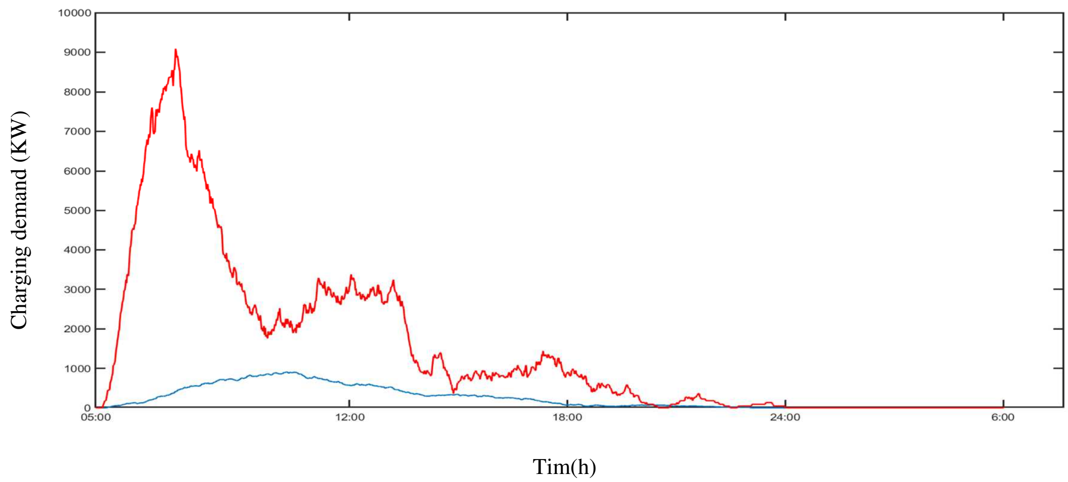
(f)

Charging demand (KW)

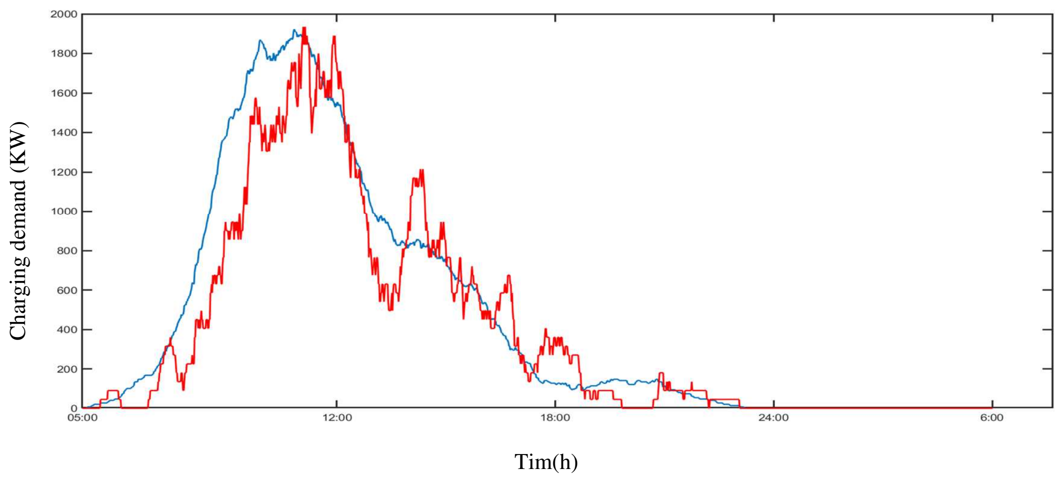


Tim(h)

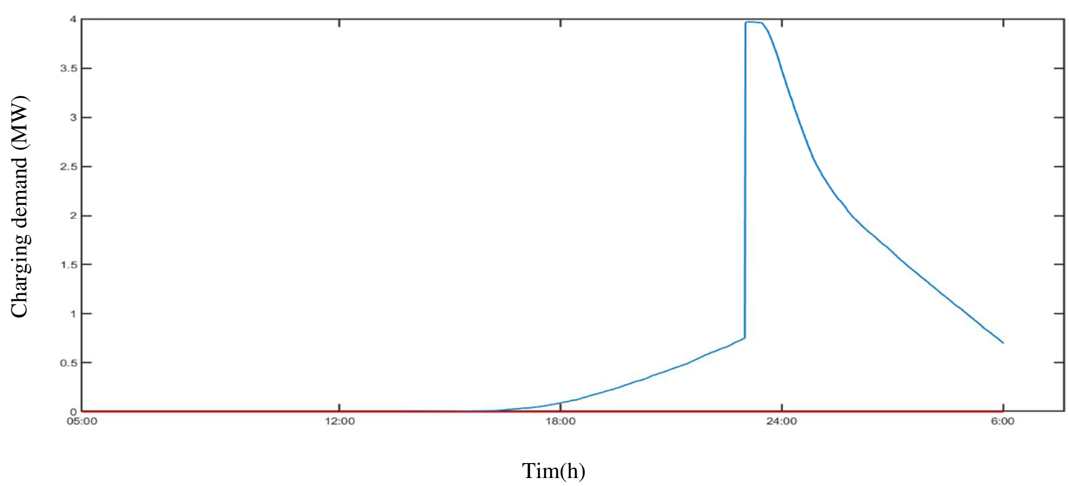
(g)



(h)



(i)



(j)

Figure 6.5. Daily charging demand at different destination types. (a) home linger, (b) work, (c) education, (d) shopping, (e)Meal(lunch), (f) health, (g) recreation, (h) others, (i) personal matters, (j)end ta home.

As can be seen from the charging demand of H1 in Figure 6.5 (a), during the day, especially at midday, a number of EV users return home for lunch and rest. In the case that they requireto charge EV, Theses EV users prefer to use fast charging due to low time dwelling. The majority of EV users in the simulation are employed (i.e., 60%), and due to convenience and long parking time, they tend to charge EVs while working at their workplaces.

Figure 6.5 (b) shows the daily charging demand of the work destination type, which is mostly slow charging demand due to the extended parking time of EVs at workplaces. Most EVs reach the workplace between 6:00-9:00, and the charging power demand increases quickly and shows a peak at 9:30. After that, the charging load demand decreases gradually as the EVs leave the workplaces.

The 10% are student users who have education destinations (regular education (e.g., university)) in their daily trips. The charging demand at education destination type is from the student users and other users with education destinations (irregular education (e.g., language institute)).

The daily charging demand of education locations is shown in Figure 6.5 (c). This charging demand has a peak in the morning mainly because of regular education and a small peak around 19. At these locations, fast charging demand is mostly lower than slow charging demand because of the relatively longer parking time.

Figure 6.5 (d) shows the daily EV charging power demand for shopping destinations, in which fast charging demand is higher than slow charging demand due to the short EV parking time. The shopping demand has several peaks in the morning and evening.

According to Figure 6.5 (e), the charging demand at meal destination type is basically low. The charging demand concentrated between 11:00-15:00, which corresponds to lunchtime.

The charging demand profile at health destinations illustrated in Figure 6.5 (f) has a peak in the morning. The fast charging demand at the health destinations is more than the slow charging due to the low dwell time of EV users at this destination time. While in the evening, the slow charging demand is more than the fast one.

Figure 6.5 (g) depicts the daily charging power demand for recreation destinations, which is essentially low on weekdays. The charging demand is not concentrated at a specific time because this location type covers several activities that are performed at different times of the day. Due to the relatively long parking time, the slow charging demand is higher than the fast-charging demand.

As shown in Figure 6.5 (h), the charging demand of 'Other' destinations is mainly fast charging. The 'Other' trip purpose includes the trips with very low dwell time at destination (e.g., pick up/off someone) that if EV requires charging, the EV user prefers to select fast charging.

The daily charging power demand for H2 is shown in Figure 6.5 (i). It is different from H1 and consists of entirely slow charging that is low between 5:00 and 18:00 and increases after that. As the number of EV users increases at home after returning from work, slow charging demand rises rapidly.

In addition, due to the preferences of EV users to charge EVs at low prices (i.e., 23:00 to 6:00), they postpone the EV charging to 23:00 hours of the night. As such, the charging demand of H2 peaks at 23:07 and then decreases gradually until 6:00 hours. Hence, the EV users set the charging time at H2 between 23:00 to 6:00 hours to take advantage of low-price energy. While as illustrated in Figure 6.6, a few EVs have charging demand at H2 after 6:00 hours, which are the EVs who arrive home late or cannot receive required charging during the nighttime charging.

