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Simulating individual mobility networks for Electric Vehicles

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Abstract

Electric mobility appears to be one of the future ways to make cities more sustainable and improve the quality of life in urban environments. However, when it comes to private vehicles, users need to evaluate how their mobility lifestyle is going to change when their fuel-based vehicle is replaced by and electric one (EV). The objective of this work is to propose a process that, through a mix of mobility data analytics, ad hoc trip planning and simulation, is able to analyze the current fuel-based mobility of a user and quantitatively describe the impact of switching to EVs on her mobility life style. Exploiting a network-based representation of human mobility (Individual Mobility Networks), four simulation scenarios are considered, distinguished by the battery recharge options that the user might have in real life: recharging only at public stations, charging also at home, or also at work, or both. For each scenario we calculate how much battery the user has to charge in each charging option and how much time he has to wait for charging, as well as how much her original mobility (performed with a combustion engine) is affected by the limits of EVs, evaluating the expected increment in travel times and distances. This work is part of the activities of the H2020 European Project Track Know (https://trackandknowproject.eu/).

Introduction

There are many motivations to choose an Electric Vehicle (EV) as private car. A first one is fuel costs. Because of the higher price of gasoline as compared to electricity, adopting an electric vehicle is a good choice for saving money. The second one is reducing air pollution in urban contexts. In fact, human presence had consistently a very negative impact on the environment, and switching to an electric vehicle is one way to reduce further damage to the Earth. Carbon dioxide emissions from traditional vehicles contribute to greenhouse gases in the atmosphere and accelerate climate change, while electric vehicles avoid that (at least directly). The third one is becoming energy independent, since electric vehicles can recharge by connecting to the electric grid and electricity can be produced through several generation methods. As a matter of fact, electric vehicles can facilitate energy independence, through the installation of renewable electricity generation facilities such as a solar array to fuel the personal.

Context And Motivation

While there many advantages for using electric vehicles, the average user still is worried about changing her life style to EVs. This aversion is to be found in the common belief that moving to an electric vehicle can have a strong impact on their daily life. One of the biggest differences between a fuel-powered vehicle and a battery-powered vehicle lies in the immediate availability of energy needed to charge it. The time required to fill a fuel tank is usually less than a quarter of an hour, while a stop to recharge the battery of an electric vehicle based on the capacity of the battery, can easily take more than an hour. Also, in the short term we can expect that recharging facilities will still be underdeveloped compared to fossil fuel stations, therefore rising the fear of not being able to perform the mobility the user needs for living. Therefore, it becomes necessary to study how much an individual's life changes with the transition to the electric vehicle in the present conditions. The objective of this thesis is making a first step to tackle this problem and provide to the users various measures of how much comfortable could be the EV for them, taking into consideration what recharge options they have.

Work Done And Obtained Results

In order to carry out such a study, we need to simulate the individual mobility (that is obtained by GPS data produced by phones and trackers in vehicles which provides a detailed view of individual movements on a large scale) of people who use fuel-based cars in simulated scenarios where they switch to electric vehicles by considering different charging options, and eventually make a comparison between the obtained results. As a matter of fact, we consider cases where the EVs can recharge at multiple locations in multiple ways. Our model analyzes charging across three use cases that all assume wired plug-in chargers: at home, at work and in public stations. Indeed, home charging will depend on whether EV owners have proper garages at their home or not. Charger penetration at work will predominantly reflect employer choice or regulatory requirements. Finally combining home and work should in theory cover most of a EV owner's energy demand, since most individual passenger cars remain parked for 8 to 12 hours at night, and home charging can be easy and often cheaper than charging elsewhere. The reasons is, in most countries, residential electricity is cheaper than commercial or industrial electricity, and most charging can happen overnight when off-peak electricity prices are lower. On the other hand, charging at home and work helps a lot to reduce the number of times that users get stuck in emergency situations because of a low amount of battery that does not even allow to reach the nearest public station. Eventually, by having possibility of charging at home, work or both, for most of the users the need of charging at public stations decreases a lot and sometimes there is no need at all to charge at public stations. Our results show that, users are expected to have no problems driving an EV if they are willing to drive just a little bit more (due to the current small availability of recharge stations on the territory) and lose little time more for charging their cars, and only a few cases remain that might face emergency situations. All methods presented in this thesis were applied to a database of human mobility trajectories in the region of Tuscany, made available by the KDD Lab (CNR) in Pisa.

Organization Of the Thesis

The thesis is organized in six chapters. In chapter 1 we will provide a brief background about electric vehicles, charging stations and their plug's speed. Also we go more in details about the advantages of charging at home. In chapter 2, we will discuss about modeling human mobility and introduce all the notions related to mobility data and trajectories we will need in the rest of the thesis. In chapter 3, we will focus on route planning and trip simulation, the concepts of open street map and open charge map and we will go more in detail in heuristic trip planning algorithms, which are a tool exploited in our simulations. In chapter 4, which is the core of the thesis, we will present methods for EV mobility simulation and what-if analysis. Indeed, in this chapter, we will talk about individual mobility networks and how they are computed then, we will discuss about having different charging options in different scenarios and the main three strategies we developed, with the related algorithms more in details. In chapter 5, we will discuss about the results of the experiments obtained by analyzing four scenarios on the simulated mobility of several real users, and compare them. Finally, at the end of this chapter we will try to analyze what is the effect in terms of change of life style for the users that switch to EVs, also in terms of increase in total length they have to drive. At the end, in chapter 6 we will conclude the thesis and discuss some possible future improvements for what has been done until now.

Contents

Chapter 1

Background on Electric Vehicles

In this chapter we present the notion of electric vehicle and it's potential advantages in daily life mobility, which is described in section 1.1. We also introduce the concept of charging station and charging types, respectively in sections 1.2 and 1.3. Finally, we illustrate a very convenient option of charging EVs at home in section 1.4.

1.1 Electric Vehicle (EV)

An electric vehicle (EV)[1] is one that operates on an electric motor, instead of an internal-combustion engine that generates power by burning a mix of fuel and gases. Therefore, such as vehicle is seen as a possible replacement for current generation automobile, in order to address the issue of rising pollution, global warming, depleting natural resources, etc. Though the concept of electric vehicles has been around for a long time, it has drawn a considerable amount of interest in the past decade amid a rising carbon footprint and other environmental impacts of fuel-based vehicles. Indeed, EVs store electricity in an energy storage device, such as a battery. The electricity powers the vehicle's wheels via an electric motor. EVs have limited energy storage capacity, which must be replenished by plugging into an electrical source. The policy related to battery-powered vehicles is mainly focused on technological optimisation and market development. Future challenges in this field include reliability and durability of batteries and super capacitors, reducing

[1] www.business-standard.com/about/what-is-electric-vehicle

battery weight and volume, safety, cost reduction, improved hybrid electric power trains, charging infrastructure and plug-in solutions.

1.2 Electric Vehicle Charging Station

An electric vehicle charging station[2], also called EV charging station, electric recharging point, charging point, electronic charging station (ECS) and electric vehicle supply equipment (EVSE), is an element in an infrastructure that supplies electric energy for the recharging of plug-in electric vehicles including electric cars, neighborhood electric vehicles and plug-in hybrids.

For charging at home or work, some electric vehicles have converters on board that can plug into a standard electrical outlet or a high-capacity appliance outlet. Others either require or can use a charging station that provides electrical conversion, monitoring, or safety functionality. These stations are also needed when traveling, and many support faster charging at higher voltages and currents than are available from residential EVSEs. Public charging stations are typically on-street facilities provided by electric utility companies or located at retail shopping centers, restaurants and parking places, operated by a range of private companies.

1.3 Charging Station Types

There are three main types of EV charging points: rapid, fast, and slow[3]. These represent the power outputs, and therefore charging speeds, available to charge an EV. Note that power is measured in kilowatts (kW).

1.3.1 Rapid Chargers

Rapid chargers are one of two types: AC or DC (Alternating or Direct Current). Current Rapid AC chargers are rated at 43 kW, while most Rapid DC units are at least 50 kW. Both will charge the majority of EVs to 80% in around 30-60 minutes, depending on

[2] www.en.wikipedia.org/wiki/Charging_station

[3] www.zap-map.com/charge-points/

battery capacity. Tesla Superchargers are also Rapid DC and charge at around $120kW$. Rapid AC devices use a tethered Type 2 connector, and Rapid DC chargers are fitted with a CCS, CHAdeMO or Tesla Type 2.

1.3.2 Fast Chargers

Fast chargers include those which provide power from $7kW$ to $22kW$, which typically fully charge an EV in 3-4 hours. Common fast connectors are a tethered Type 1 or a Type 2 socket (via a connector cable supplied with the vehicle).

1.3.3 Slow Chargers

Slow units (up to $3kW$) are best used for overnight charging and usually take between 6 and 12 hours for a pure-EV, or 2-4 hours for a hybrid electric vehicle (PHEV). EVs charge on slow devices using a cable which connects the vehicle to a 3-pin or Type 2 socket.

1.4 Recharging At Home

Because residential charging[4] is convenient and inexpensive, most plug-in electric vehicle drivers do more than 80% of their charging at home. Charging in a single-family home, usually in a garage, allows you to take advantage of low, stable residential electricity rates. The cost to run your car over the course of a year can be less than running an air conditioner. Charging at a multi-family residential complex, like a condo or apartment, is possible, but can be complex and more similar to public charging.

1.4.1 Costs To Charge At Home

Fuel costs for EVs are lower than for conventional vehicles. Based on the national average of 12.6 cents/kwh, fully charging an all-electric vehicle with a 100 mile range and depleted battery would only cost about the same as operating an average central air conditioner for six hours. Because plug-in hybrid electric vehicles have smaller batteries, each individual charge costs even less. General Motors estimates the annual energy use of a Chevy Volt is

[4] `www.energy.gov/eere/electricvehicles/charging-home`

2,520 kWh, which is less than required for a typical water heater. In comparison, over the past ten years, U.S. regular conventional retail gasoline prices have fluctuated from below \$1.50 to over \$4, reducing annual household budgets by as much as \$1,500 per average passenger car. If you charge primarily at night and your utility offers special off-peak rates, your costs may be even lower. Home charging can use either the relatively simple Level 1 electric vehicle supply equipment (EVSE) or the slightly more complex Level 2 EVSE. Charging with Level 2 EVSE is faster and can be more convenient, but requires special equipment that is more expensive to install than Level 1.

1.4.2 Level 1 EVSE

Level 1 EVSE provides charging through a 120 volt (V) AC plug. Level 1 adds about 2 to 5 miles of range to a vehicle per hour of charging time, making it suitable for plug-in hybrid electric vehicles and depending on circumstances, even some all-electric vehicles.
Charging with Level 1 EVSE will not require any special equipment besides an outlet, but does require a dedicated branch circuit. For the connector, nearly all EVs come with a portable Level 1 EVSE cordset, which has a standard three-prong household plug on one end for the outlet and a standard J1772 connector for the vehicle.

1.4.3 Level 2 EVSE

Level 2 EVSE provides charging through a 240 V AC plug. Level 2 adds about 10 to 60 miles of range to a vehicle per hour of charging time, making it suitable for all EVs.
Using Level 2 EVSE requires drivers install special charging equipment as well as have a dedicated electrical circuit of 20 to 100 amps. Most houses already have 240 V service for appliances such as clothes dryers and electric ranges. The price of Level 2 residential EVSE varies, but typically ranges from \$500 to \$2,000. For homes with adequate electrical service, installation is usually relatively inexpensive. However, it can be substantial if an electrical service upgrade is required. As EVSE installations must comply with local, state, and national codes and regulations. The safety risks of installing and using home EVSE are very low, similar to those associated with other large appliances like clothes dryers. Residential EVSE are generally installed in garages, but home owners can also purchase

outdoor rated EVSE built to withstand weather and other types of stresses. EVSE cords are built to withstand some abuse even being run over by a car and the power flow through the cord is cut off when the vehicle is not charging. There is a variety of equipment for Level 2 EVSE available, ranging from simple models with standard safety features and status lights to more advanced products have features with enhanced displays, charging timers, smartphone connections, and keypads.

Chapter 2

Modeling Human Mobility

First of all, we introduce all the notions required to understand the analysis done in the thesis. Then, since we work with trajectories and coordinates we start by explaining some basic knowledge about geolocation data: in Section 2.1 we give some basic definitions of trajectories and introduce basic analyses that can be performed on mobility data. In the second part of the chapter, we can extract the set of locations from the trajectories. The steps to do so are described in Section 2.3. In a few words, we can summarize the process as extracting the starting and stopping points of each trajectory. With a given set of locations, we can convert the trajectories to movements. Thus, instead of connecting two points the movements connect two locations. This process is reported in Section 2.4.

2.1 Geolocation Data

We can start from the most general definitions that make up the foundation of our analysis. With the term Geolocation, we refer to the use of the geographic coordinate system to define the position of points on earth. This extra information can be useful to work on the context where data are taken. A coordinate is usually expressed through 3 values: latitude, longitude and elevation. In our case elevation is not relevant. The latitude specifies the north-south position of a point. It is expressed as an angle that is 0°at the Equator and respectively -90° and 90° in the two poles. The longitude instead specifies the east-west position as the angular distance from the Prime Meridian of Greenwich. It ranges from

0° (in Greenwich) and ±180° in the two directions.

2.1.1 Distance Functions

To compute simple operations on the points, we have to define the notion of distance function between coordinates. This way we can compute path lengths and decide whether two points can be considered close to each other. There are many ways to compute the distance between coordinates. The main issue is how we approximate the earth's surface: we can consider it to be flat, spherical or ellipsoidal. The differences between these approaches are the accuracy of the result and the computation complexity [1].

Flat Surface In the first case, we project either the spherical or the ellipsoidal representation of the earth on a plane and then we can proceed with some linear distance function such as the euclidean distance. This is a very fast approximation, indeed, to compute a distance, it is necessary just a couple of basic algebraic operations. Moreover, we can further reduce the calculation by considering the squared distance instead. However, this measure is accurate enough only for very small distances as the earth's surface is not flat. So using a linear distance would lead to very misleading results on longer trajectories or near the poles. We can conclude that this is not the best approach to consider.

Spherical Surface The spherical approach can be divided into three methodologies: the tunnel distance, the Rhumb lines and the great circle distance [2]. The first simply draws a straight line between the two points going inside the sphere. The second approach is a path of constant bearing, hence where the line crosses all meridians at the same angle. Contrary to the tunnel distance, it is an actual path on the surface but, still, it is not the shortest path possible. The great circle distance [3] instead is defined as the shortest path on the surface between two points. For this reason, it is also the one followed by planes to use less fuel.

