POLITECNICO DI TORINO

Corso di Laurea Magistrale

In Ingegneria Civile

Tesi di Laurea Magistrale

Verifica delle esigenze della mobilità elettrica nell’area metropolitana di Torino

Relatore
Prof. Francesco Paolo Deflorio

Correlatrice
Dott.ssa Cristiana Botta

Candidato
Andrea Spirito

Anno Accademico 2020-2021

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ACI	Automobile Club d’Italia
AFV	Alternative Fuel Vehicle
CFCD	Cellular-Based FCD
COP	Conference of Parties
EIA	Energy Information Administration
EV	Electric Vehicle
FCD	Floating Car Data
GBDM	Generalized Bass Diffusion Model
GPS	Global Positioning System
HEV	Hybrid Electric Vehicle
ITS	Intelligent Transport Systems
LCV	Light Commercial Vehicle
NLLS	Non Linear Least Square
PNIEC	Piano Nazionale Integrato per l’Energia e il Clima
SoC	State of Charge
TD	Travelled Distance
UNRAE	Unione Nazionale Rappresentanti Autoveicoli Esteri
ZTL	Limited Traffic Zone

Chapter 1: Introduction

A common change, witnessed almost daily, affects the way people “perceive” and “experience” the City and its suburban areas. The ongoing process of the mobility change and the spread of new transport systems are the two main trends that affect everyday life of transport planners. These trends are juxtaposed with the need to reduce the social and the environmental impacts, such as congestion and pollution, in order to increase safety and air quality. Studies have demonstrated that electric mobility reduces significantly the atmospheric emissions linked to the automotive sector (PM10, PM 2.5, oxides of nitrogen NO_x). Moreover, electric mobility reduces the energy consumption - especially fossil-fuel - in the transport sector, and it provides significant advantages over noise pollution and over the quality of the urban landscape. Therefore, automotive manufacturers all over the world are investing heavily in Electric Vehicles (EV) design and manufacturing.

1.1 Research goal

The goal of this thesis is to analyse the traffic flow patterns related to the Turin metropolitan area Floating Car Data (FCD) to better understand city users’ behaviours and to accommodate the development of the electric mobility. More specifically, a large amount of movement data was processed in order to reconstruct trajectories and extract the starting and ending points of the trips. Analysing the data, it was possible to construct Origin-Destination matrices in Turin metropolitan area. The one-month FCD in Turin - and its metropolitan area – was used as test dataset. Studying and understanding how people move daily may allow to locate new hubs for EVs in which people might recharge their vehicles. Moreover, a study about the estimation of the diffusion of the electric vehicles in Turin was conducted according to the Bass model. This forecast was then used to set a year in which determine the potential power distribution needed in all the zones of the study area to accommodate the future electric demand.

1.2 Sustainable mobility

Since the subscription of the Kyoto Protocol in 1997, European Union (EU) and its Member States have been involved in a process aimed to the climate change through the adoption of International and National policies to decarbonise the economy. In 2015, this process was confirmed during the XXI Conference of Parties (COP) held in Paris, where a global agreement on the reduction of climate change was negotiated. According to the organizing committee at the outset of the talks, the expected key result was an agreement to set a goal of limiting global warning below 2 °C compared to pre-industrial levels. The agreement calls for zero net anthropogenic greenhouse gas emissions to be reached during the second half of the 21st century. The Parties will also pursue efforts to limit the temperature increase to 1,5 °C. Italy signed up the agreement on 22nd April 2016. The agreement was approved by 184 out of 197 Parties. Italy is deeply engaged in sustainability concerns. Therefore, many efforts are occurring to improve environmental sustainability, safety and accessibility of energy costs. The scope is to acquire tools aimed to identify objectives, policies and measures consistent with the European framework. The paper "*Elementi per una Roadmap della Mobilità Sostenibile*", drafted in 2017, provides the current context about Italian mobility and environmental impacts, as well as a deepening on the opportunities offered by the technological evolution of the transport means. According to the paper, the development of a vehicle supply chain based on the innovative technologies is crucial to the development of a new transport system based on alternative fuels. Furthermore, the Roadmap highlights the role of the support measures, given mainly by local Policies in favour of the sustainable mobility. The most serious challenges and critical issues occur in cities, where congestion, pollution and road safety are main concerns to be solved.