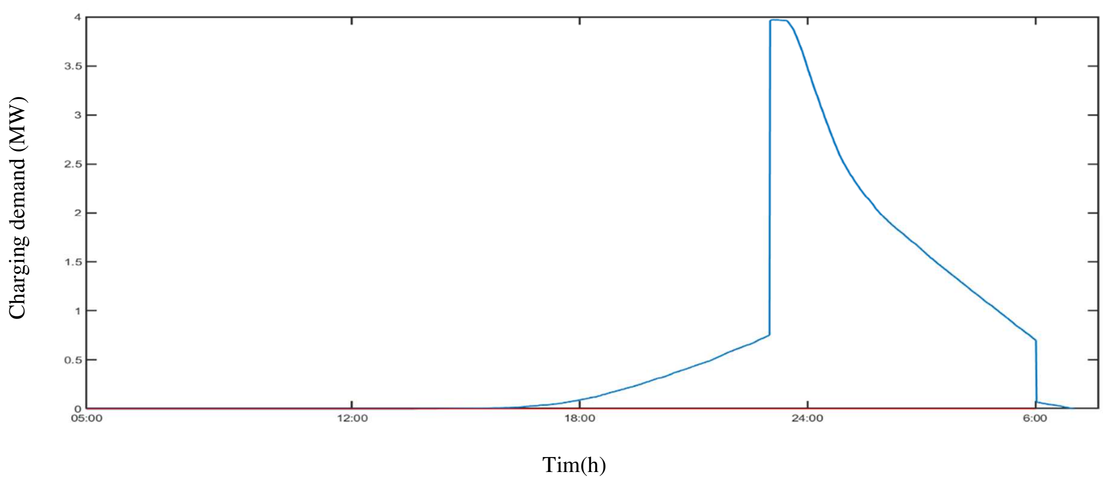


Figure 6.6. Daily charging demand of H2

6.5.Daily urban charging power demands

The urban electromobility simulation in the multi-purposes and multi-locations framework in the EV-transportation -land use-energy integrated systems result in the spatial power load of slow charging for home, work, and public destination types in the study area. Accordingly, the total charging load amount (KWh) and daily charging power load profiles for home, work, and public charging of each land use block are obtained through urban electromobility simulation. The FCSs meet the fast charging demand, while the slow charging demands are met locally at the urban land-uses.

6.5.1. Daily slow charging power load at different urban land-uses

The slow charging demands of urban land-uses are obtained from the proposed urban electromobility simulation. The charging demand of each land use block is the sum of EVs' charging power demand at the land use. Accordingly, by distinguishing between the charging demands at home, work, and public destination locations, each land-use block's total daily charging power demand is calculated as home charging demand, work charging demand, and public charging demand. It is worth noting that each block may have one or more of the mentioned charging demands according to its use. Figures 6.7 to 6.9 show the spatial power load demand of the day for each land-use block of the study area.

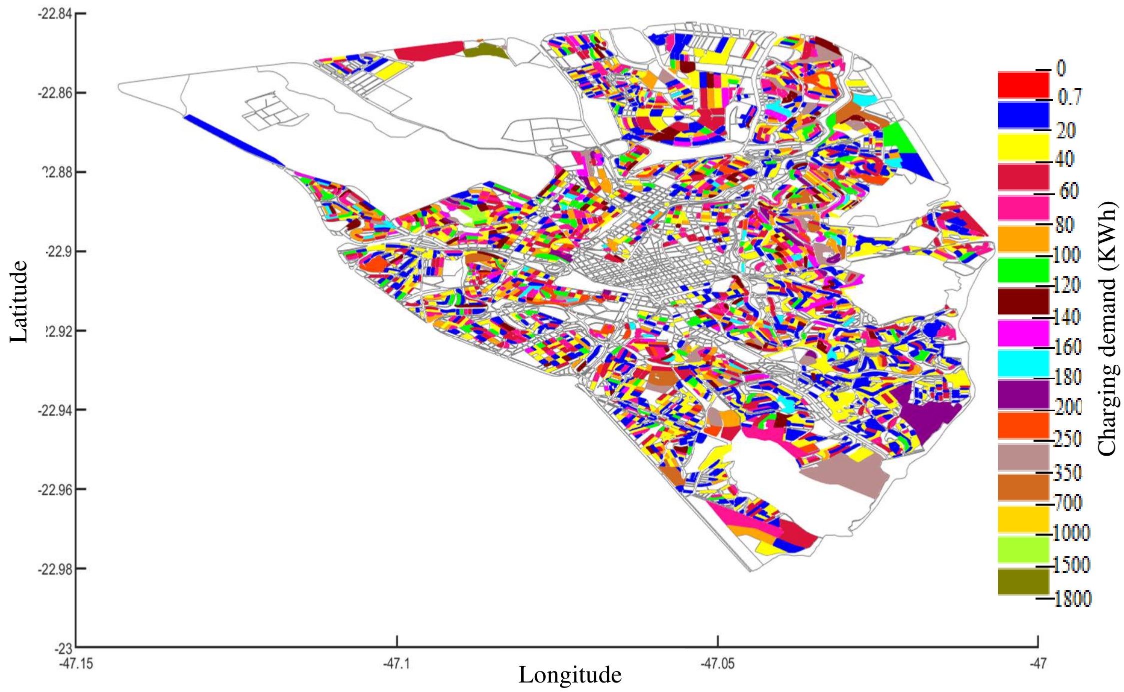


Figure 6.7. Total home charging power demand, KWh, of the urban land-uses.

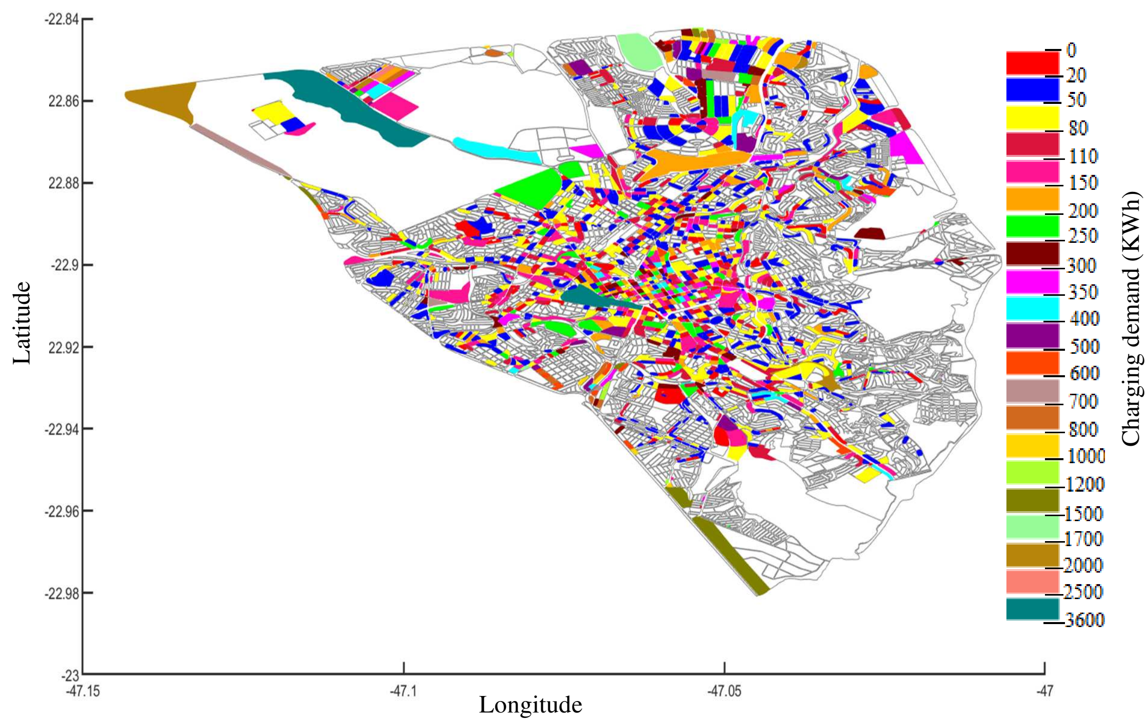


Figure 6.8. Total work charging power demand, KWH, of the urban land-uses.

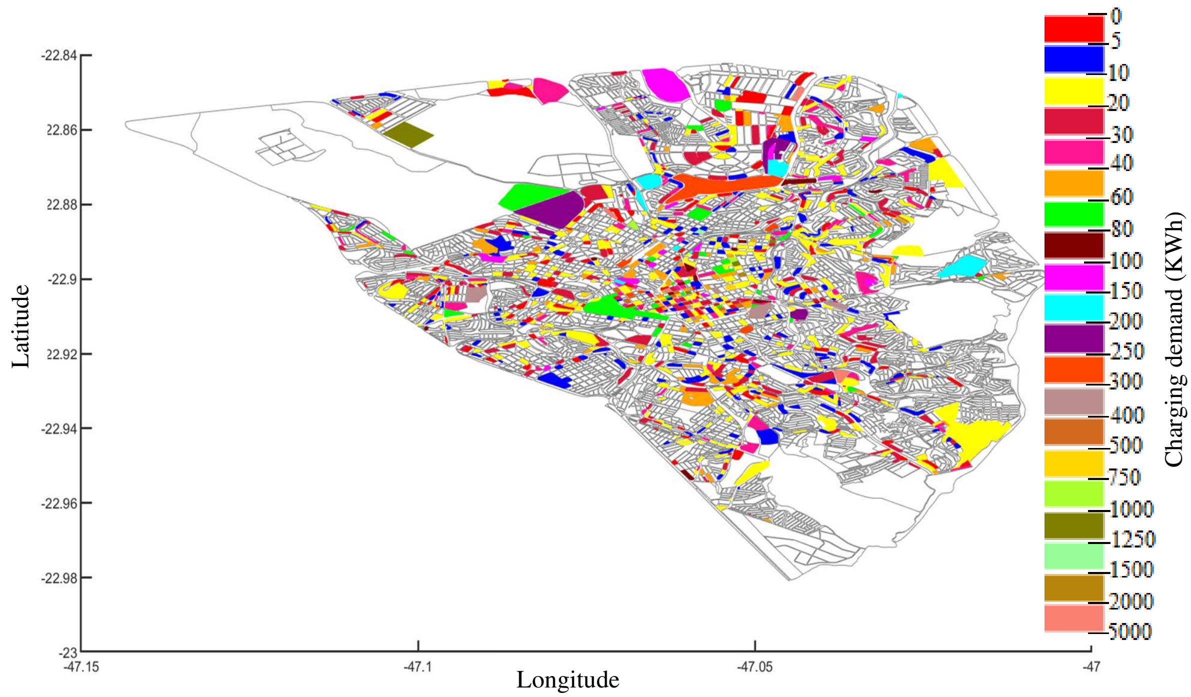


Figure 6.9. Total public charging power demand, KWH, of the urban land-uses.