The idea is that there is only one circumference going through any two points (assuming they are not coinciding nor directly opposite). More formally we can define the great circle as:

Definition 2.1 (Great Circle)**.** *A great circle is the intersection of a sphere and a plane that passes through the center point of the sphere.*

Since the earth is nearly spherical this measure gives good results, with just about 0.5% of error according to the algorithm used to compute it. We will use the haversine formula which is numerically better-conditioned especially for small distances. Given two points a and b we can compute the distance d among them as:

$$d = 2R \arcsin(\sqrt{\sin^2\left(\frac{lat_b - lat_a}{2}\right) + \cos(lat_a)\cos(lat_b)\sin^2\left(\frac{lon_b - lon_a}{2}\right)},$$

where R is the radius of the sphere, so in our case the earth, which is 6.371 km. Even if more computationally complex w.r.t. to the other methods, the gain in accuracy is sufficient to prefer this formula for most situations.

Ellipsoidal Surface The most accurate measure is obtained by considering the earth's shape as ellipsoidal. The most used algorithm is by Thaddeus Vincenty that applies an iterative method to compute the distance. It is best used for computing very long distances (several hundreds of miles). For our application, since we will compare only very close points, the difference between the great circle distance and vincenty is almost negligible. The difference in the computation time is not a lot (the great circle takes about half the time of vincenty) but we gain is just about 0.17% of accuracy [4]. So we will use the haversine formula for computing our distances.

2.2 Mobility Data

Now that we have a starting knowledge of geographic coordinates we can begin to discuss the general characteristics of mobility data [5]. With the term mobility data, we refer to spatio-temporal data that describes the movement of something. The most common ones are relative to the mobility of people or vehicles, but it can be referred to anything such as animals or natural phenomena. To collect this data it is necessary to use some kind of device to record the position of the object. The easiest way is to use something that sends GPS signals, that can be stored and that represents a sequence of ordered points that were visited. From those points, we can build a trajectory.

Definition 2.2 (Trajectory)**.** *A trajectory is a trace generated by a moving object in geographical spaces, usually represented by a series of chronologically ordered points, for example,* $p_1 \rightarrow p_2 \rightarrow \ldots \rightarrow p_n$*, where each point consists of a geospatial coordinate set and a time stamp such as* $p = (x, y, t)$*.*

Given a trajectory t we refer to it's i-th point p_i with the notation $t[i]$, and to its number of points with $len(t)$. For sake of readability we call the first point of the trajectory $t.first$ as an alias for $t[1]$ and $t.last$ in place of $t[len(t)]$. Also, we indicate the longitude, latitude and timestamp components of point $t[i]$ respectively with the notation $t[i].lat$, $t[i].lon$, and $t[i].ts$. For a timestamp ts we indicate its associated date and time of the day with $date(ts)$ and $time(ts)$ respectively. However we consider the points forming the trajectory since they are collected at discrete intervals of time while a movement is a continuous line we need a way to connect those points. The easiest way is simply by using a straight line. We can, however, compute something more complex by projecting the points on a map and connecting two points following the underlying roads. In our analysis since the signals are frequent enough, we can simply use a straight line to connect the points without oversimplifying the trajectory.

Trajectory Segmentation. In many applications, especially if the points cover a long period, it is not very significant to work with just one long trajectory. Indeed, we can see it as a collection of different movements that pairwise have the starting and ending point in common. This gives us a much richer knowledge of the movement and allows us also to perform more complex operations on the data. We call this operation trajectory segmentation. A more formal definition is:

Definition 2.3 (Trajectory Segmentation)**.** *Trajectory segmentation is the process that divides a trajectory into fragments by time interval, spatial shape, or semantic meanings.*

The problem consists in detecting these special points that indicate some type of variation in the movement. In particular, according to the technique we choose, they may represent different things.

- *Time interval.* In this case, the splitting points can be interpreted as a break in the reception of the signals, indicating, therefore, a stop in the movement. We can detect these points by looking at the time interval between two consecutive samplings. If it is larger than a given threshold we can split there the trajectory.

- *Spatial Shape.* We can define a sub-trajectory as a movement from one place to another. Therefore, if there is a sudden change in the direction we can interpret it as a change in destination and, consequently, use this turning point to split.
- *Semantic Meaning.* Even if there is no actual stop in the reception of the signal or a change in direction we can identify a more subtle kind of stop. Indeed, if there is a series of points that stay within an area for a certain period, we can classify them as *staying points.*

2.3 Location Detection

In this section we describe a procedure to infer a set of significant locations of a user, based on the points where she stopped, adapted to the needs of our problem and of the data available. Let's start with some basic definitions that allow us to formalize the algorithm.

Definition 2.4 (Individual History)**.** *Given a vehicle v, we can define it's individual history as $H_v = \langle t_1, \dots, t_n \rangle$, hence the set of trajectories traveled by v in a certain time period.*

From the set of trajectories, we can remove the ones that are too short, i.e. those generated by a GPS error. Then we extract only the start and finish point of each trajectory, which are the positions where we assume the vehicle made a stop.

Definition 2.5 (Stops)**.** *Given the history H_v of a vehicle v, we define the set of points where v stopped as $S_v = \bigcup_{t \in H_v} \{t.first, t.last\}$.*

The set of stops is useful as it represents the first draft of what the possible locations might be. Even if we already informally talked about location, we can give it a proper definition that already gives a hint on how to compute them.

Definition 2.6 (Location)**.** *We indicate with $L_v = \{l_1, \dots, l_k\}$ the set of locations of a vehicle v, which are a partitioning of S_v into disjoint sets of similar stops. We define a location $l = \{p_1, \dots, p_l\}$ as a set of stop points which are close each other.*

2.4 Movements Extraction

The next step in analyzing the mobility of an individual is the extraction of the movements.

Definition 2.7 (Movements)**.** *Given a vehicle v and two of it's locations $l, l' \in L_v$, the movement $m_{l,l'}$ (abbreviated to m, when clear from the context) is defined as $m_{l,l'} = \{t \in H_v | t.first \in l \wedge t.last \in l'\}$, i.e. the set of all trajectories that start from location l and end in location l'. We indicate with $M_v = \{m_{l,l'} | l, l' \in L_v\}$ the set of movements of the vehicle v.*

The movements are the direct translation of the trajectories to a different space: while the trajectories defines the connections between stop points, the movements connects one location to another. In order to compute the movements, for each trajectory we have to extract its stop points and convert them into their corresponding location. Each set of trajectories moving from and to the same location will form a movement. We can give an ID to each one of them to identify them. As for the location, also in this case we compute a set of attributes for each vehicle to better describe the movement and be able to compare them:

1. *movement_traj*. Key-value mapping from each movements ID to it's starting and ending locations and to the list of trajectory ID in it.

2. *movement_prototype*. Key-value mapping from each movement ID to list of approximate locations defining the movement. It is computed by comparing the similarity between the trajectories in the movement and by finding the one that better represents them.

3. *loc_nextlocs* Key-value mapping from each location ID to each subsequent location ID and the weight of that movement.

4. *traj_from_to_loc* Key-value mapping from trajectory ID to it's couple of starting and ending location ID.

5. *lft_mid* Key-value mapping from the couples of starting and ending locations ID to the movement ID between them.

6. *graph.* Graph representation of the History of the vehicle. It is an abstraction from the geographical coordinates where the locations are the nodes, the movements are the edges and the number of trajectories for each movement represents the edge weight.

Chapter 3

Route Planning And Trip Simulation

In this chapter we introduce some fundamental concepts that are the foundation of this thesis, Since a graph structure was required, we also present the approaches such that: Open Street Map (OSM) and Open Charge Map in sections 3.2 and 3.3. The coordinates provided by the Open Charge Map platform were used to recover the position of the charging stations. Finally, in section 3.4 we explain an heuristics trip planing algorithm for EVs which is a core component of our work, and that will be exploited in the next chapters.

3.1 Graph

A graph in mathematics is the configuration formed by a set of points (vertices or nodes) and a set of lines (arcs) that join pairs of nodes [6]. A graph is the best structure to represent a road network as it allows to store additional information for each node and for each edge. Nodes can, for example, keep the values of the geographical coordinates of the point, information relating to the function of that node (supermarket, gas station, pharmacy, bar, etc.), address of the point and other useful information. Edges can also be labeled with useful information such as: the name of the street that the edge represents, the geometry of the road, the weight of the edge, the slope of the road, the type of road and many others. In addition, the graph nodes usually also store the adjacency list, a very useful tool to extract information for which a visit to the graph is necessary, for example, when one is interested in knowing the neighbors of a certain node.

3.2 Open Street Map (OSM)

Open Street Map is a platform that provides geographic data on maps from all around the world. It is built by a community of mappers who contribute and maintain data on roads, paths, cafes, railway stations and so on in all over the world so, through a call of the function:

- ox.graph_from_place (city, network type = networkType)

The map of the region of interest is obtained in the form of a graph. Once the graph of the region has been obtained, it must be modified in order to meet the requirements necessary to solve the problem. In our case it was necessary to take into account the fact that, an electric vehicle has a limited autonomy, it does not have the possibility to refuel whenever and wherever it wants. Beside that, the consumption of an electric vehicle depends on the speed and the distance traveled, and by the slope of the road. Therefore it's necessary to calculate the maximum travel speeds on the roads, the altitude of the nodes and subsequently, the slopes of the respective edges.
Finally, the consumption by the vehicle on the edge was calculated. All this additional information has been inserted into the nodes and edges of the graph in order to obtain a structure containing the necessary information.

3.2.1 Speed On The Edges

Regarding to the speed on the edges, the data provided by Open Street Map are scarce, inaccurate and often missing, for using the MaxSpeed attribute which is the attribute that should provide information on the maximum speed of the arc, in fact, only 10% of the road segments have a maximum speed value specified. To remedy the lack of data, an expedient had to be used to estimate them.
The Highway attribute was chosen as it is present on each edge. This attribute represents the type of road and takes the following values: ['alley', 'crossing', 'disused', 'emergency

bay', 'living street', 'motorway', 'motorway link', 'no', 'primary', 'primary link', 'razed', 'residential', 'rest area', 'road', 'secondary', 'secondary link', 'tertiary', 'tertiary link', 'trunk', 'trunk link', 'unclassified', 'yes'].
By starting from these values, a dictionary was created with the type of road and the respective speed limit as the key. The speed limits were chosen on the basis of a conversion table on the State Police website: {'alley': 50, 'crossing': 50, 'disused': 50, 'emergency bay': 50, 'living street': 50, 'motorway': 130, 'motorway link': 130, 'no': 50, 'primary': 110, 'primary link': 110, 'razed': 50, 'residential': 50, 'rest area': 50, 'road': 50, 'secondary': 90, 'secondary link': 90, 'tertiary': 70, 'tertiary link': 70, 'trunk': 110, 'trunk link': 110, 'unclassified': 50, 'yes': 50}
Figure 3.1 of Tuscany was then created with colored roads based on the maximum travel speed to see if the results were consistent with the infrastructure of the Tuscany road network. It was also compared with the Figure 3.2 made previously, using the MaxSpeed attribute. The speed values are distributed according to a chromatic scale that goes from red for the lowest speeds to green for the highest speeds. It can also be noted that the predominant color is yellow, the color that represents the speed of 50km/h. This is consistent with the initial distribution of maximum speeds. It can be noted how the use of the Highway attribute has increased the amount of maximum speed values and how the distribution of speed values is consistent with the Italian road infrastructure.

Figure 3.1: Maximum speed in Tuscany using the attribute MaxSpeed

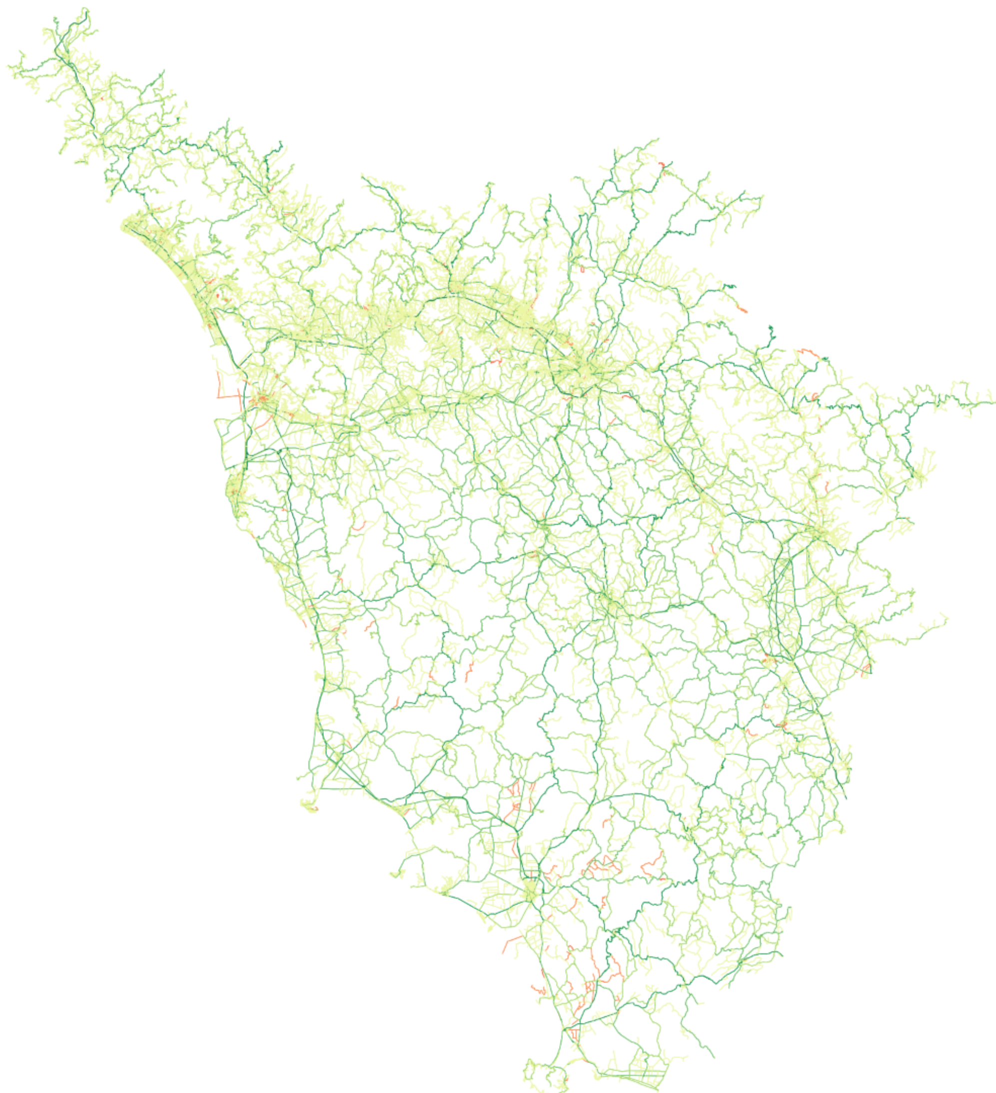


Figure 3.2: Maximum speed of Tuscany using the attribute Highway

3.2.2 Roads Slope

Each node represents an intersection between two or more edges and to calculate the consumption of the vehicle on the edge, it's slope is necessary among the others. To calculate the slope of the edge, we started from the altitude of the nodes. The SRTM[1] library was used to obtain the elevation (Figure 3.3). The difference in height was calculated from (Figure 3.4). In the calculation of the difference in height it was noticed that some were not gradual but they have presented themselves with jumps of several meters. This happens because the altitude data are calculated on the ground and therefore do not consider infrastructures such as tunnels, bridges and overpasses. To overcome this problem it was decided to consider the slope on those sections. Another problem was the lack of altitude values for some nodes. In this case, it was decided to assign to the altitude value, the average of the values of the neighboring nodes to the nodes that they did not have them. Once in possession of coherent elevation values of the nodes, the Euclidean distance between the nodes was calculated using the formula:

$$Distance = \sqrt{LongRoad^2 + Difference^2}$$

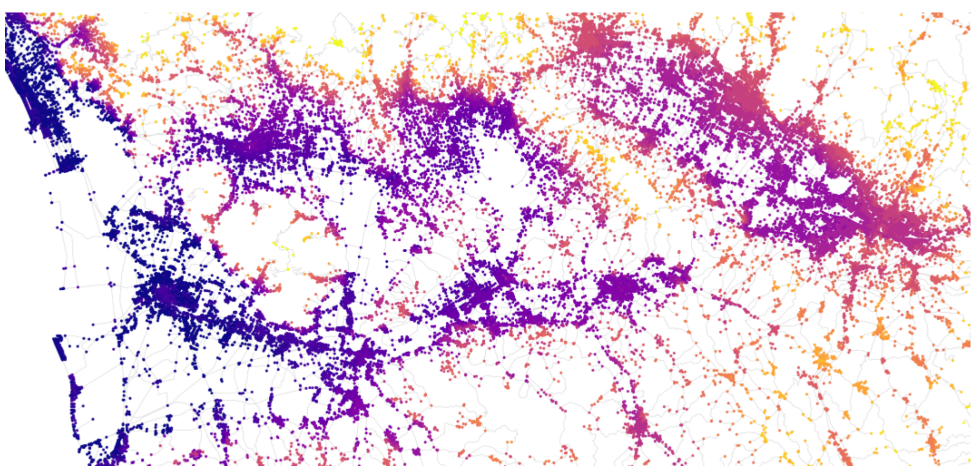


Figure 3.3: nodes altitude portion of Tuscany

[1]The Shuttle Radar Topography Mission which is an international company that has managed to obtain a digital elevation model on an almost global scale.

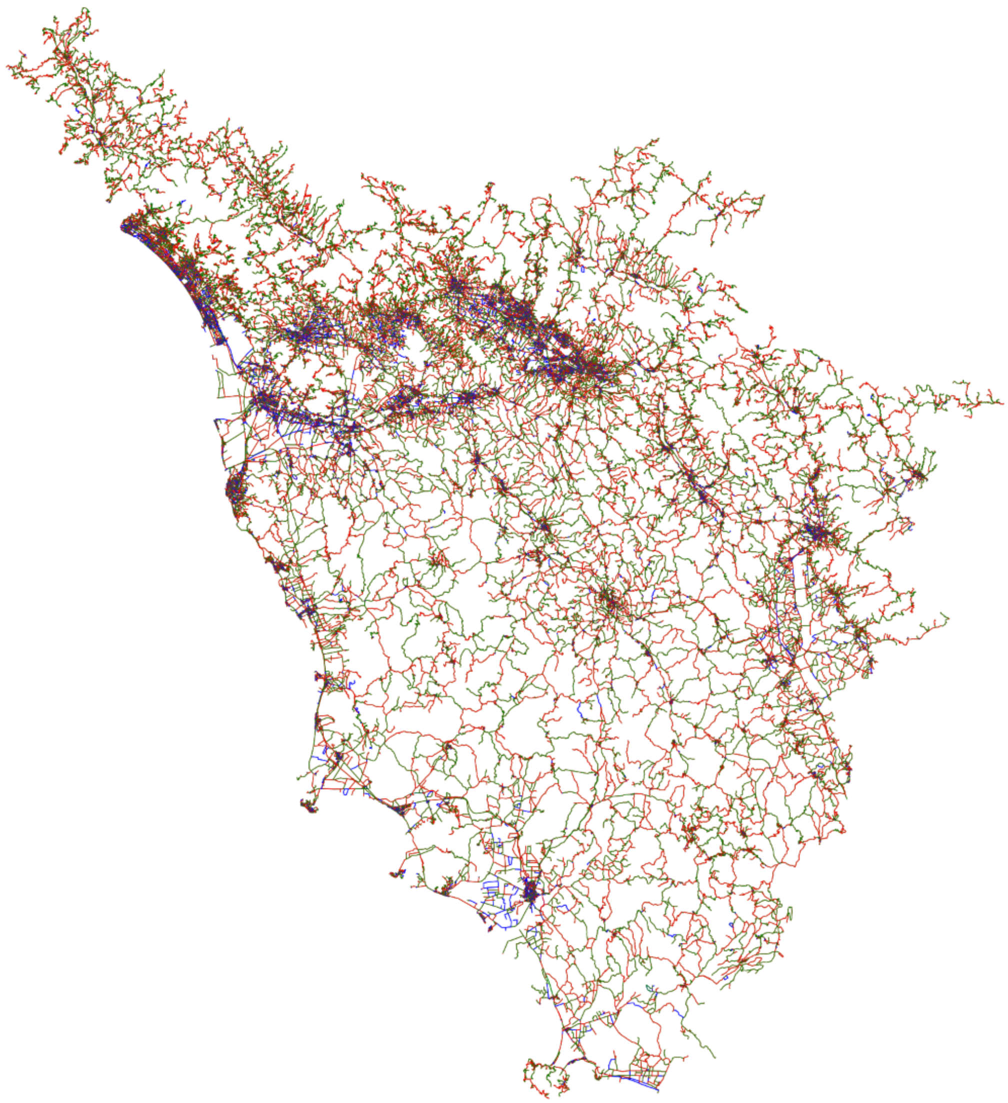


Figure 3.4: Slope arches of Tuscany

3.2.3 Calculation Of Consumption

Once all the necessary values have been calculated, the consumption is calculated. We started from the consumption function developed in a previous thesis work[7]. The capacity value of the battery is considered $40kW$. The consumption function presented, was applied to each edge of the graph and was derived from it, the consumption value on the edge for the electric vehicle also is chosen as the prototype. For simplicity, the speed and the slope on the edge were assumed constant and for the arch travel speed the maximum speed limit for that edge was chosen.

3.3 Open Charge Map

Open Charge Map is a non-profit, non-commercial service hosted and supported by a community of businesses, charities, developers and enthusiasts around the world and is defined as "the global public database of charging stations"[2]. Through the Open Charge Map API a request is made to the server[3], specifying the geographic area of interest, a JSON file is obtained containing the latitude and longitude of the nodes in that area and other information on the type of recharge provided.

3.3.1 Integration Of Charging Stations

To integrate the charging stations into the existing structure, it was initially decided to attribute the ownership of the charge node to the node closest to the geographical coordinates. So, it became clear that some charge nodes, especially those located inside luxury resorts, were too far from their closest node. To solve the problem of inserting these particular nodes, it was therefore decided to add a new node with charge node properties. For the creation of these new nodes, the distance between the geographical coordinates of each node and it's closest node was first calculated, then the nodes with a distance greater than a certain value were chosen, for these nodes the closest edge was searched. Through a specially created function, the geometry of the edge was broken down into points, the point of the edge closest to the node was chosen and it was transformed into a node with charge node properties.
In Figure 3.5 in the following page we can see the distribution of the charging stations, the nodes of the graph colored in blue, on the territory of Tuscany.

[2] http:/openchargemap.org/site/
[3] https://api.openchargemap.io/v3/poi/

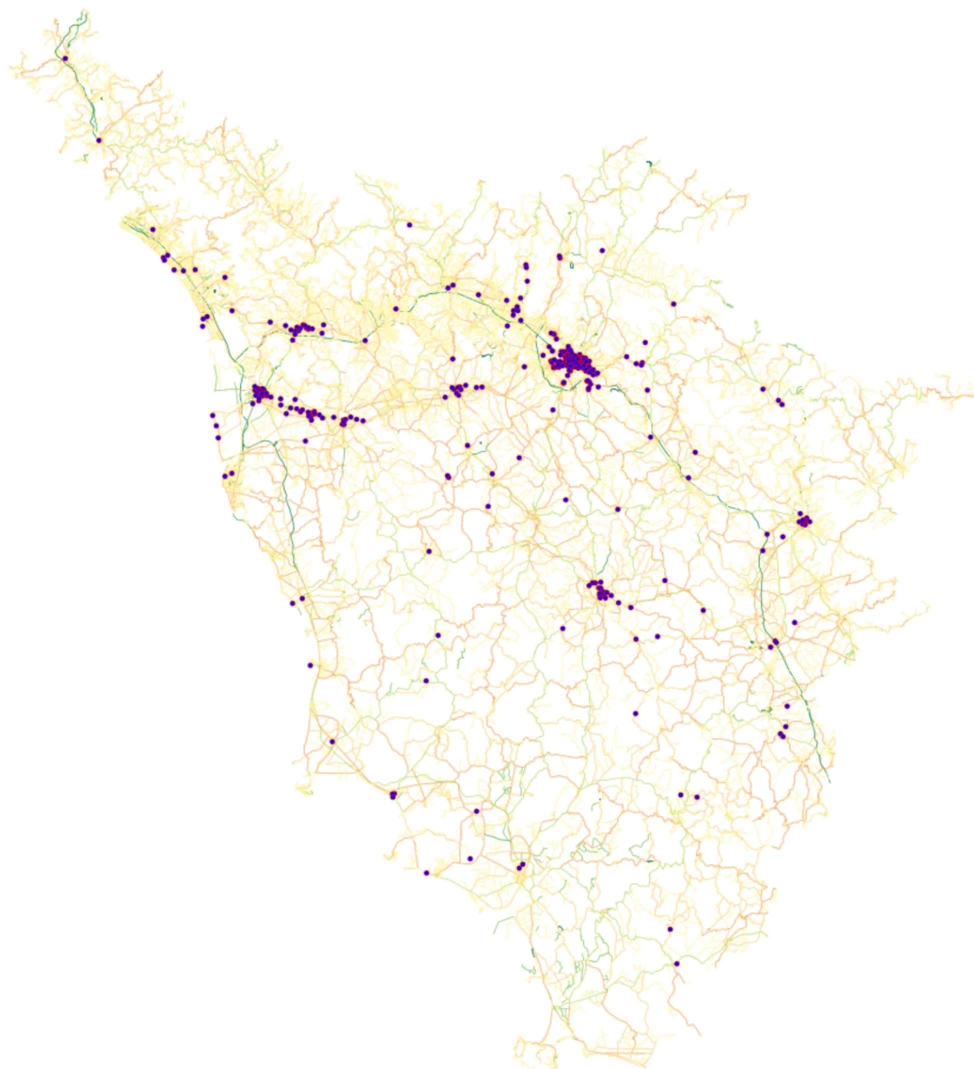


Figure 3.5: Charging stations of Tuscany, Italy

3.4 Heuristics Trip Planing Algorithm For EV

This algorithm is based on known algorithms, capable of planning trips for electric vehicles which is starting from the need to plan the trip. In fact, the problem of minimum routes was considered, assessing the applicability to the problem of two algorithms, Dijkstra and

Bellman-Ford. Also, the implementation of a graph representing the road infrastructure was enhanced, enriched by the presence of charging stations. Actually, a modified version of Dijkstra's algorithm was designed and implemented which provides a minimum path taking into consideration the residual load, slope of the road and therefore vehicle consumption variables. The concept of *stations subgraph* of the nodes was used, that is a graph almost completely connected where the nodes represent the charging stations and the edges the optimal paths. The first version of Dijkstra's algorithm for electric vehicles was used, which in addition to the previous variables also takes into account the stops to recharge the vehicle, thus finding the fastest route even when there is a need to stop to recharge the battery of the vehicle. Finally the heuristics have been proposed to speed up the process of selecting the best route in case the vehicle must make at least one stop to recharge the battery.

3.5 Studies On Route Planning

About the route planning task many works have been published and several techniques tested. One of the mayor challenge is to find the optimal solution to save energy consumption,do not waste time and travel the shortest feasible path. A detailed overview about recent advances in algorithms for route planning in transportation networks can be found in [8]. Classic route planning approaches apply Dijkstra's algorithm to a graph representation of the mobility network [9]. For faster queries, speedup techniques have been proposed, with different benefits in terms of preprocessing time and space, query speed, and simplicity. Constrained Shortest Path (CSP) formulations try to find the most energy efficient route without exceeding a certain driving time or finding the fasted route that does not violate battery constraints [10]. For example in [11] authors extend this problem respecting battery constraints, minimize overall trip time, including time spent at the charging stations. The solutions proposed include all types of stations: battery swapping stations, regular charging stations with various charging powers and superchargers. In [12] the problem of finding an optimal routing and recharging policy is explored using a grid network with uncertain charging station availability. Similarly, one can consider some trade-offs between driving time and energy consumption: in [13] a set of routes for EVs mobility is computed by Pareto optimisation considering how to save energy driving road segments at different speeds. In literature many works focus their attention in finding the most energy efficient path for battery powered electric cars [14]. In [15] the problem of finding a minimum cost path when the vehicle must recharge along the way is modeled as a dynamic problem. Authors also consider that battery charging times are nonlinear using a particular cost function which takes this aspect into consideration. Indeed while nearly linear for low state of charge, the charging rate decreases when arriving the battery limit. In [12] this aspect is modeled by matching a linear with an exponential function for high state of charge. For electric vehicles, most papers have focused the attention on the integration of battery capacity constraints and negative edge weights (a result of recuperation) into classical single-criterion route planning algorithms optimizing energy consumption [16, 17]. However, such paths may have disproportionate detours: driving slower saves energy at the cost of greatly longer travel time.

The majority of the previous works predicted the electricity demand from the EVs charging without considering historical data. They are mainly based on the traffic patterns, the charging and the battery characteristics of the EVs. However, in [18, 19] the concept of forecasting the charging demand is introduced. In [18], a model for Short-Term Load Forecasting for EV charging was implemented using neural network. In [20] an artificial intelligence EV load forecasting technique is introduced using Support Vector Machine. Charging events for one year were created using national statistical data, to cover the lack of real historical data of EV's charging events. After the model was trained, the SVM model provided a forecast for the day ahead EV demand.

Chapter 4

EV Mobility Simulation And What-If Analysis

In this chapter we focus on the main part of the thesis. First in section 4.1 we introduce Individual Mobility Networks (IMNs) and define the process to build them, then we try to explain some basic functions that are the base of our main algorithm, in section 4.3 we describe all the process of finding shortest path between two nodes and if there is need to charge, the information about public stations.
In the next step we talk about different charging options regarding to different scenarios in section 4.4. Finally, we talk about three main strategies and illustrate the behavior of the two algorithms in sections 4.5 and 4.6.