According to the Integrated National Energy and Climate Plan (PNIEC) there is an extreme need to adopt measures that aim to the electrification, particularly in Civil and Transport sectors, as a tool to improve air quality and environment. Italy plans to accelerate the transition from traditional fuels to renewables, promoting decarbonization in favour of electrification. It is demonstrated that a sustainable mobility significantly affects the desirable achievement of the targets fixed by PNIEC. To support this thesis, simulations were realized in 4 metropolitan areas (Turin was one of those) to investigate the potential of the e-mobility to reduce pollution and gas emissions. All the four cities may be considered as fertile areas for the spread of electric mobility.

The results refer to 2030 and they are obtained through the application of the new PNIEC Policies.

Metropolitan City	City population	Metropolitan population	Motorization rate (cars/1000 inhab.)	TPL modal share
Bari	323.370	1.257.520	514	9%
Bologna	389.261	1.011.291	518	21%
Milano	1.366.180	3.234.658	509	38%
Torino	882.523	2.269.120	615	26%

Table 1. Cities considered in the test (TRT)

Variable	Bari	Bologna	Milano	Torino
Conventional car travel (veh*km/year, variation %)	-27,5 %	-28,0 %	-26,8 %	-27,6 %
CO_2 emissions (tons/year, var %)	-17,1 %	-15,1 %	-13,7 %	-14,1 %
E-mobility (var %) : - Hybrid EV (plug-in) - EV (battery)	 12,1 % 4,3 %	 12,2 % 4,3 %	 12,2 % 4,6 %	 12,2 % 4,6 %
Atmosphere emissions (tons/year, var %) :				
PM_{10}	-24,7 %	-23,5 %	-19,0 %	-20,5 %
CO	-19,6 %	-16,9 %	-16,2 %	-19,7 %
Nox	-33,2 %	-31,0 %	-21,9 %	-26,1 %
VOC	-12,9 %	-7,8 %	-5,0 %	-8,5 %
Energy consumption (TOE/year, var %)	-14,5 %	-13,1 %	-11,4 %	-12,0 %

Table 2. Test results (TRT).

Overall, the 2030 scenario shows benefits in the reduction of CO_2 emission compared to the current scenario due to the penetration of the electric mobility and the consequent reduction of the consumption from fossil sources.

1.3 City of Turin

City of Turin was included in the “Programma Operativo Nazionale (PON) for the metropolitan cities 2014-2020”. This program was launched by European Union with the aim to push its Countries towards a higher electric sustainability and improvements in the quality of life in urban areas throughout the adoption of massive investments. PON was adopted on 4th July 2015 and consisted in over 827 million euros of financial endowment, including Community resources, with a percentage of co-financing of Community support equal to 70,52% of the total amount available.

1.4 Floating Car Data

In recent years, traffic monitoring systems have become crucial devices for transport planners. The increasingly rapid spread of the Intelligent Transport Systems (ITS) has brought innovation and improvements in many transport sectors so that problems such as traffic congestion could be solved. ITS deals with data information technology in vehicles, between vehicles (Vehicle-to-Vehicle or V2V), and between vehicles and fixed location (Vehicle-to-anything or V2X) that could be used to provide road information to guide the users of the transportation systems and to facilitate traffic monitoring.

There are many technologies that have been developed to provide traffic data in ITS. Policy makers face difficulties when deciding to invest in the expansion of their infrastructure based on inductive loops and cameras, or to invest in a FCD system that is a new and better approach to gather traffic information for most ITS. The traffic data collection from mobile sensors, nodes or probes is a technique adopted since many years, usually for integration with the data collection obtained through fixed devices. The information collected enables various applications such as real-time traffic monitoring, time-dynamic routing and fleet management. It is based on the collection of localization data, speed, the direction of travel and time information from devices in vehicles that are being driven. Based on these data, movement data can be monitored, travel times can be calculated, and traffic reports can be generated.

Location is used for fleet tracking and management in freight services, public transportation, emergency services. Geo-localized vehicles/people are today widely exploited as mobile probes for traffic monitoring and infomobility services. There are two types of FCD: GPS-based, and cellular-based systems.