Besides the total power demands at urban land-use blocks, the charging power at each time with an interval of one minute for each land-use block is calculated through urban electromobility simulation. The charging power demand of each land use block at time *t* is the sum of the charging power received by EVs that are simultaneously connected to chargers at time *t*. For instance, the spatial power load of the urban land-use blocks for home charging, workplace charging, and public charging power (in kW) at their power peak times are illustrated in Figure 6.10 to Figure 6.12. The peak times for home charging, workplace charging, and public charging are 23:07, 9:27, and 9:54, respectively.

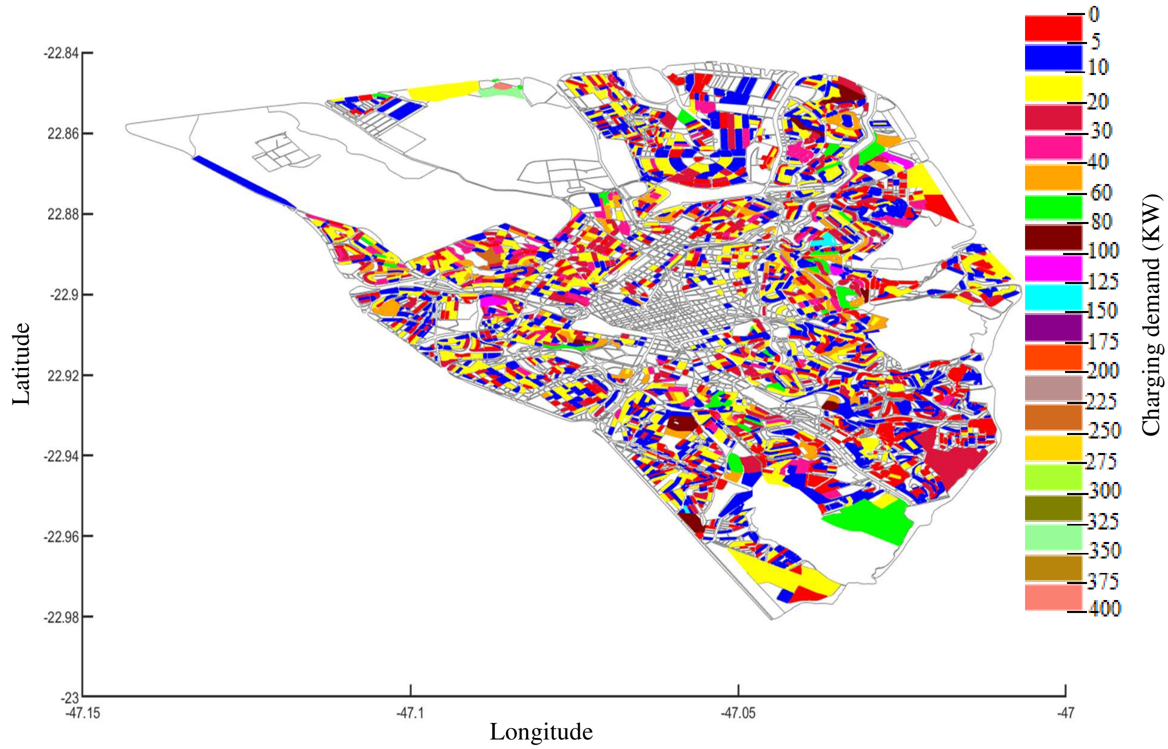


Figure 6.10. Spatial home charging power load (kW) of the urban land-uses at peak time t=23:07

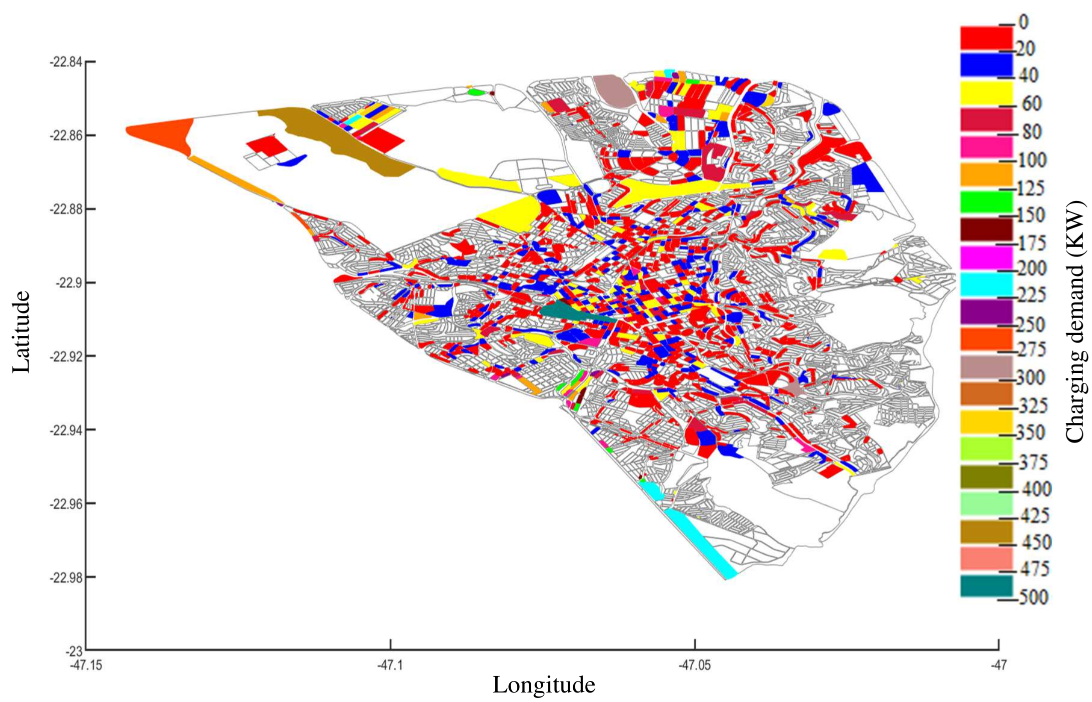


Figure 6.11. Spatial work charging power load (kW) of the urban land-uses at peak time t=9:27

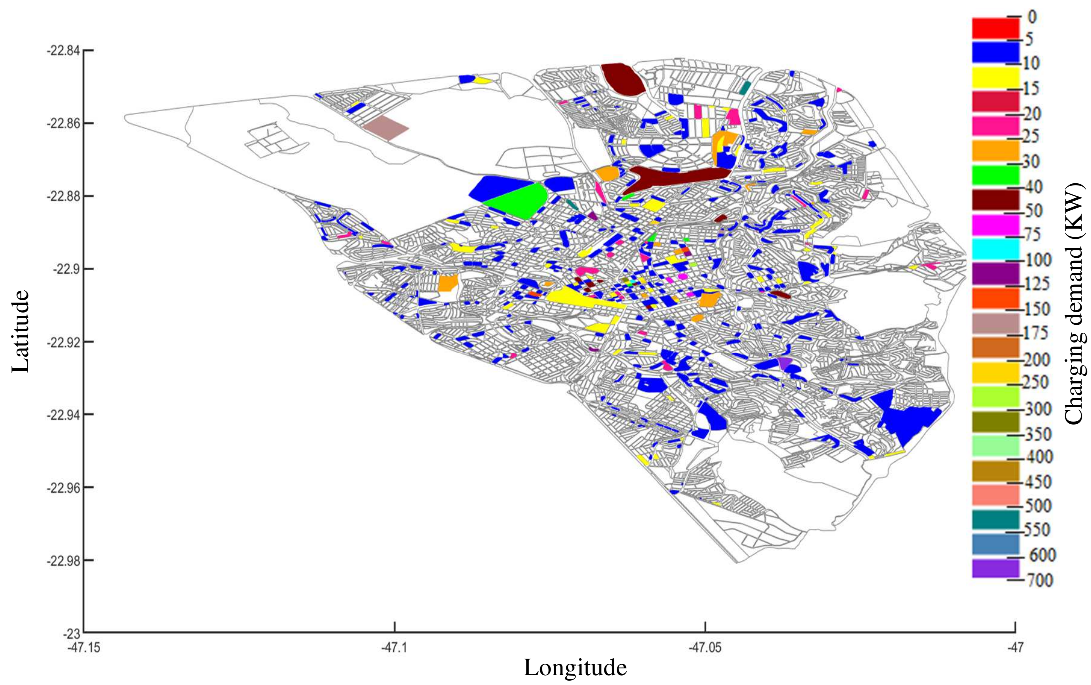


Figure 6.12. Spatial public charging power load (kW) of the urban land-uses at peak time t=9:54

6.5.1.1.Charger numbers for public charging in urban land-use blocks

The home charging power loads are from the homes that have charger piles in their homes. Moreover, the work charging power loads arise from workplaces that are equipped with charging facilities to provide energy for their employees. Hence, the charger numbers at these private locations are decided by their owner. On the contrary, urban planners should determine the required charge piles in public locations to meet public charging demands. Therefore, the number of charger piles at each urban land-use block can be determined based on the obtained daily public charging demand profile. In this regard, based on the daily charging profile with the one-minute resolution, the charging pile's number is considered as the maximum number of EVs that are simultaneously connected to the charger at the land-use block. Accordingly, Figure 6.13 shows the charging piles number at each land-use block to meet the public charging power demand.