4.1 Individual Mobility Network

Given the individual history H_v of a vehicle v, we can extract its Individual Mobility Network G_v. An IMN describes the individual mobility of a user through a graph representation of her locations and movements, grasping the relevant properties of individual mobility and removing unnecessary details. We can give a formal definition of IMN as:

Definition 4.1 (Individual Mobility Network)**.** *Given a vehicle v, we indicate with $G_v = (L_v, M_v)$ its Individual Mobility Network, where L_v is the set of nodes and M_v is the set of edges. On the nodes and edges we define the following functions:*

- $\omega : L \to \mathbb{N}$, *returns the number of stops in location* $l \in L_v$.
- $\tau : L \to \mathbb{R}$, *returns the average time spent in location* $l \in L_v$.
- $\rho : L \to Time$, *returns the average time of arrival of* v *along all the movements* $m \in M_v$ *reaching location* $l \in L_v$.
- $\pi_t : L \to \mathbb{R}$, *returns the average time travelled by* v *along all the movements* $m \in M_v$ *reaching location* $l \in L_v$.
- $\pi_d : L \to \mathbb{R}$, *returns the average distance travelled by* v *along all the movements* $m \in M_v$ *reaching location* $l \in L_v$.

Nodes represent locations L_v and edges represent movements M_v between locations. To clarify the concept of IMN, let us consider the Figure 4.1 which describes the IMN extracted from the mobility of an individual who visited seven distinct locations. Location a has been visited by the vehicle v for a total of $\omega(a) = 25$ times, i.e., 25 stops, with a typical stay of $\tau(a) = 7h40min$. On the other hand, it only stopped in location f for $\omega(f) = 3$ times with a typical stay of $\tau(f) = 1h10min$. Edges (c, f) and (e, f) lead to location f, typically arriving at time $\rho(f) = 18.10$ traveling $\pi_t(f) = 15min$ and $\pi_d(f) = 10km$.

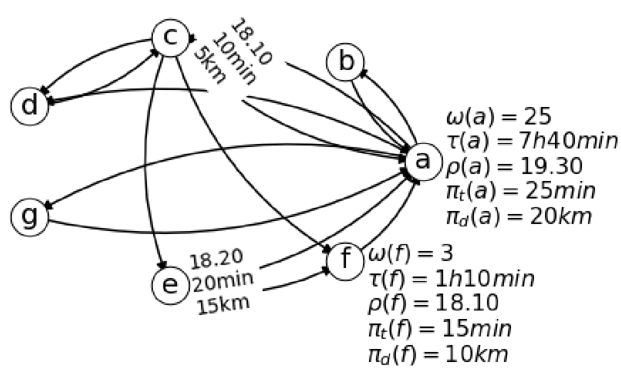


Figure 4.1: Representation of an IMN. The edges represent the existence of a route between the locations, functions characterize each location.

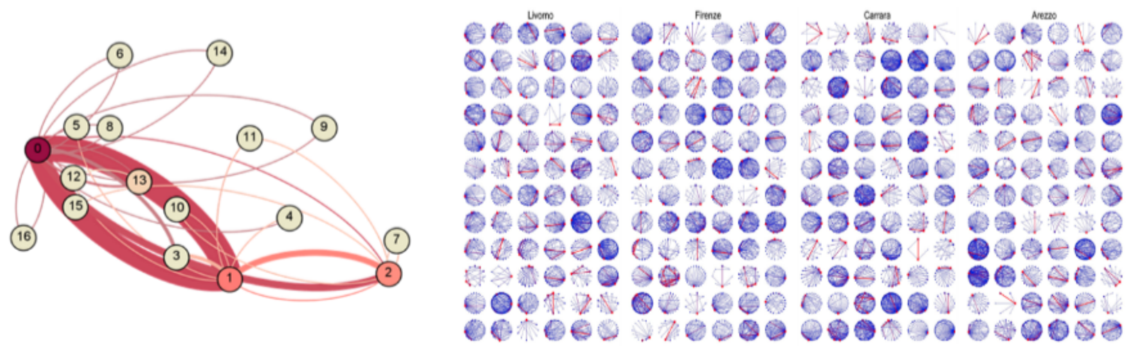


Figure 4.2: Example of IMN from Tuscany,Thicker and red nodes/edges represent frequent ones.

The IMN is built by using the data of the locations and the movements and by adding some more useful information. Besides the ones deriving from the previous calculation the other attributes added are:

1. *traj_points_from_to*. Key-value mapping from trajectory ID to the couple of starting and ending points ID.

2. *regular_locations*. Set of location IDs of the most visited places. In order to decide which locations should be considered regular and which not, it was studied the distribution of the frequencies. For each vehicle is was computed a personalized threshold by automatically identifying a knee where to set the minimum support.

3. *location_features*. This map contains a set of features for each location, such as the distance or the count of the frequency to the next location, the usual time spent in the location or the absolute number of visits or the same count divided in time slots.

4. *mov_features*. The same thing has been done with the movements by computing features like the average movement length and duration or the movement support.

4.2 Charging Time Model

The time needed for charging the battery significantly depends on the type of charging station we consider. With rapid charge stations, for full charging up to 80% of the battery

capacity it takes on average 1.06 minutes per kWh, and from 80% to 100% it is 1.5 minutes per kWh, considering battery capacity is $40kW$.
For the fast and slow stations, the charging time is linear. In fact, in the fast charging is 6 minutes and for slow one is 9 minutes per kWh.

4.3 Charging Information At Charging Stations

This function uses the heuristics trip planing algorithm for finding the shortest path from origin to destination, including charging stations on the way respect to the initial battery on the network graph. As a matter of fact, for the coordinates of the origin and destination of each trip (latitude,longitude) we compute their corresponding Osm Id by calling the function:

- osmId=ox.get_nearest_node(Graph,(latitude,longitude))

That maps the start/end position to the nearest node in the network graph according to its coordinates. In fact, this osmId is the id of the node in the network graph. Now we start describing one of the main task of the algorithm, that is computing the amount of recharge battery and charging time at each charging stations, initially under the assumption of reaching full charge.
As an example, imagine the user wants to go from node A to node E. So, by using the trip planing algorithm, the user has to go from node A to node B which is the first charging station, from node B to node C, which is the second charging station, then from node C to D (normal node) and from D to E, which is the destination. In our Algorithm, with this extracted information of the nodes and paths, we retrieve some information from the road network graph, in particular: consumption, travel time and distance from one node to the next one in the sequence.
Finally, we create a dictionary with the keys which are pairs of Osm Ids of nodes. In our example, the keys are:

- $(nodeA, nodeB)$
- $(nodeB, nodeC)$

- $(nodeC, nodeD)$
- $(nodeD, nodeE)$

The values of each key consist of the consumption in kilowatt, travel time in second and distance in kilometer between two nodes. If the second element in the pair represents a charging station (meaning that the user arrives to the charging station) the information about plug's speed level is also added.

4.4 Charging Options For What-If Analysis

In this section we are going to describe the main algorithm that considers, for each user to analyse, his trips organized in an individual mobility network. The behavior of this algorithm is different according to the simulation scenario we will consider – in the next sections we will introduce four of them. First, the algorithm finds the most visited nodes of each user and considers the first one as home and second one as work, then for each trajectory of the user, it calls the charging information function that we have discussed in section 4.3, giving as inputs the start node and end node of the trajectory, and the initial battery level. Then, it computes how much battery the user has when he arrives to the charging station, how much battery and how much time (according to our charging time model) he needs to recharge, and eventually the amount of battery when he arrives to the destination (all amount of batteries are in Kwh and charging time in $minutes$). The key variable in this process is the battery level that is provided as an input to the charging information function at each call: if the user is in the first trip, it passes the initial battery that we have considered at the start of the trip; after the first trip is finished, it starts the next trip which has as start point the end of the last trip, and for which we use as initial battery level the value returned by our charging information function on the previous trip. As mentioned above, we consider different simulation scenarios, each based on different assumptions and constraints about where and when the user can recharge the battery. We explain them in the next four subsections.

4.4.1 Home Scenario

In this scenario the user can not only recharge on public stations when needed (thus making deviations for the actual trip and wasting time while waiting for the recharge), but we also have an additional charging station which is home. Every time the user arrives to his home (identified as explained above), if the time that user stays at home is more than a specific minimum amount (in this thesis we considered 4 hours) he can charge at home, so for the next trip, when the user leaves the home he starts his trip with the full battery.

4.4.2 Work Scenario

This scenario is the same as home scenario with a difference that we consider the place where the user works as charging station and all the conditions are the same as home.

4.4.3 Home And Work Scenario

In this scenario we consider both home and work as charging stations. In the experiment chapter, we will see that results show in this case, most of the users do not need to charge at public stations or they charge less time respect to the other scenarios because they always have possibility to charge at two main places that they go in their trips.

4.4.4 Public Station Scenario

Here we do not allow charging neither at home nor at work, so the user just charges at the public stations. Obviously the need of charging at public station is increased as compared to the other scenarios.

4.4.5 Emergency Situations

As it will be discussed in the next sections, there is a situation that causes our simulation algorithms to run into an emergency situation. That is raised when the initial battery at the start point is not enough even for reaching to the first charging station, In the following, we will first provide a simple simulation strategy that just accepts emergency situations when they happen, and then an improved solution that tries to recover from it by retrospectively changing the recharge choices made in the past trips.

4.5 Basic Simulation Strategy

In this strategy we consider that when the emergency happens the user has to call emergency so in this way he can charge full battery at that point and starts his next trip with the full battery. This is our first and basic solution. The pseudo code of the first strategy is shown procedure "BasicSimulation", and is described in the following. Our inputs are:

- G : network graph.
- Data : the user data that is a big dictionary contains all the information of one user in the IMN.
- Id : user id in IMN.
- Bat : initial battery at the first trip.
- StayTime : stay time (*minute*) that we consider for charge at home/work this means, if user stay more than this time he can charge.
- Hflag : the flag that when is true we consider home scenario.
- Wflag : the flag that when is true we consider work scenario.

First of all we pass the Data to the *FindHomeWork* function that finds the home and work osmIds of user, then we extract from Data, movements prototype that is a dictionary of dictionaries. In fact, each dictionary inside, contains all the information about one trajectory such that: trajectory movements coordinates, length of the trajectory, travel time and consumption. Afterwards, we start to find the start point (first movement coordinate) and end point (last movement coordinate) osmIds of the trajectory. Now we compute the start time and end time, which means the time that user starts the trajectory and the time that user ends trajectory. After that we call *ChargingInfoAtChargingStation* function that gets as the inputs the G, start time, end time and battery. If user is in the first trip the battery is the initial battery that we consider (*Bat*) and if he is in the next trips the battery is the amount of *ArriveBat* (the battery when user arrives at the end point) that returns from itself (in the previous trip). As a matter of fact, this function finds if there is need to charge between two points or not and according to this, it returns some outputs such that:

- *EmergencyFlag*, that means if user with this amount of battery can not reach even to the first public station this flag is true otherwise is false.
- *ResultDict* that is a dictionary (we already discussed in section 4.3) containing the stop points and charging points data; and
- *ArriveBat* that we have mentioned it before.

In the next step we check if the *ResultDict* is not empty (we have to charge) we call the *ChargeFullAtPublic* function to compute the amount of battery that user has to recharge and charging time at each public station that he has to go through the way and if it is empty and he is not in emergency situation, this means that there is no need to charge and we just find the consumption between two points and reduce it from the current battery. If *ResultDict* is empty and *EmergencyFlag* is true he has to charge at emergency situation. The next steps are checking the scenarios, indeed we check if the *HfFlag* is true and user arrives to the home, if the stay time is greater than the considered time (here we have considered 4 hours) we call the function *ChargeFullAtLocation* that computes the charged battery and charging time at home and the same condition is checked for the work scenario. A complete trace of the operations performed is stored, and later used for post-analysis.

```
procedure BasicSimulation(G, Data, id, Bat, StayTime, Hflag, Wflag)
    Home, Work ← FindHomeWork(Data)                          ▷ home and work OSM ids
    TrajDictS ← Data[movementPrototype]
    i ← 0
    for TrajDict in TrajDictS do                 ▷ Dictionary of trajectories information.
        m ← 0
        for Movement in TrajDict[object] do           ▷ Movements of one trajectory.
            if m = 0 then
                StartPoint ← (Movement[1], Movement[0])
                Start ← GetNearestNode(G, StartPoint)
            if m = LenOfMovement − 1 then
                EndPoint ← (Movement[1], Movement[0])
                End ← GetNearestNode(G, EndPoint)
            m ← m + 1
        if i = 0 then
            ArriveBat ← Bat
        StartTime ← TrajDictS[i + 1][StartTime]
        EndTime ← TrajDictS[i][EndTime]
        ResultDict, ArriveBat, EmergencyFlag =
        ChargingInfoAtChargingStation(G, Start, End, ArriveBat)
```

```
        if ResultDict is NotEmpty then
            ArriveBat ← ChargeFullAtPublic(Id, ResultDict, ArriveBat, public, EndTime)
        else
            if EmergencyFlag = False then
                ConsNeed ← FindingConsumptionBetweenNodes(Start, End)
                ArriveBat ← ArriveBat − ConsNeed
            else
                ArriveBat ← ChargeFullAtLocation(Id, ArriveBat, emergency, EndTime)
        if Hflag = True then
            if End = Home then
                TimeStayAtHome ← computeDifferentOfDate(StartTime, EndTime)
                if TimeStayAtHome > StayTime then
                    ArriveBat ← ChargeFullAtLocation(Id, ArriveBat, home, EndTime)
        if Wflag = True then
            if End = Work then
                TimeStayAtWork ← computeDifferentOfDate(StartTime, EndTime)
                if TimeStayAtWork > StayTime then
                    ArriveBat ← ChargeFullAtLocation(Id, ArriveBat, work, EndTime)
        i ← i + 1
```

4.6 Look-Forward Simulation Strategy

In the second strategy we need a more tricky way to reduce the emergency situations for the user with changing the amount of initial battery that he started in his previous trips. Indeed ,when the user arrives to the emergency situation the algorithm rolls back to the previous trip and changes it's initial battery to 5 percent less than the consumption between two nodes to force the algorithm to recharge at the previous trip, so in this way he can arrive with more battery for starting the next trip (the trip that he has faced with emergency situation). We have considered three different conditions if the algorithm has to roll back such as :

- The first ”roll-back” works.
- The first ”roll-back” fails.
- In the ”roll-back” he met a recharge (at the public station or at home/work).