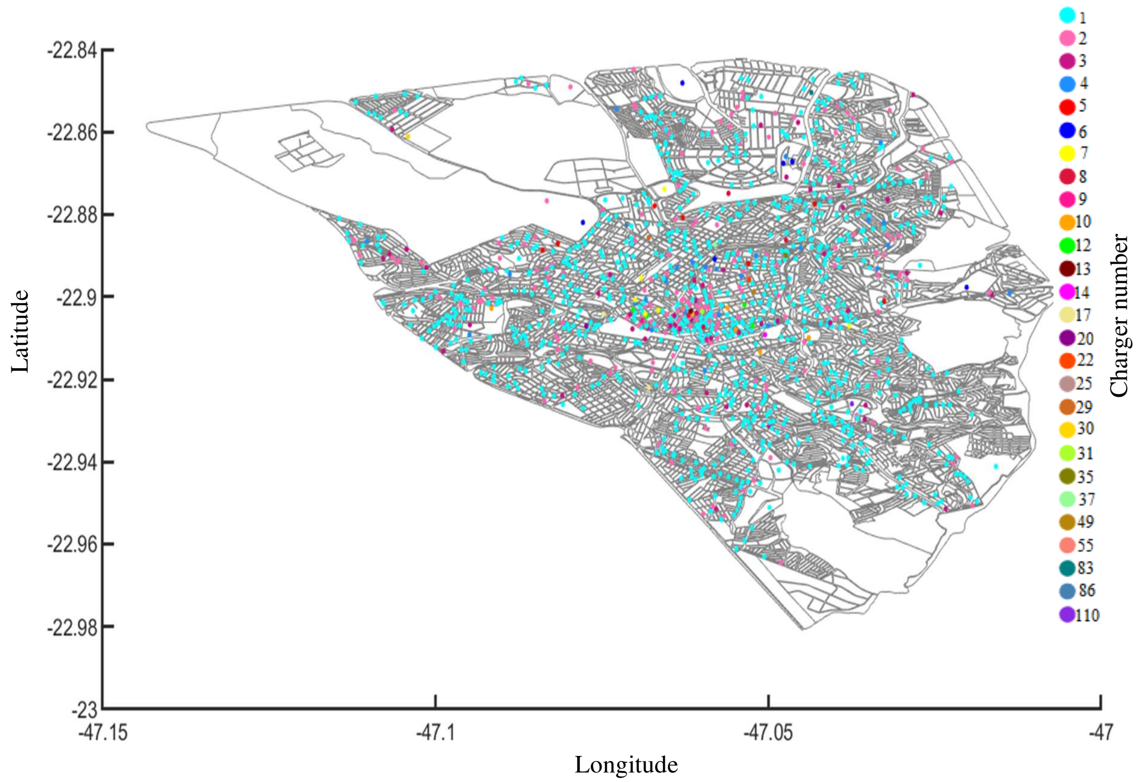


Figure 6.13. The charging pile's number at each urban land-use.

6.5.2. Daily fast-charging power load of the urban area

The home and workplace are only equipped with level I and II slow charging facilities, respectively. The EVs with fast charging demand should go to FCSs that are assumed to have level III fast DC chargers. Therefore, to satisfy the total daily fast charging power demand of the study area illustrated in Figure 6.4, the size and site of optimal numbers of FCSs are obtained based on the proposed model in the electromobility simulation. Figure 6.14 shows the candidate number of FCS locations in the urban area.

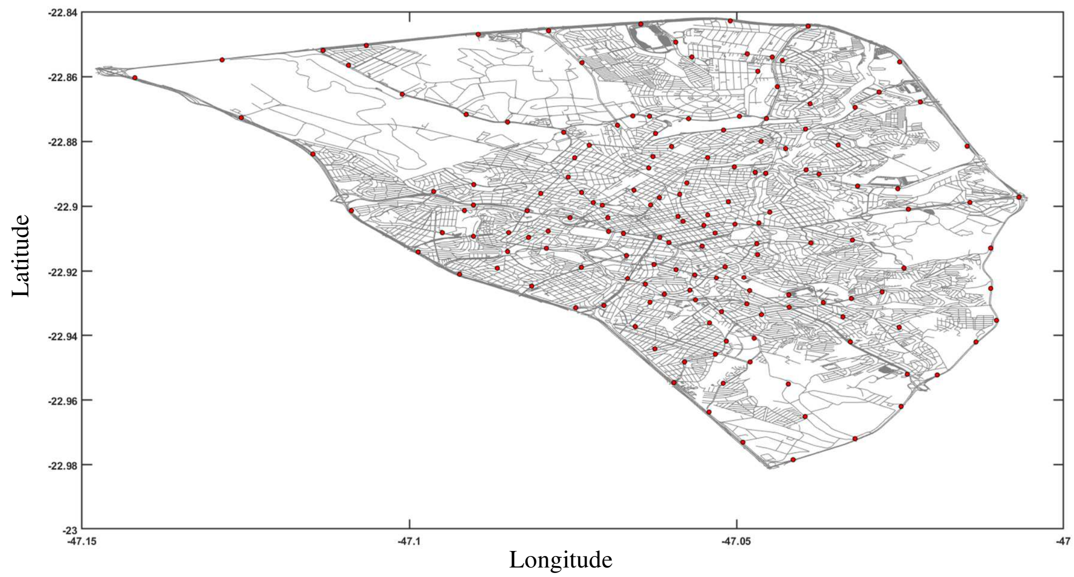
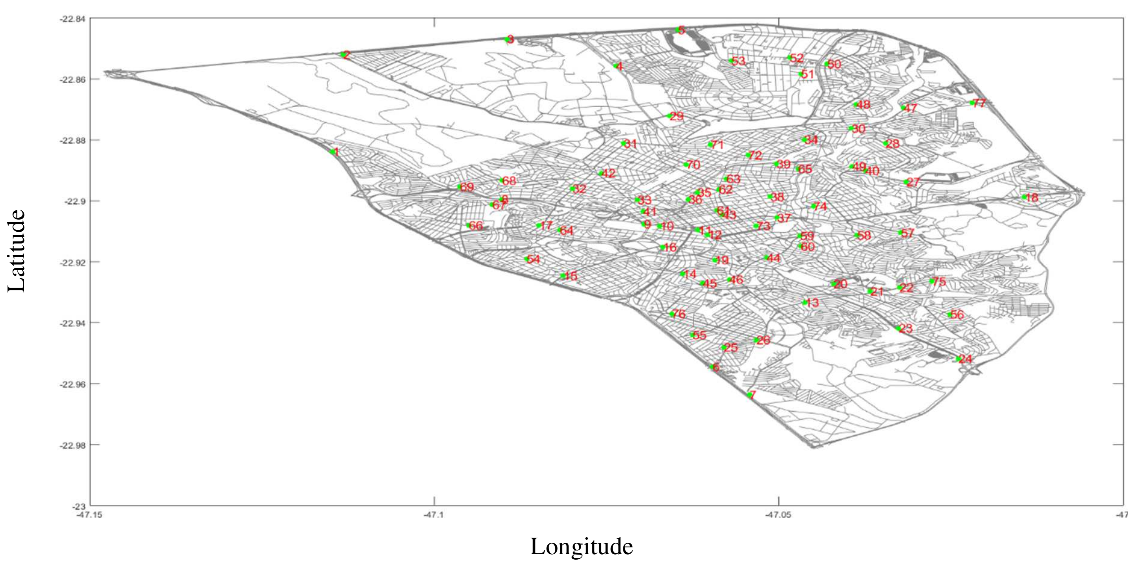
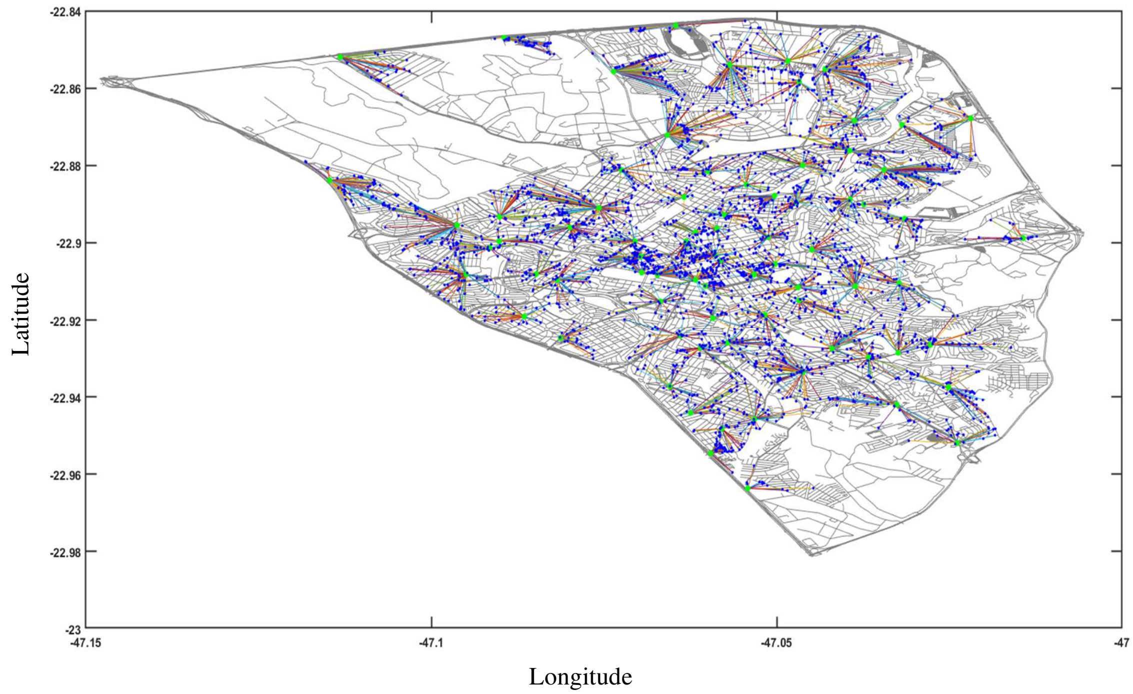


Figure 6.14. The FCSs candidate locations in the urban area.

According to the urban electromobility simulation, the fast charging demand locations are obtained, and each EV with fast charging demand is assigned to the nearest FCS. According to the obtained results of urban electromobility simulation and the proposed model of FCS planning, the optimal FCSs are obtained from the FCSs candidate. The obtained FCSs and their assigned fast charging demand points are shown in Figure 6.15.



(a)



(b)

Figure 6.15. (a) Optimal locations of FCSs and (b) their assigned fast demand points.

The daily power load of each FCS is obtained with resolution on-minute so that the power load at each minute is the sum of the power drawn by the active chargers at that minute. The daily power load profiles for FCSs are illustrated in Figure 6.16.

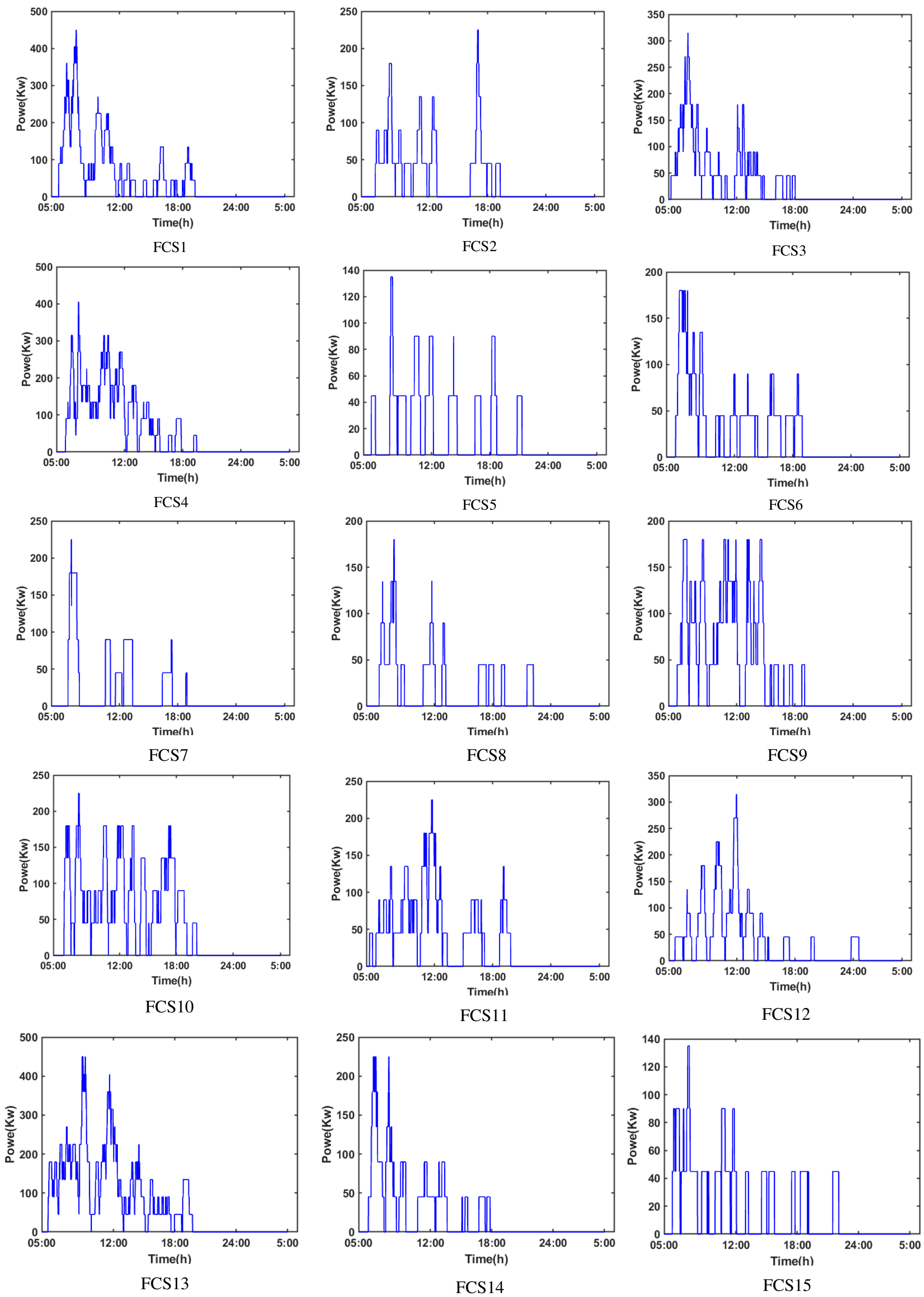
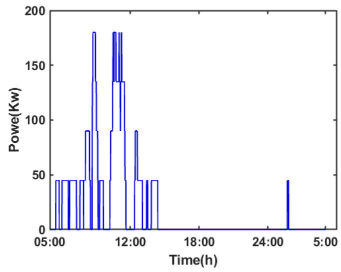
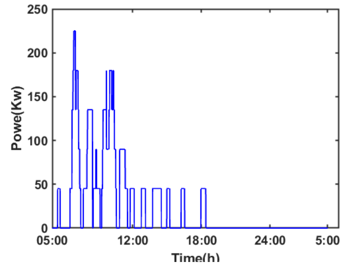


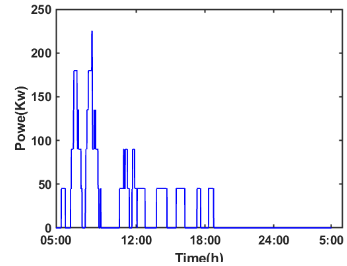
Figure 6.16. Daily power load profile of FCSs in the urban area.