If the algorithm deals with the first condition, we get rid of the emergency and continue the next trip with the new (most likely larger) initial battery.
For the second condition, in this situation the algorithm again rolls back to the last 2 trips and if it works, the user charges at the second-last trip and continues the trips forward with the new initial battery. Similarly, if in the last 2 trips by reducing the initial battery the user can not reach the first public station and faces an emergency again (in the second-last trip), this time the algorithm rolls back to the last 3 trips and it continues this process backward till the user can recharge and after that algorithm keeps on moving forward.
For the third condition, sometimes maybe beyond these roll backs, user comes back to the place where there was already a charging station. In this situation we can not reduce the amount of initial battery at that point because in the algorithm we have considered that when user leaves the charging stations he has full battery so in this situation the algorithm stops this process and goes forward again to the last point where the user got an emergency, and here there is no way, so the user has to call emergency.
Every time the algorithm adopts the battery reduction trick mentioned above, the amount removed is kept in the battery as hidden battery, so when the algorithm forces the user to charge, when he arrives to the charging station this hidden battery is added to the amount of battery that he has when he arrives to public station. With this strategy, the problem of emergency is reduced sensibly. The pseudocode of the algorihtm is shown in procedure “LookForwardSimulation” and is described below. This algorithm is the extended version of the first one, the main procedure is the same and the only difference is emergency part, so here when the user finds himself in the emergency situation *RollbackEmergency* flag changes to true. In the main loop (line 6 to 18) first it checks if the *RollbackEmergency* is true, the algorithm rolls back to the previous trip and retrieves the start battery (the battery when user starts the trip) and end battery (the battery when user arrives to the end point) of the previous trip. If the start battery of the previous trip is equal to the

battery capacity, this means that user left the charging station in the previous trip so, the algorithm stops and turns back to the last point (the user got emergency) and forces user to charge emergency there. Otherwise, it decreases the start battery of the last trip to the 5% less than the consumption to its end point, in order to force the user to charge at previous trip and also stores the remaining amount of actual battery which is reduced in the *HiddenBat* and finally turns the *RollBackEmergency* flag false and continues the rest of the trips. If with that reduced amount of battery the user got emergency again also in the previous trip, the algorithm continues these rollbacks to finally recharge at the previous trips. The other difference with the first algorithm is that, here whenever the user wants to charge at each charging station (public/home/work) the algorithm checks the hidden battery and if there is a hidden battery, this amount is added to the battery that user has when he arrives to the charging station (he charges less and in this way we keep that hidden amount inside the battery).

```
procedure LookForwardSimulation(G, Data, Id, Bat, StayTime, Hflag, Wflag, BatCap)
    Home, Work ← FindHomeWork(Data)
    TrajDictS ← Data[movementPrototype]
    i ← 0
    for TrajDict in TrajDictS do
        if RollBackEmergency = True then
            i ← i − 1
            InfoLastTrip ← StartEndBat[i]        ▷ start and end battery of last trip
            if InfoLastTrip[0] = BatCap then
                i ← max(Counter)
                ArriveBat =
                ChargeFullAtLocation(Id, StartEndBat[i][0], emergency, EndTime)
            else
                BatNeedToArrive ← InfoLastTrip[0] − InfoLastTrip[1]
                NewBat ← BatNeedToArrive − ((BatNeedToArrive ∗ 5)/100)
        HiddenBat.append(InfoLastTrip[0] − NewBat)
        RollBackEmergency ← False
        ArriveBat ← NewBat
        m ← 0
        for Movement in TrajDict[object] do
            if m = 0 then
                StartPint ← (Movement[1], Movement[0])
                Start ← GetNearestNode(G, StartPoint)
            if m = LenOfMovement − 1 then
                EndPoint ← (Movement[1], Movement[0])
                End ← GetNearestNode(G, EndPoint)
            m ← m + 1
```

```
if i = 0 then
    ArriveBat ← Battery
StartTime ← ListOfDict[i + 1][StartTime]
EndTime ← ListOfDict[i][EndTime]
StartBat ← ArriveBat
ResultDict, ArriveBat, EmergencyFlag =
ChargingInfoAtChargingStation(Start, End, ArriveBat)
if ResultDict is NotEmpty then
    if HiddenBat is Not Empty then
        ArriveBat ← HiddenBat[0] + ArriveBat
        HiddenBat ← empty
    ArriveBat ← ChargeFullAtPublic(Id, ResultDict, ArriveBat, emergency, EndTime)
else
    if EmergencyFlag = False then
        ConsNeed ← FindingConsumptionBetweenNodes(Start, End)
        ArriveBat ← ArriveBat − ConsNeed
    else
        RollBackEmergency ← True

if Hflag = True then
    if End = Home then
        TimeStayAtHome ← computeDifferentOfDate(StartTime, EndTime)
        if TimeStayAtHome > StayTime then
            if HiddenBat is Not Empty then
                ArriveBat ← HiddenBat[0] + ArriveBat
                HiddenBat ← empty
        ArriveBat =
        ChargeFullAtLocation(Id, ArriveBat, home, EndTime)
```

if $Wflag = True$ **then**
  if $End = Work$ **then**
    $TimeStayAtWork \leftarrow computeDifferentOfDate(StartTime, EndTime)$
    if $TimeStayAtWork > StayTime$ **then**
      if $HiddenBat\ is\ Not\ Empty$ **then**
        $ArriveBat \leftarrow HiddenBat[0] + ArriveBat$
        $HiddenBat \leftarrow empty$
      $ArriveBat =$
      $ChargeFullAtLocation(Id, ArriveBat, work, EndTime)$
$EndBat \leftarrow ArriveBat$
$StartEndBat[i] \leftarrow [StartBat, EndBat]$

$i \leftarrow i + 1$
$Counter.append(i)$

4.7 Time Efficient Simulation Strategy

The focus of this strategy is time efficiency, in particular we aim to reduce the time spent (and wasted) in recharging at a public station. By analyzing the data that is extracted from the look-forward simulation strategy, the more efficient way is that when user stops in a public station to recharge, if the next trip after the stop leads to home and work, and we are in a scenario where it is possible to recharge there, then it is not necessary to charge till full battery at the public station. Indeed, we can limit the recharge to the consumption that the user needs to arrive to the home/work, in this way the user waits less time at charging station and the majority of charging time is spent at home/work.
For instance, imagine the user is in home scenario and he starts his trip with $5kW$ initial battery and he has to charge at public station on the way, the consumption from start point to the public station is $1.8kW$ so, when he arrives to the public station he has $3.2kW$ battery. In this strategy the algorithm checks if the next destination is home, in

which case it finds the consumption to arrive to the home, for example is $12kW$, so in this situation there is no need to charge fully at public station, and the user charges $12 - 3.2$, i.e. just enough to reach $12kW$s, he can arrive to the home and then charges full battery there. Indeed, our experimental results show that almost 85% of charging time is saved because he spends this time at home.

Chapter 5

Experiments And Results

In this chapter we present the results of the experiments obtained by analyzing four scenarios on individual mobility network, in the section 5.2 you see the global statistics of the charged battery and charging time in different scenarios, then in sections 5.3,5.4,5.5 respectively, we explain about the frequencies, total amount of charged battery and total charging time for each charging stations in different scenarios and compare them with the corresponding plots. In section 5.6 we choose two sample users and make a comparison between their EV profiles, finally in section 5.7 we analyze the difference between the total length of the real trips and simulated one.

5.1 Experimental Setting

The experiments have been performed over a dataset of anonymous GPS traces describing private vehicles. The data has been collected through ad hoc devices mounted on board for car insurance purposes. In particular, in this chapter we considered a sample of 50 users moving in Tuscany, with traces relative to 2-month period of January-February 2017. The algorithms have been implemented in Python 3, and tested over a Linux platform.

5.2 Global Statistics Of Recharging Time And Battery

In this section we computed all the simulations and collected all the statistics, then we produced for each scenario several measurements such that average $\pm$ standard deviation (std) for each type of charging stations.

	battery home	battery work	battery public	battery emergency	time home	time work	time public	time emergency
home	127.63±86.81	0.0±0.0	11.82±33.91	2.27±11.66	765.75±520.88	0.0±0.0	65.69±201.52	13.61±69.95
work	0.0±0.0	56.85±50.95	29.16±41.67	0.61±4.24	0.0±0.0	341.11±305.72	142.29±217.57	3.64±25.46
home and work	80.2±71.25	28.06±49.98	4.41±13.11	1.97±7.83	481.22±427.48	168.38±299.85	20.66±66.29	11.84±46.98
public	0.0±0.0	0.0±0.0	48.6±53.05	5.91±12.74	0.0±0.0	0.0±0.0	245.84±232.24	35.45±76.42

Figure 5.1: This table reports different scenarios in the rows and on the left four columns the total amount of battery (kW) that recharged during the simulation and on the right four columns, represents the total charging time ($minute$) at different charging locations.

As you can see in the home scenario the average amount of battery and charging time for the home charging are more than the other locations with a big difference, so this means that by having possibility of charging at home the need of charging at public station and emergency is obviously reduced.
In the work scenario the results show us in this case, the need of using public stations are more than the previous scenario and although the average battery and charging time in work charging is more than public station but, the differences are low. Here the interesting point is, in the work scenario need of emergency charge is lower than the other scenarios.
In the home/work scenario the users are charged at home more than the work and then public station and emergency. For emergency charging, the average is very low rather than the other locations and this is the same situation for all four scenarios. As you can see there is a high difference in average between the home and the other charging locations both for recharged battery and charging time, whereas this difference between work and public station are lower, however the users charged at work more than public stations.
If we make a comparison between this scenario and home scenario, we can see that in both scenarios users are charging at home more than the other locations and having possibility of charging at work helps users to spending less time at public stations and need of using public station in general decreased a lot.
To conclude, from the obtained results we can say that for the users that saving the time is really important for them, home/work scenario is the best possible choice for them. In the public scenario the user can just charge at public stations the point here is that in

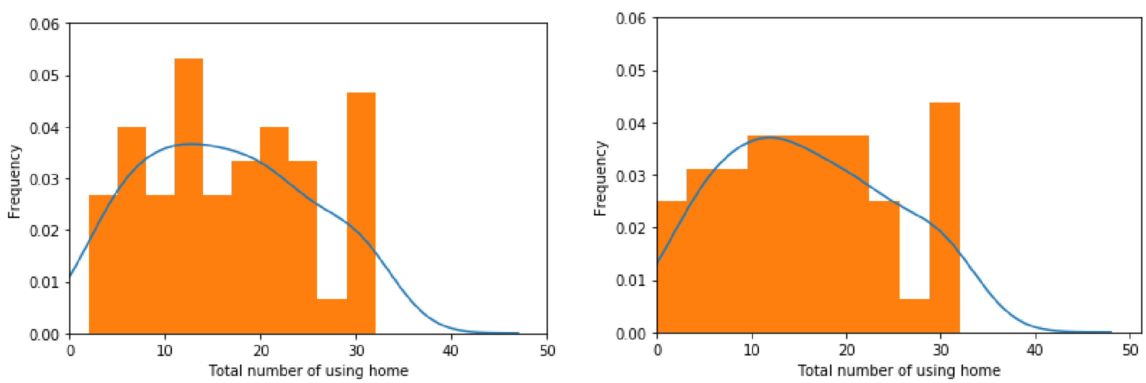
this scenario the need of emergency charging are more than the others as we expected.

5.3 Studying Charge Frequencies

In this section we are going to show in general, the frequencies of using charging locations in different scenarios with the plots to compare the results.

5.3.1 Frequencies Of Home Charges

In this section we avoid from plotting work and public scenarios because in these two scenarios there are no possibility to charge at home.



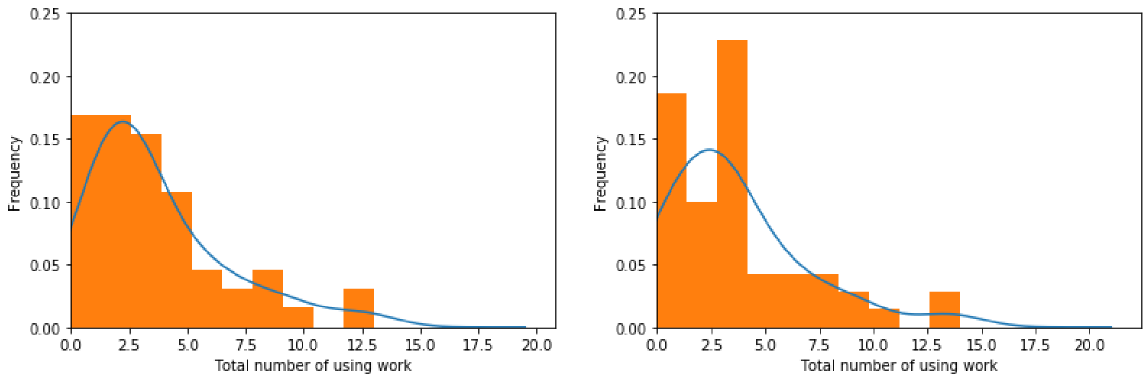
(a) Home scenario **(b)** Home and work scenario

Figure 5.2: Distribution of number of charges at home for home and home/work scenarios.

This figure shows that, in both scenarios, total frequency of home as charging location are more or less the same, of course the distribution of number of charges in home scenario in some parts are more than the other but, the averages are almost the same.

5.3.2 Frequencies Of Work Charges

In this section also, we avoid from plotting home and public scenarios because in these two scenarios, there are no possibility to charge at work.

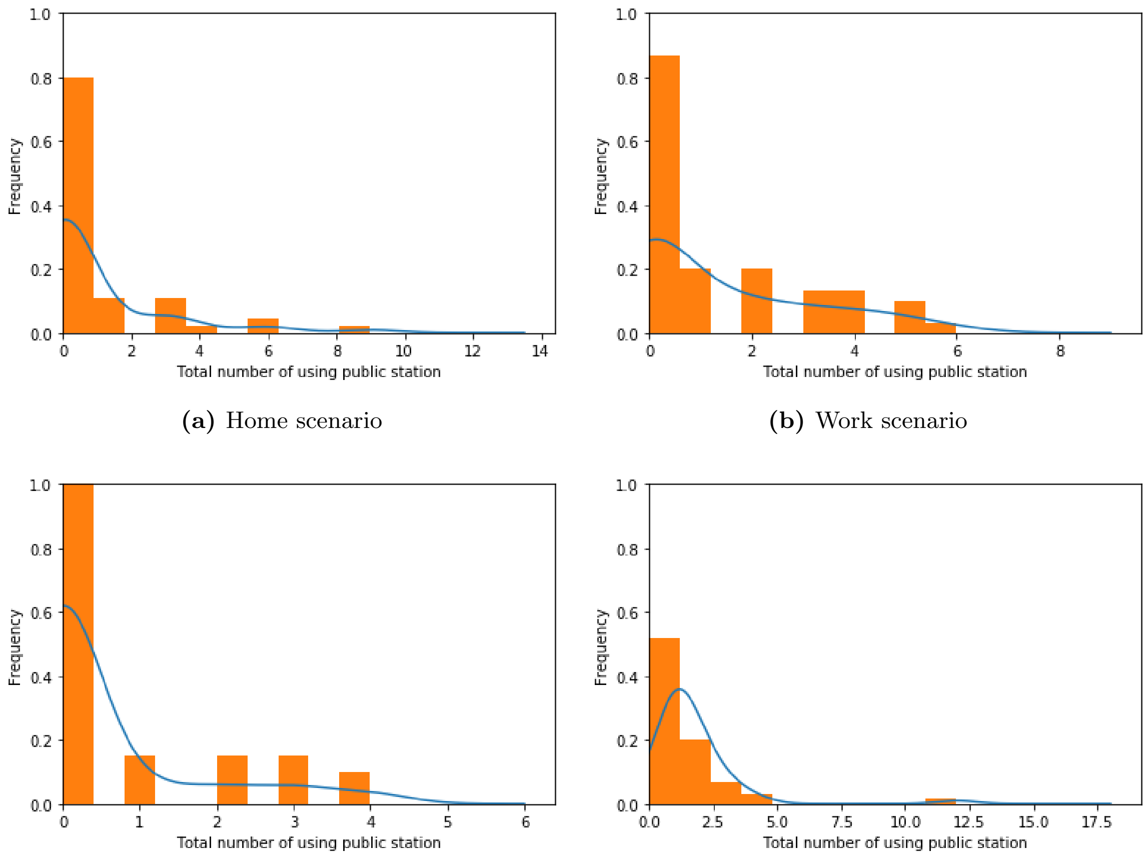


(a) Work scenario **(b)** Home and work scenario

Figure 5.3: Distribution of number of charges at work for work and home/work scenarios.