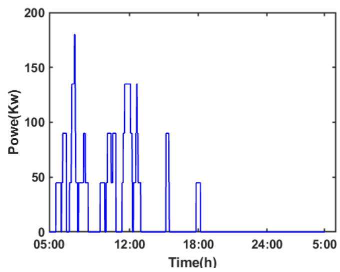
FCS16



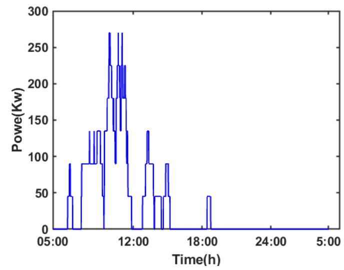
FCS17



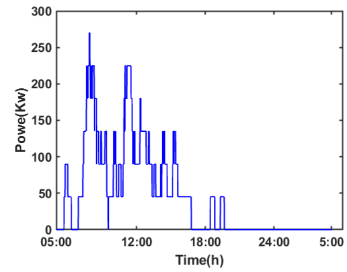
FCS18



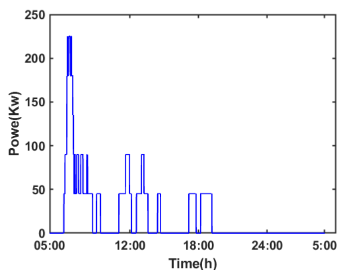
FCS19



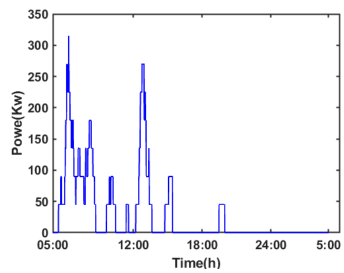
FCS20



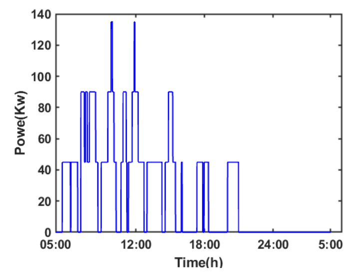
FCS21



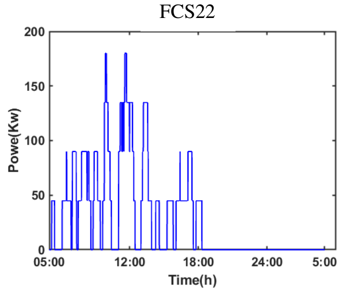
FCS22



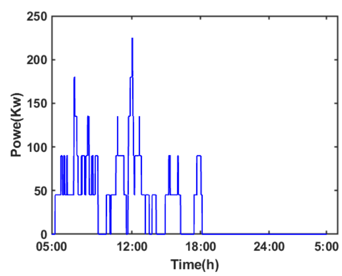
FCS23



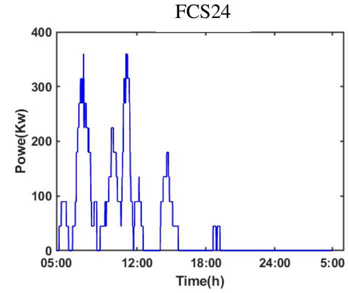
FCS24



FCS25



FCS26



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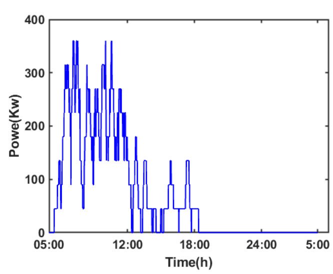

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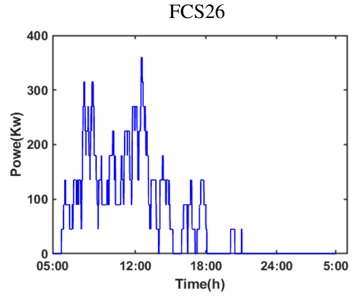

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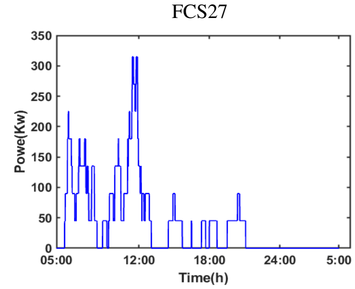

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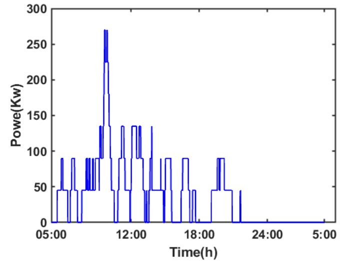

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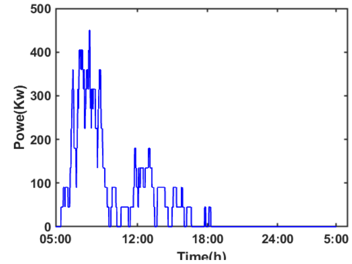

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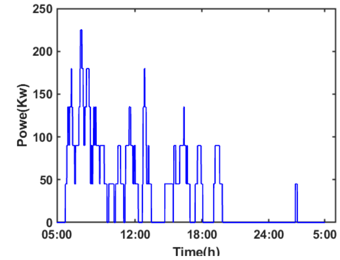

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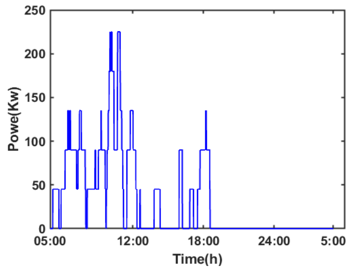

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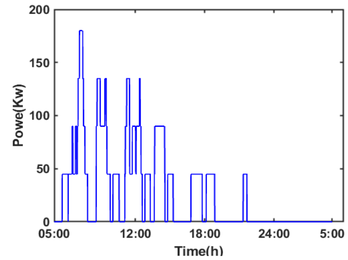

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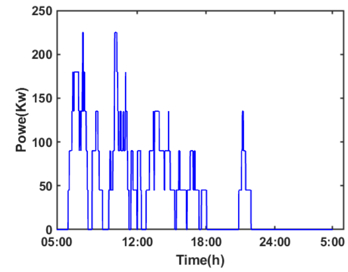

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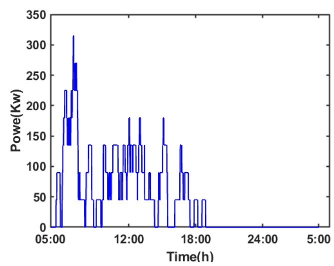

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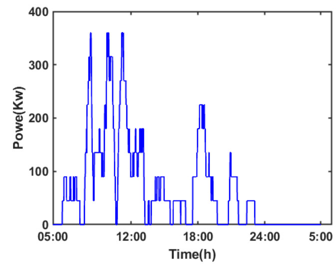

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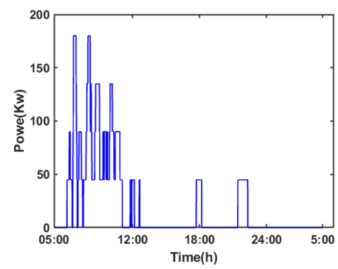

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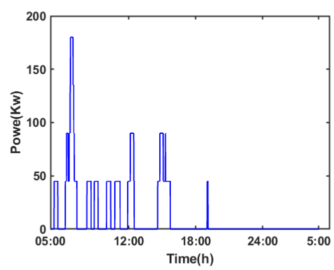

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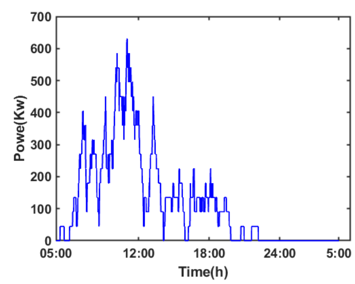

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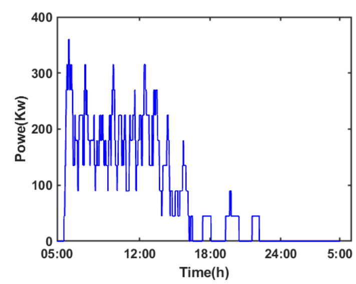

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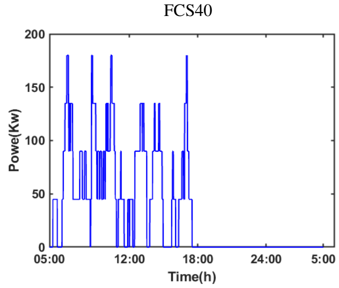

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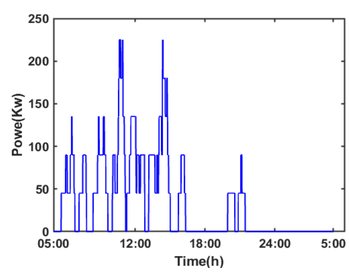

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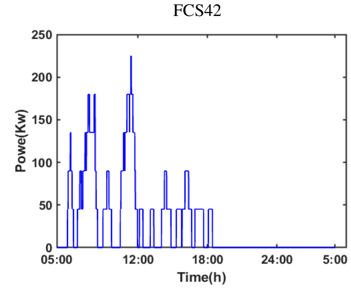

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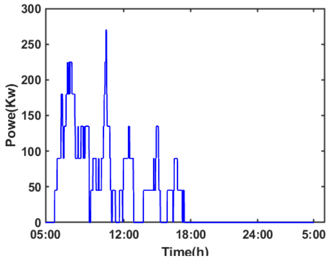

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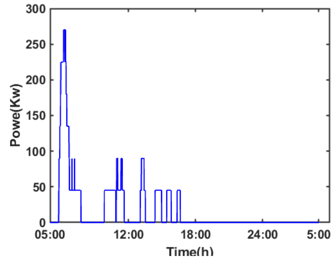

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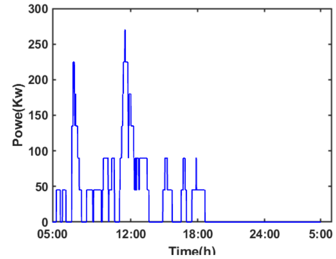

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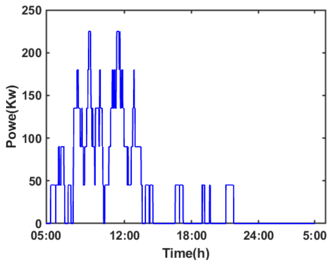