As you can see here again, the results are very similar, the averages are close to each other, with small differences in the low-frequency charges – some users move several of their charges to home, although overall the difference is not large.

5.3.3 Frequencies Of Public Station Charges



(a) Home scenario

(b) Work scenario

(c) Home and work scenario

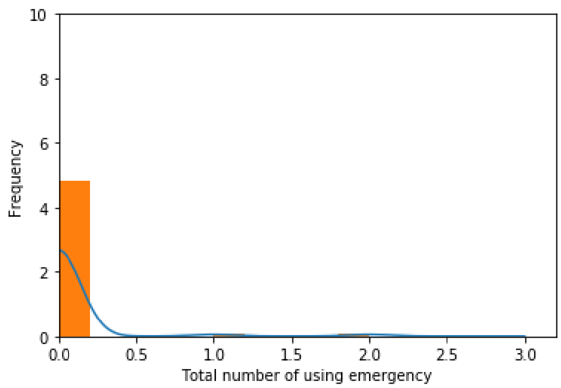
(d) Public scenario

Figure 5.4: Distribution of number of charges at public station in all scenarios.

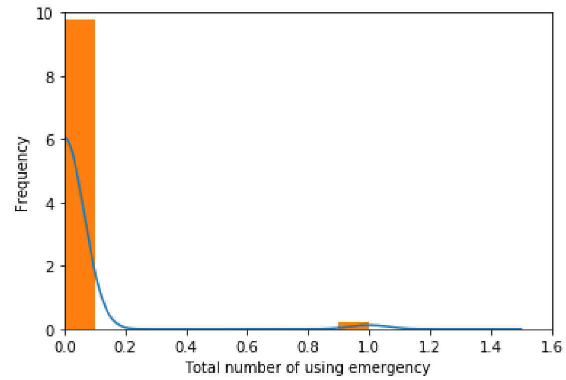
Looking at this figure, we can see that, In (a) the average is lower than (b) although, the maximum number which contain small frequency in (a) is bigger than (b) but, we can see the frequency of using public station in general in work scenario is more than home scenario. The average in (a) as we expected is more than (c), as we said before, with possibility of charging both at home and work the number of times that user use the public stations are reduced. About (d) obviously the average and maximum number are bigger than the other scenarios (notice that the x-scale is larger than the other plots). Finally the plots show that, the frequency of using public station in (b) is more than

(c) it's clear that when user can charge also at home the need of using public station is decreased.

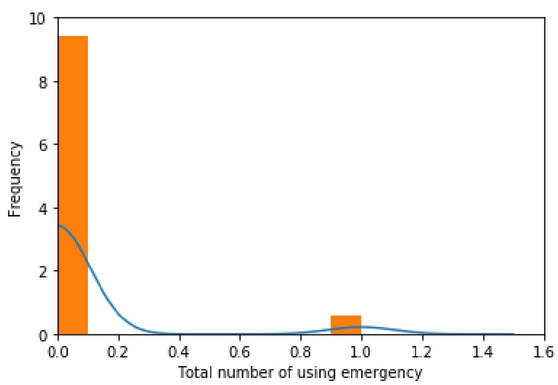
5.3.4 Frequencies Of Emergency Charges



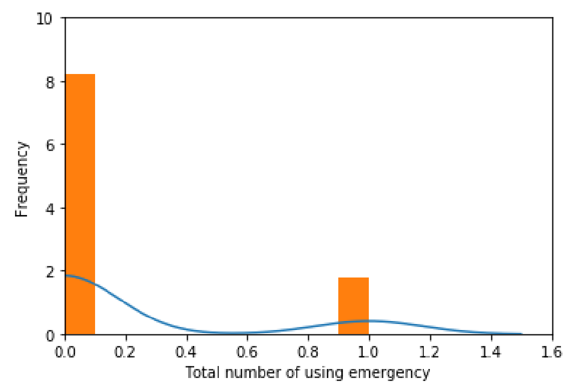
(a) Home scenario



(b) Work scenario



(c) Home and work scenario



(d) Public scenario

Figure 5.5: Distribution of number of charges at emergency in all scenarios.

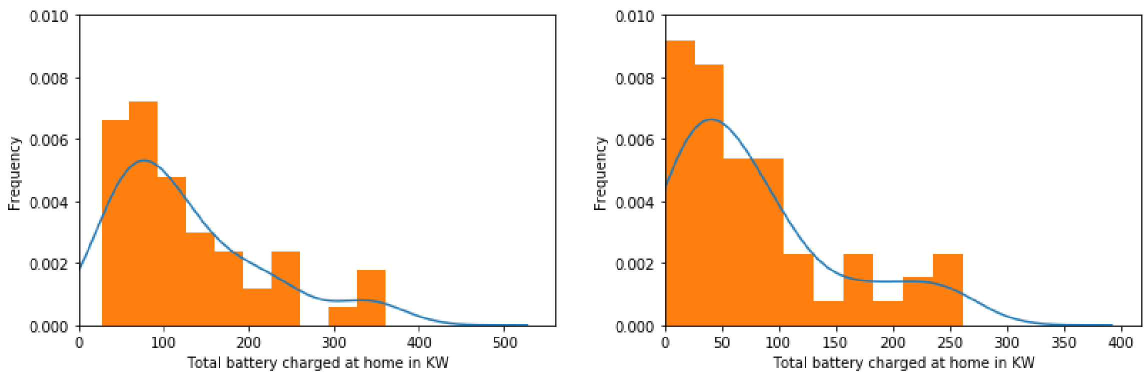
The plots about frequency of emergency recharges show that in (d), i.e. the public station-only scenario, the average frequency of emergency charging is more than the other scenarios. In (a) and (b) and (c) the averages are almost the same while, in (a) and (c) are equal, consider that the distribution is different in each of them. So, we can conclude here that, if the user is in public scenario and he can not charge at home or work he can face more with emergency situation[1].

5.4 Studying Amount Of Battery Charged

In this section we analyze the total amount of charged battery in each types of charging locations for different scenarios and compare the results with plots.

5.4.1 Total Battery Charged At Home

As we have mentioned before, here we don't consider work and public scenarios.



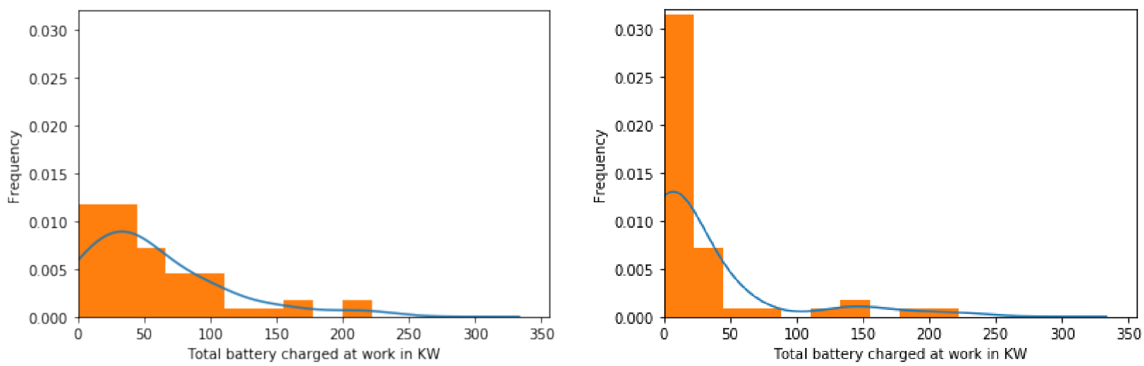
(a) Home scenario **(b)** Home and work scenario

Figure 5.6: Total amount of charged battery at home in kW for home and home/work scenarios.

This figure shows that, the average amount of total battery that is charged at home in (a) is more than (b) also we can see the maximum number which is maximum amount of battery in KW in home scenario is more than the other, so we can say that if user can charge also at work the amount of battery which is charged at home is reduced.

[1]From an application viewpoint, we remark that the results shown here are considering the availability of recharge stations as it is today, further limited by what is visible on the crowdsourced list of stations provided by OpenChargeMap. Ongoing and future extensions of the public energy grid for EVs are expected to strongly reduce the emergency situations.

5.4.2 Total Battery Charged At Work



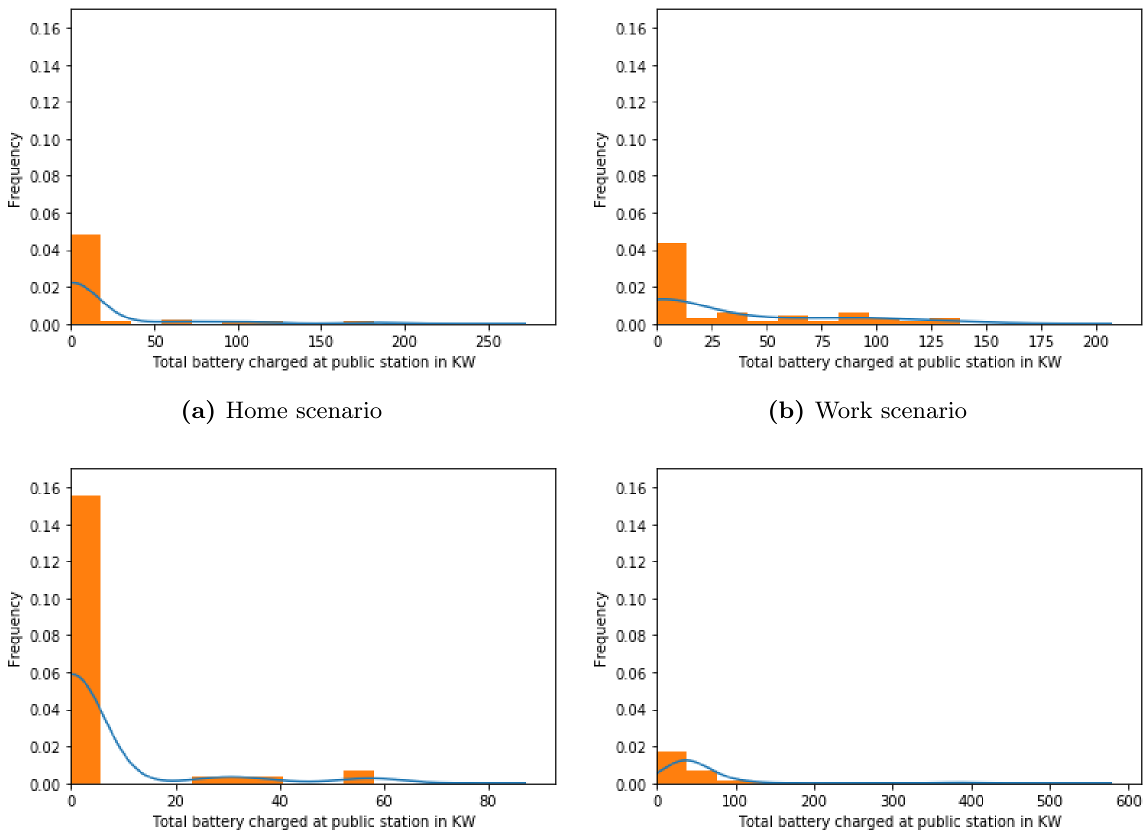
(a) Work scenario

(b) Home and work scenario

Figure 5.7: Total amount of charged battery at work in kW for work and home/work scenarios.

By analyzing this figure we can easily find that, the average total amount of battery charged at (a) is more than (b) which is completely expected because without charging at home, the need of charging at work is increased.

5.4.3 Total Battery Charged At Public Station



(a) Home scenario

(b) Work scenario

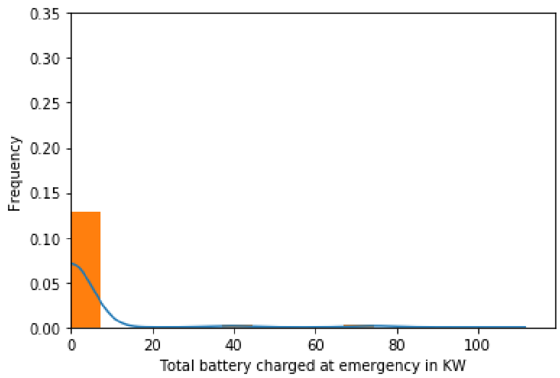
(c) Home and work scenario

(d) Public scenario

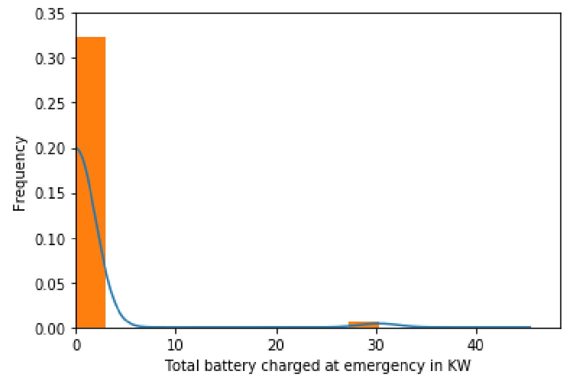
Figure 5.8: Total amount of charged battery at public station in kW for all scenarios.

In this figure we can obviously see, the amount of charged battery at public station is decreased respectively in this order: (d) , (b) , (a) and (c) , of course in public scenario the average total amount of charged battery is more than the other because the users just have to charge at public stations, the point here is that, in (d) we can see the frequency is less than the other which means that users use less time public stations but instead, they have charged more amount of battery. The other point is that, by adding home as charging location the amount of charged battery at public station is reduced, As you can see in both (a) and (c) respect to (d). Notice that at (c) we have the lowest number of total charged battery, since we have possibility to charge both at home and work and eventually, in work scenario in general total charge battery at public station is more than (a) and (c).