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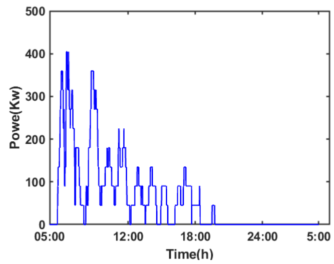

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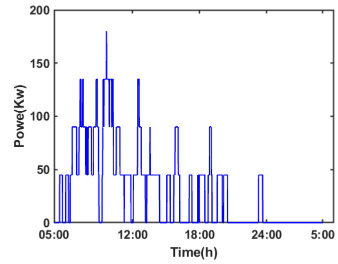

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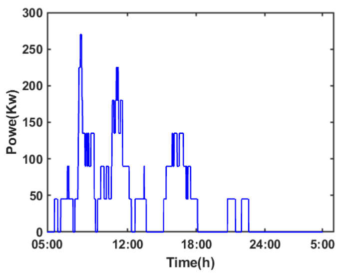

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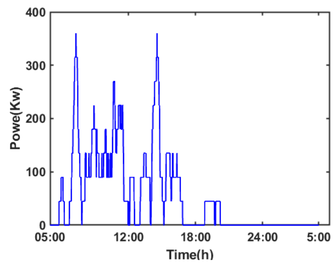

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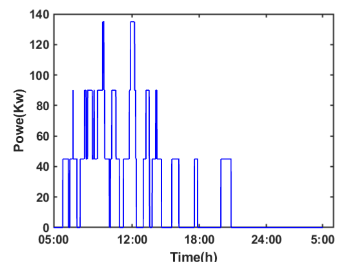

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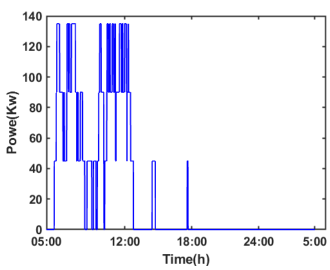

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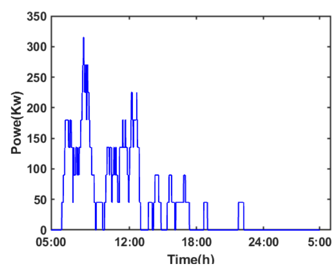

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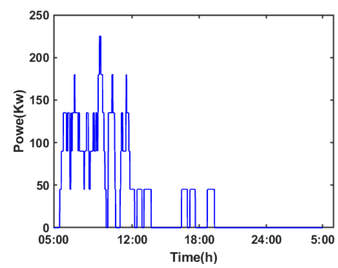

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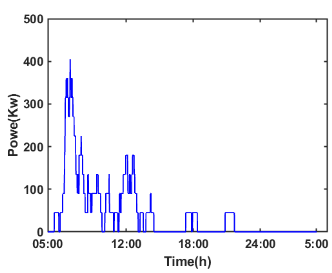

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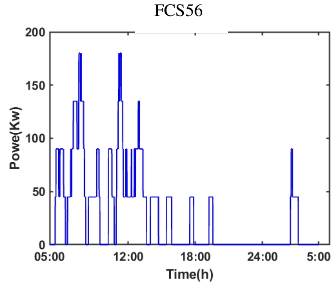

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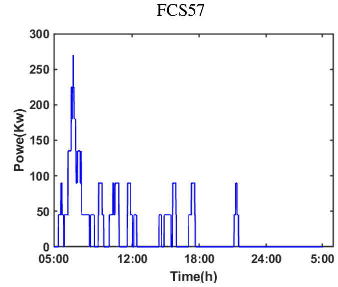

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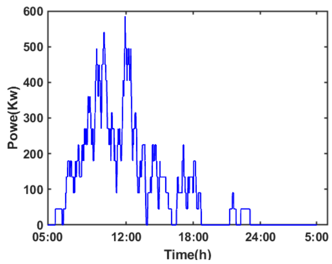

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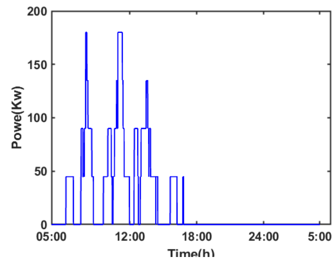

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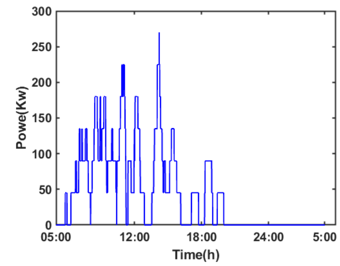

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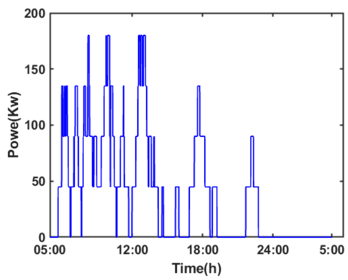

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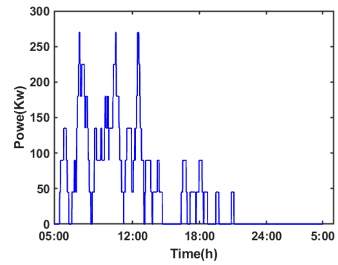

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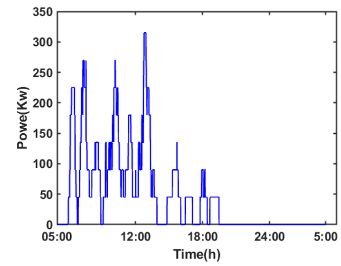

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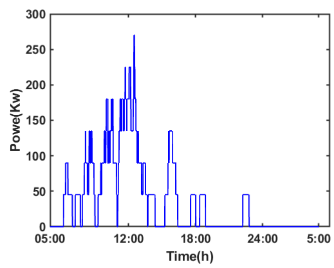

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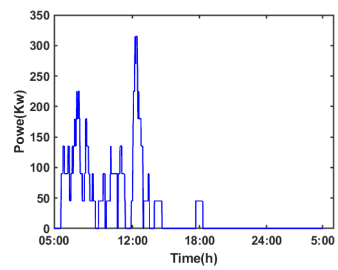

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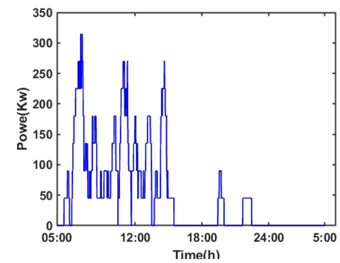

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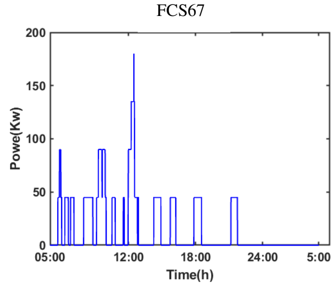

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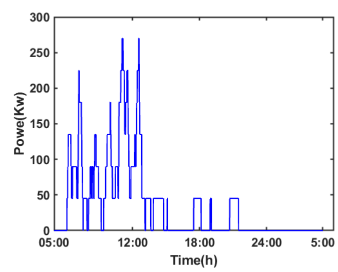

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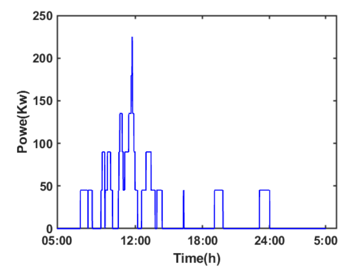

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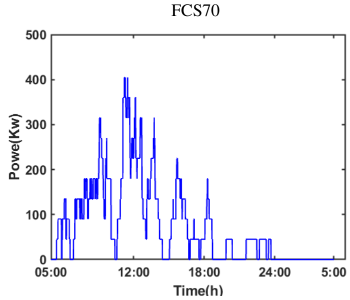

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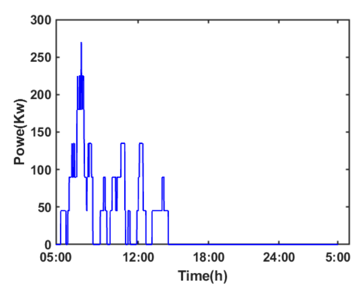

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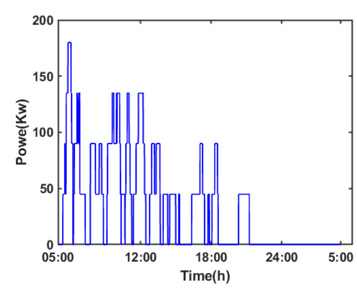

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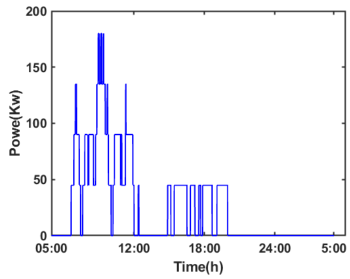

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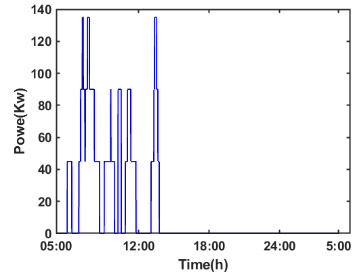