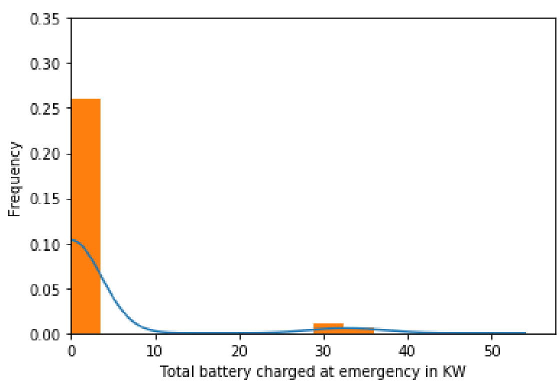
5.4.4 Total Battery Charged At Emergency



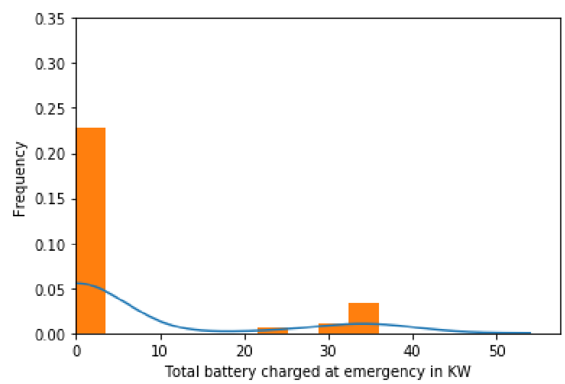
(a) Home scenario



(b) Work scenario



(c) Home and work scenario



(d) Public scenario

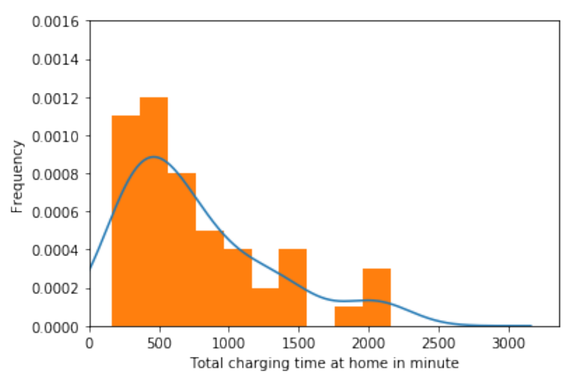
Figure 5.9: Total amount of charged battery at emergency in kW for all scenarios.

As we expected the average total amount of battery which is charged at emergency, in public scenario is more than the other even the frequency is more. In (b) the average is less than the (a) and (c) but the frequency is almost greater, especially from (a) this means that, in work scenario, the number of times that users need to charge at emergency is more but the amount of battery which is charged each time is less. In (a) and (c) the average is more or less the same but there is a difference in frequency.

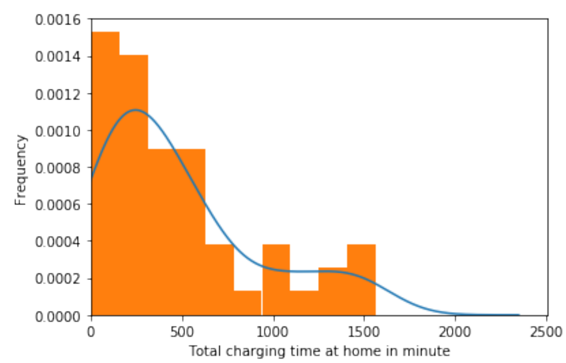
5.5 Studying Total Recharge Time

In this section we analyze the total time that user has to spend for charging, the results in this section is the same as the previous section with different scales. Notice that charging time at home and work has no problem but in fact, for public station and emergency situation is wasting the time, because user has to wait at station, our goal is to minimize this wasted time and suggest to the users, kind of scenarios that have less waiting time at public station and emergency.

5.5.1 Total Charging Time At Home



(a) Home scenario

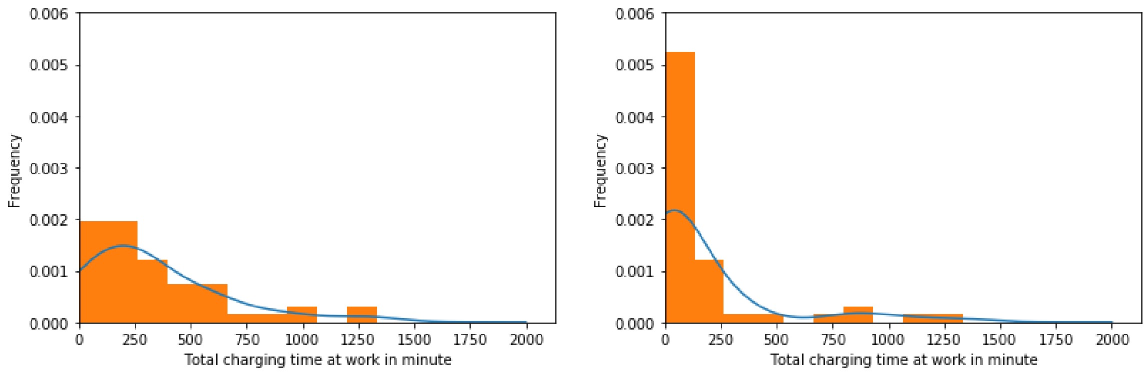


(b) Home and work scenario

Figure 5.10: Total charging time at home in minute for home and home/work scenarios.

The plots clearly show that, by referring to the previous section, we can say, in (a) because the total amount of battery is more than (b) so certainly, the charging time is also more.

5.5.2 Total Charging Time At Work

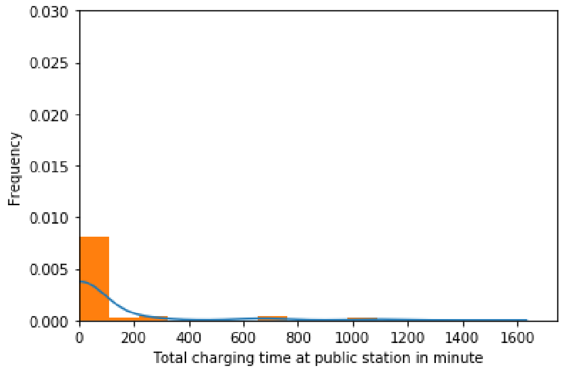


(a) Work scenario **(b)** Home and work scenario

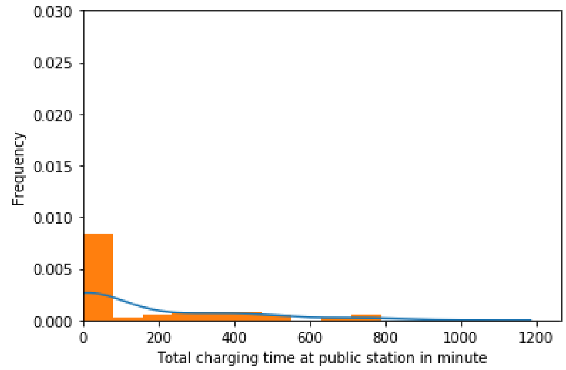
Figure 5.11: Total charging time at work in minute for work and home/work scenarios.

Here again, in work scenario obviously because the total amount of battery at work is more than home/work scenario, the user has to spend more time for charging at work.

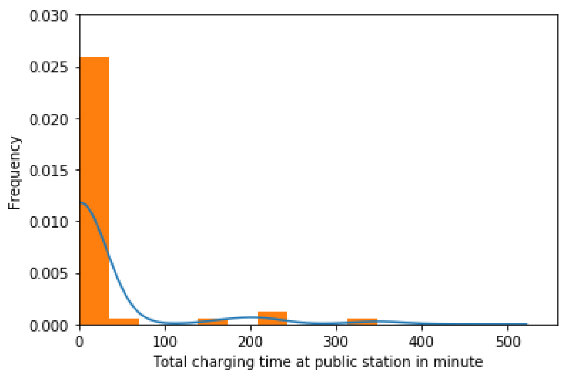
5.5.3 Total Charging Time At Public Station



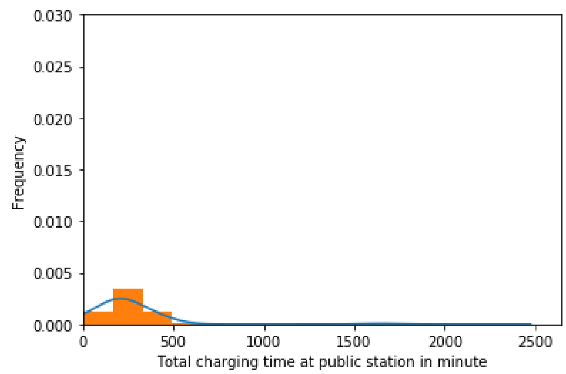
(a) Home scenario



(b) Work scenario



(c) Home and work scenario

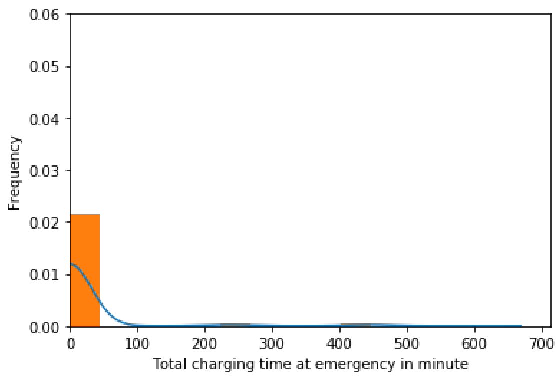


(d) Public scenario

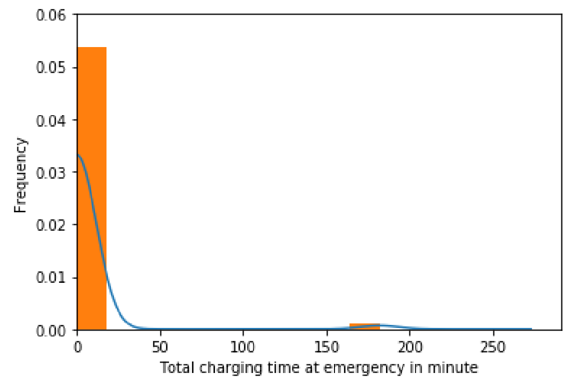
Figure 5.12: Total charging time at public station in minute for all scenarios.

This figure presents that, waiting time is decreased respectively: (d) ,(b) ,(a) and (c) which is exactly what we expected from the total charged battery section. As the users charge more they have to wait more.

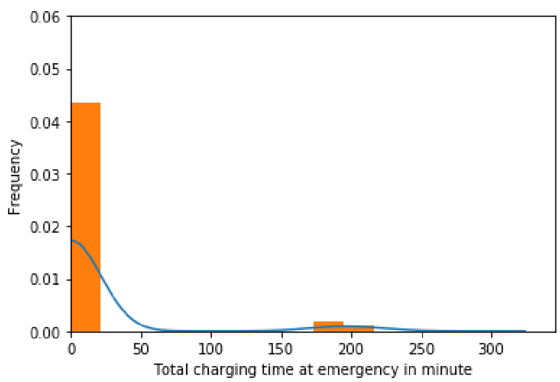
5.5.4 Total Charging Time At Emergency



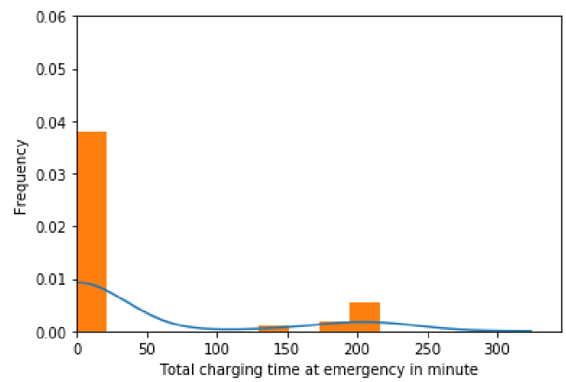
(a) Home scenario



(b) Work scenario



(c) Home and work scenario



(d) Public scenario

Figure 5.13: Total charging time at emergency in minute for all scenarios.

The same result for the emergency which is completely match with the total charged battery section.

5.6 Sample Users And Their EV Profiles

In this section we focus on analyzing the behavior of two users in the same period (january - february 2017) for all the scenarios, then we go more in details to prove that, in the different scenarios we have different frequencies of recharging and at the end, make a

comparison between the results to decide which scenario is more suitable for them.
Here we have 4 plots for each user that simulate in every scenario the frequency and amount of charged battery in all charging stations depend on the scenarios. In the plots you can see four different colors to separate the different types of charging stations to be more clear :

- *Red* : *public station*
- *Green* : *home*
- *Blue* : *work*

5.6.1 First User Charging At Home

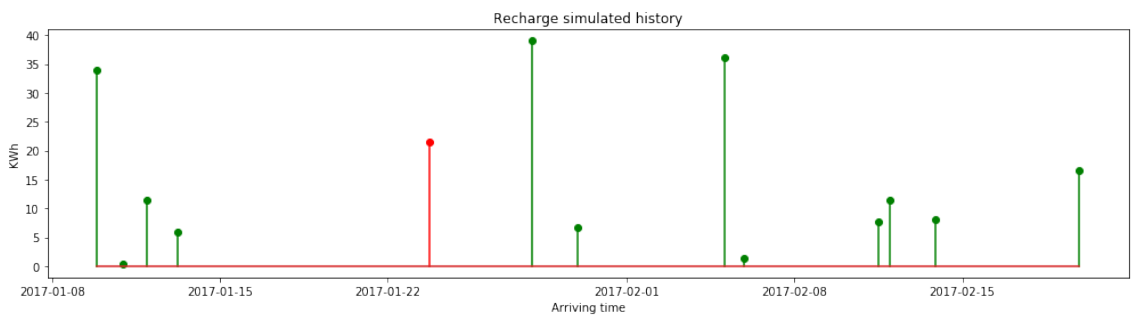


Figure 5.14: Frequency of charging in home scenario for the first user.

In this figure, we can see, in the period of two months this user charged 12 times at home which is 92.31% of frequency and just 1 time at public station. Indeed, this is a good result because the time that user has to spend for charging at public station is save a lot and he mostly charged in a situation that he is at home.