FCS77

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For each FCS, the number of charges is also determined based on the proposed FCS planning model. Figure 6.17 shows the charger number of FCSs in the urban area

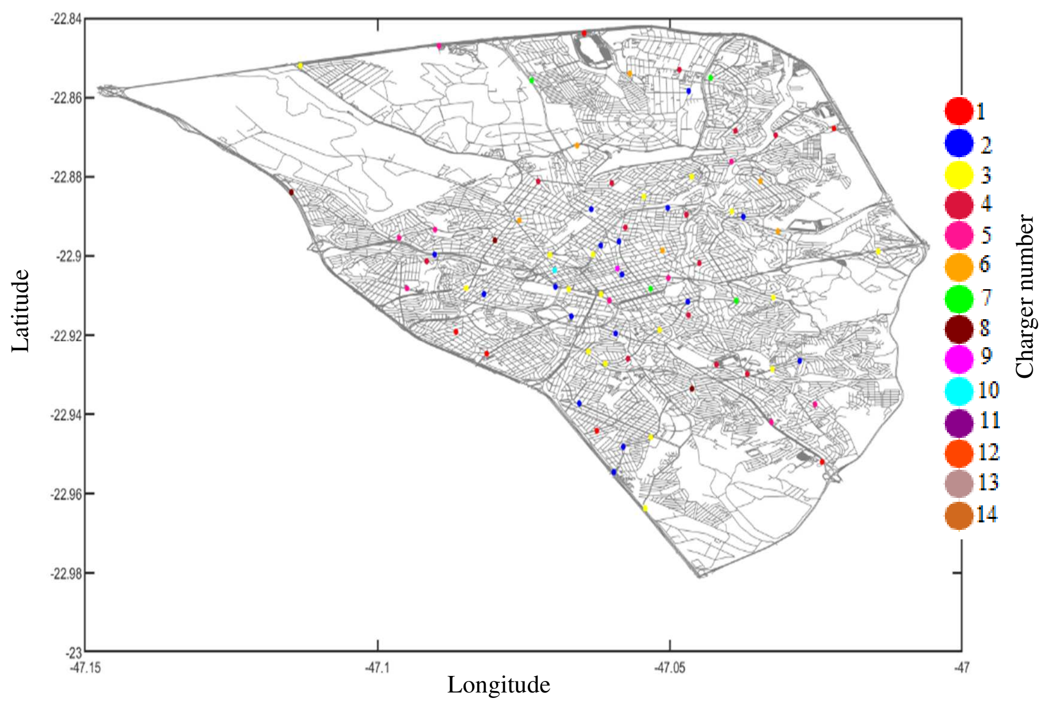

Figure 6.17. The charger's number of each FCS in the urban area.

Chapter 7

7. Conclusion and Recommendations for Future Research

7.1. Conclusion

This thesis proposes novel modeling and simulation of urban electromobility in the integration framework of EV-transportation-land use-energy to predict the urban charging power demand distributions and charging infrastructures planning. In this context, based on the existing interaction between EV users and EV, urban transportation system, urban land-uses, and urban energy systems, the users' driving and charging behaviors are analyzed and modeled to simulate the daily travels of EVs in the urban area. The daily travels simulation eventually leads to predicting the spatial-temporal urban charging power demands, which are used for charging infrastructure planning in the urban area.

The actual street network and land-use spatial models constructed based on real-world data and the travel survey data provide a platform for simulating the spatial-temporal attributes of EV daily travel in the study area. The urban land use model provides the Geographical features of activity locations that the users select as destinations for their daily trips. The urban street network model enables the determination of daily trips' trajectories. Moreover, in the absence of EV travel data, the travel survey data of conventional vehicles provides regional travel characteristics of drivers in the study area that are used to develop probabilistic models to reflect the stochastic nature of EV daily trips. Thus, the EV travels are simulated in the multi-purpose multi-location context, which helps achieve a more accurate model of urban electromobility simulation.

In addition to the urban street network topology, the traffic flow on the urban streets strongly influenced the EV user driving behavior and EV energy consumption. Since collecting the actual traffic data of all urban streets is very difficult and perhaps impossible, this research develops a new tool by using the constructed urban street network, MATLAB, and online traffic information of the Google map to extract the traffic condition of streets of the study area.

Another opportunity that the actual urban street network provided is calculating the average urban street slope that is affects the EV driving energy consumption. The real-world DEM data of the study area is utilized to estimate the slopes of the streets. Since the DEM and OSM data are both described by Lat/Longs, by overlapping the DEM raster and street segments, the average slope of each segment is calculated.

Contrary to the existing studies, the integrated model of the urban street network and land use makes it possible to simulate urban mobility comprehensively. The land use contains the potential activity locations of EV trips, and the street network provides the potential paths between these activity locations. The graph-based model of the street network allows modeling the trip route choice of EV users. In this regard, the minimum-energy trip route predicting is modeled based on the EV energy consumption model, street network dynamic traffic status, and routing algorithm. In addition to predicting the destination and trip route of the EV travels, the street network and traffic models help model EV's driving pattern on the selected trip route. Hence, to represent the stochastic nature of EV driving, the stochastic driving cycle unique to each EV trip is generated based on street characteristics and traffic conditions of the trip route's street segments. Therefore, the spatial-temporal features of EV travels are determined in detail by modeling the EV user driving behavior simulating with taking into account the interdependency between the user, EV, transportation system, and land-use.

The EV energy consumption on the street network ultimately leads to charging demand at charging locations. Hence, besides the driving behavior, the charging behavior of users should be modeled to achieve an accurate urban electromobility simulation. EVs' charging demand causes EV users to interact with urban energy systems. The urban energy systems provide the energy to EV charging through charging stations located at land use or urban street network. The charging stations are the interface between EVs, transportation system, and land-use. Therefore, EV's driving and charging behavior are modeled in integrating EV-transportation-land use and energy to achieve accurate charging demand of the urban area. The charging behaviors of users are modeled according to the main influencing parameters on users' decisions like user preferences, users' access to charging opportunities, SoC of EV, users range anxiety. As such, the EV users are classified into four groups based on their access to the charging location. Different strategies are modeled to emulate the charging decision of each group of EV users.

The daily travels of EVs are simulated based on proposed models of EV user driving and charging behaviors to predict the urban area's slow and fast charging demand, which is then utilized in charging infrastructure planning.

The numerical simulation of urban electromobility for EVs in the study area is conducted to predict spatial-temporal charging power demand distributions for a typical weekday. The slow charging power demands are distributed at urban land uses and fast charging power demands at FCS candidates. Land use's slow charging demand is divided into home, work, and public charging demand. Based on the simulation result analysis, it is concluded that the highest percentage of urban charging demand is the slow charging at home and work. The prediction results demonstrated that EV users prefer to charge at home or the workplace rather than public charging stations. Charging at work and home is more convenient and economical for EV users because they provide great convenience and flexibility to charge EV batteries. Hence, the charging at home and work for EV users is principal, and public charging is the complement. The slow public charging demands are met locally by the charging pile at each land use, which the number of charging piles at each land use is determined based on daily public charging power profile. To satisfy the fast public charging demand, the optimal number of FCSs from FCS candidates is obtained. The number of chargers at each selected FCS is determined based on the trade-off between the arrival time of EVs at FCS and waiting time.

As a result, if there are insufficient chargers at homes and workplaces, the EV users who don't have access to home/work charging have to rely solely on charging public destinations. Hence, the charging demand at public locations is increased. Also, the public charging stations could provide unique incentives and better-charging services to attract EV users to public charging. Therefore, planning adequate public charging infrastructures can satisfy the charging demand of users that don't have access to home and work charging facilities. Hence, the optimal planning adequate public charging station can facilitate the EV penetration in the urban transportation system.

Due to the limited knowledge and experiences of EV traveling in the urban areas, and in the absence of empirical data about EV users' driving and charging behaviors, the proposed urban electromobility simulation in this thesis can provide a vision of urban charging energy demand prediction and charging infrastructures planning to develop and implement urban energy management solutions for its sustainable future.

7.2. Recommendations for future research

The future research directions for further investigating the methods and results presented in this thesis are as follow:

(1) This thesis investigates the urban electromobility simulation to predict the urban charging demand and plan the charging infrastructures based on EV driving and charging behavior. In the absence of empirical data of EV users' driving and changing behavior, the models are developed based on conventional cars' data and users' rational behavior to charge EVs under different conditions. In the future, the proposed models can be combined with the real-world data from the EV user's driving and charging behaviors, EV driving speed, etc.

(2) In the proposed model in this research, the limitation imposed by the power grid is not considered in the charging demand prediction and charging infrastructure planning. In addition to the urban power grid, the renewable energy can be considered in the energy system in the proposed integrated framework in this thesis. Thus, with the inclusion of realistic data and considering the constraints of the energy systems, the proposed model would be extended by adding new parameters affecting EV users' behaviors in their daily travels that eventually affect their charging demands.

(3) Due to the complexity of the integrated framework of the urban transportation system and land use, planning the charging infrastructure by mathematical optimization methods is difficult and leads to taxing computational efforts. The proposed work can be extended by exploring the adequate optimization methods for urban charging infrastructures planning.

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