5.6.2 First User Charging At Work

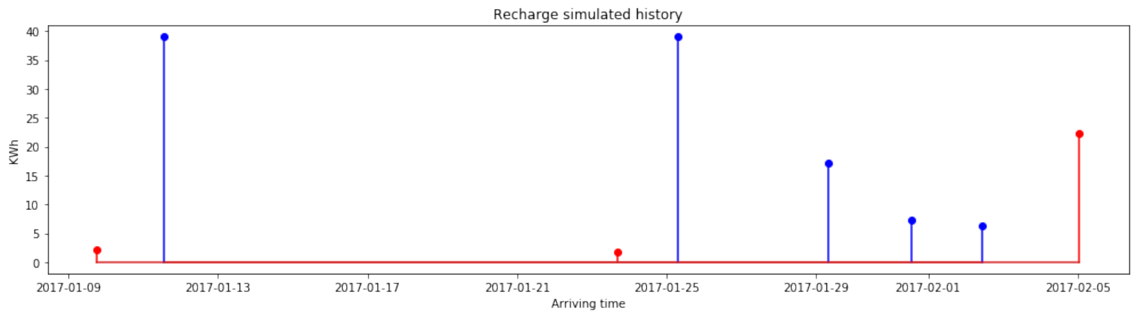


Figure 5.15: Frequency of charging in work scenario for the first user.

In the work scenario this user has charged 5 times at work and 3 times at public station. The frequency of the work also the amount of charged battery is more than public station. Actually as it has been proven, in this scenario user usually, charges more at public station, you can see as well, whenever user is at public station and the next stop is work he charged less amount of battery (the needed consumption to arrive to work) that is the aim of time efficient simulation strategy that helps to saving the time of the user.

5.6.3 First User Charging At Home And Work

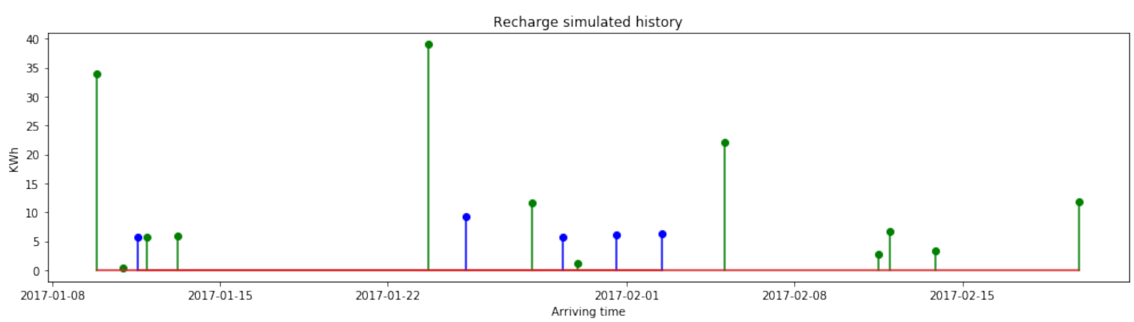


Figure 5.16: Frequency of charging in home/work scenario for the first user.

This scenario is the grateful scenario for this user since the user never use public station. The frequency of home (12) is almost more than 2 times of the frequency of work (5). To conclude, here we can say, having chance to charge both at home and work decreases a lot the demand of charging at public station in most of the cases and that is a good result for the user to change his life style to electric vehicle because it doesn't affect on the wasting time of the user.

5.6.4 First User Charging At Public Station

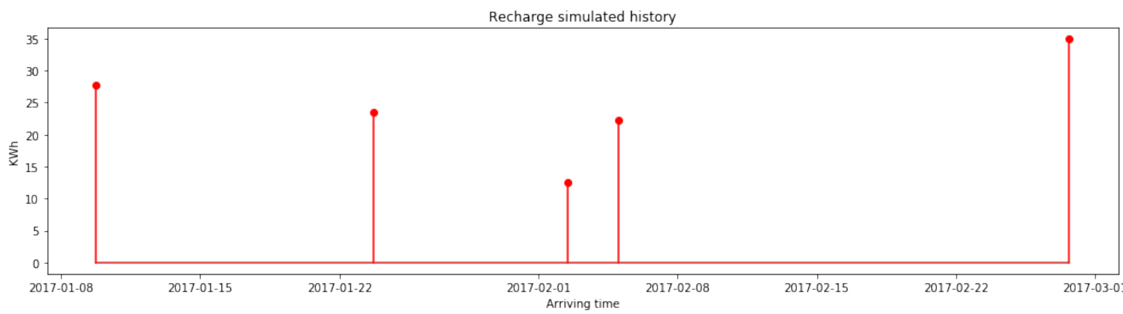


Figure 5.17: Frequency of charging in public station scenario for the first user.

Finally, you can see here in the public scenario the frequency, moreover, the total amount of charged battery and eventually waiting time is much more than the other scenarios. This figure presents that the frequency is 5 which is the most frequency rather than the other scenarios.

5.6.5 Second User Charging At Home

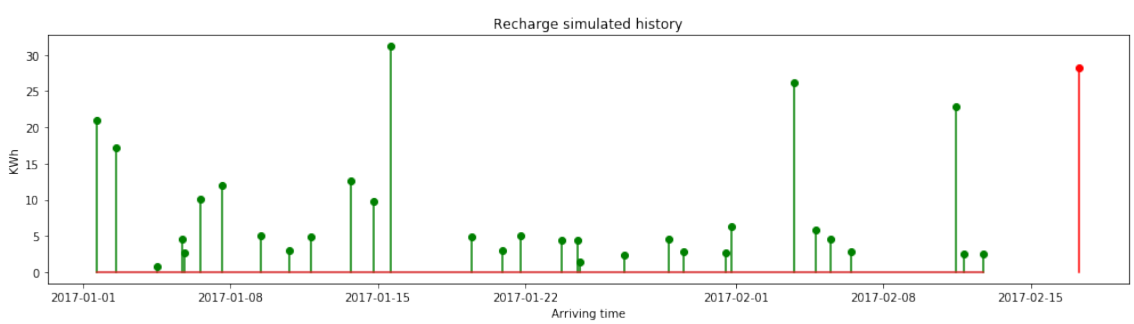


Figure 5.18: Frequency of charging in home scenario for the second user.

This figure presents, the user charged at home 31 times which is very frequently but with small amount of recharged battery (with some exceptions) in every charge whereas, he charged just 1 time at public station. The result here more or less is the same as the first user and most percentages of the frequency is for home charging.

5.6.6 Second User Charging At Work

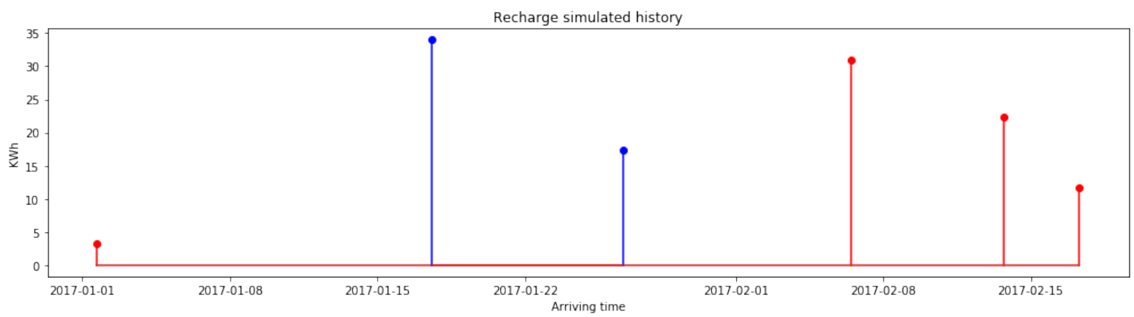


Figure 5.19: Frequency of charging in work scenario for the second user.

In the this scenario user just charged 2 times at work and 4 times at public station with almost more frequency and more amount of charged battery at public station that was expected as usual.

5.6.7 Second User Charging At Home And Work

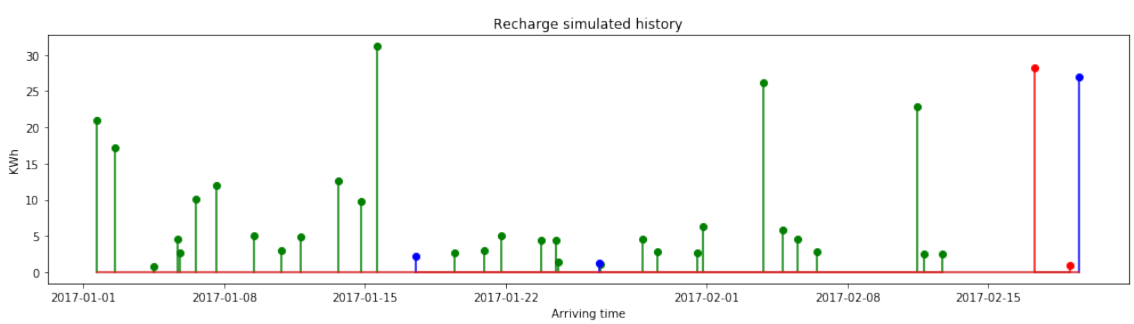


Figure 5.20: Frequency of charging in home/work scenario for the second user.

By looking at this figure you can see, the user charged 31 times at home , 3 times at work and 2 times at public station. There is a big difference between the frequency of home with work and public station however, even if this user charged less time at work but it helps the user to spend less time at public station.

5.6.8 Second User Charging At Public

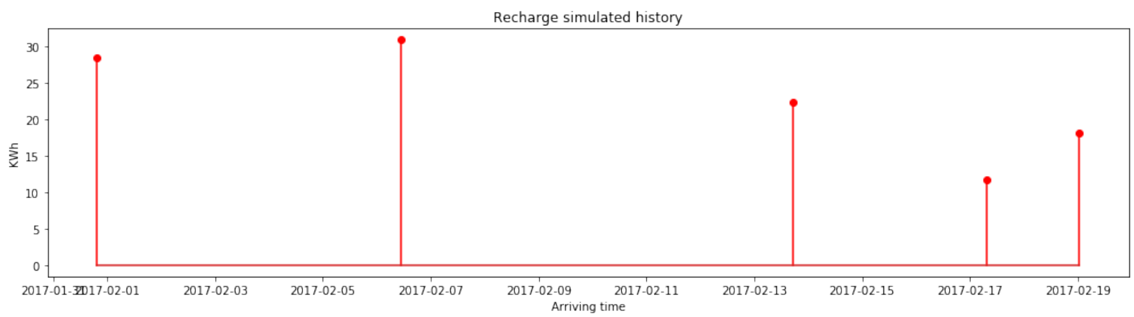


Figure 5.21: Frequency of charging in public station scenario for the second user.

Like the first user also here you can see the same situation. This user charged 5 times at public station with particularly high amount of recharged battery rather than the other scenarios.

As a final observation , from analyzing the result assuming our goal is reducing the waiting time at public station, for the both users the best scenarios are home and home/work because the frequency also the total battery that user has to recharge at public station and eventually the waiting time is less than the other scenarios.

5.7 General Statistics Of Real Trips Versus Simulated Ones

In this section we decide to evaluate, if using electric vehicle causes any effect on the total kilometer that user has to drive or not, so we have computed all the total amount of kilometers that users drive for both real and simulated individual mobility network and made a comparison between them.

5.7.1 Global Statistics

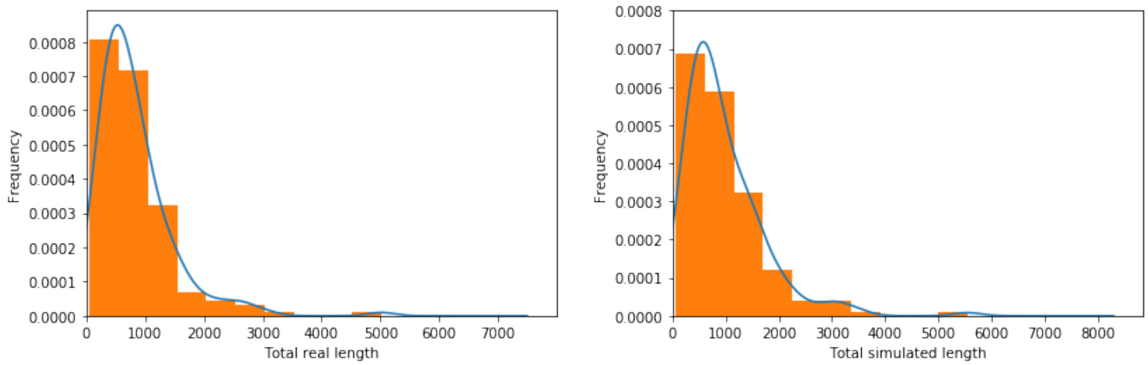
As we mentioned above, we have decided to show you the differences with the collected statistics that are produced for all aggregates.

	real_length	simulate_length
average	822.90	968.72
median	668.73	758.51
min	58.31	61.71
max	5016.58	5551.01
STD	639.67	746.62

Figure 5.22: This table reports different measurements in rows, on the left column the total length (km) of the real trips and in right column represents the total length (km) of the simulated trips.

In this figure, statistics prove that in the simulated mobility network in general the total length that user has to go as we expected is more than the real one but the difference is low in all the above measurements, therefore, with the difference of averages we can conclude that the user has to go almost 18% kilometer more in two months which is affordable number for changing life style to electric vehicles.

5.7.2 Real Versus Simulated Length



(a) real total length **(b)** simulated total length

Figure 5.23: Real Versus Simulated Length

These plots confirm the previous results, there is a simply slight increase in all the lengths, so this tells you that in general, we have increase of the average. The distribution is all the same but shifted a little bit to the right which means the values are all increased from the real length to the simulated one.

Chapter 6

Conclusions And Future Works

6.1 Conclusions

In this thesis we developed and tested methods for studying how much comfortable can be for a user to switch his life to an electric vehicle, and how much his life is changed according to the time and length that he has to drive. We did the simulation for EVs from real trajectories of users and by implementing our algorithms we presented how much they charged their batteries and how much time they waited for charging. Also, we illustrated how they changed their trips according to the trip planning algorithm in order to reach the public stations. The final results show us that the changes are relatively small, at least for most users, this means that switching to EVs is expected not to change a lot users's life, and the real issues, due to the emergency situations (i.e. cases where the EV seems not fit for the user's needs) are relatively few in all the scenarios.

6.2 Future Works

The work that we have done till now cannot be considered conclusive, in fact, a lot of works and improvements can be done to strengthen the new methodology we have introduced and to integrate it with the existent literature. Therefore we want to leave some ideas for possible applications of the algorithm in the future. As future works, to improve what we started with this thesis, we suggest following new experiments on the bigger datasets because the dataset that we have analyzed in this thesis is only from Tuscany, Italy. This helps you to find more ideas about improving the facilities of charging stations and make comparison between different provinces or even countries and use the experiments and ideas of those regions where the people can match easily their life with EV to improve the weak regions. The algorithm could also be used as a tool to simulate routes, based on real data on the use of fuel-base vehicles, in order to be able to estimate the most suitable areas for the installation of new charging stations, going to identify clusters where the density of vehicles in low battery conditions is higher. The other suggestion is considering new scenarios by identifying the other most visited places of the users like shopping centers, restaurants, grandparent house and so on, recognizing the nearest charging station to these places and add more scenarios to the charging options for the users and in summary try to simulate the EV life in a way that is as much as possible close to the real life.

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