- **GPS-based FCD system:**

GPS system utilizes the GPS receiver system which is already attached on the car to gather information about the vehicles. Exploiting this technology, the floating data is derived from a different type of devices. Then the data is communicated with the service provider using the regular on-board radio unit or via cellular network data. Therefore, the system can locate the exact location and movement of that specific car, for instance, calculating the instantaneous speed. The working principle is shown in the Figure 1.

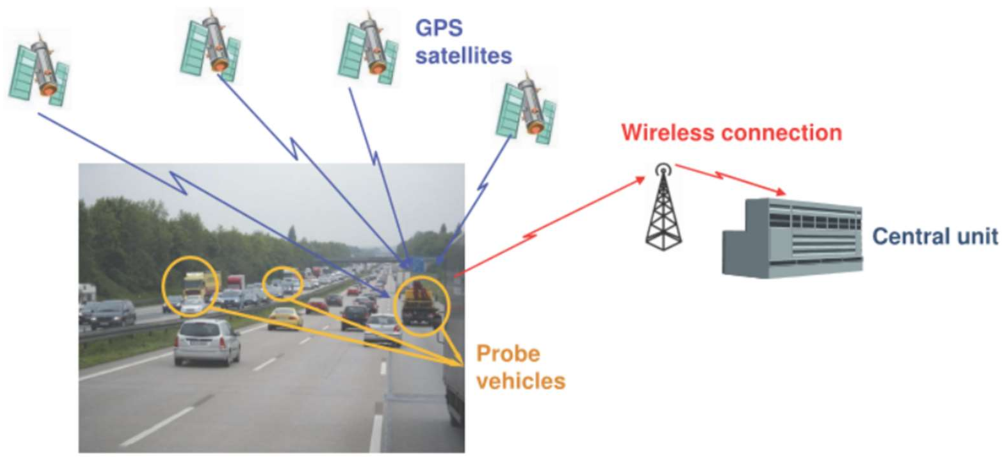


Figure 1. Communication from GPS (wireless positioning, Nicoli).

- **Cellular-based FCD (CFCD System):**

CFCD is derived from cellular networks. The main benefit is that no special devices or hardware are needed, and every mobile phone becomes a sensor. The location and movement of the mobile phones are determined using one of the several location technologies available by the mobile network. Many mobile handsets that are constantly on the move makes it possible to extract high quality data from the network. Then the data will be sent to the data centre through the regular on-board radio unit or via cellular network data. The figure below shows how the process works.

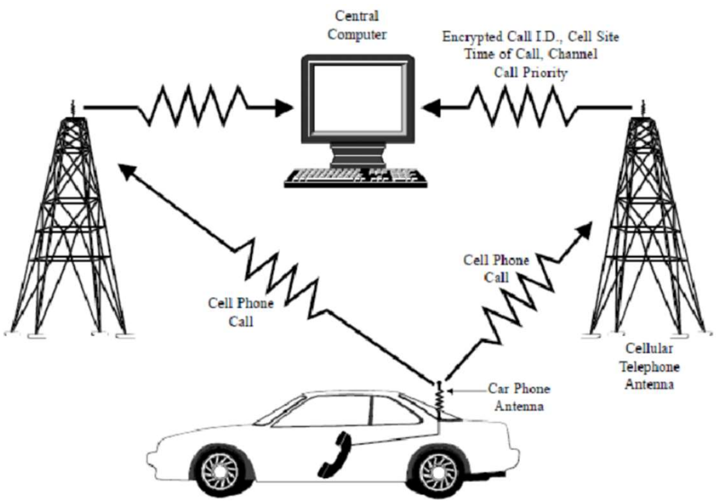


Figure 2. Communication from cellular phone (FHWA).

In this work, GPS-based FCD were provided by TIM. Data were extracted from a fleet of 35.535 vehicles travelling monthly in Turin metropolitan area.

Chapter 2: FCD Analysis

2.1 Data availability

In order to study and analyse traffic flows in Turin and its metropolitan area, Floating Car Data were provided by TIM. The mining process refers to November 2019 and all the GPS data are anonymous and not attributable to any vehicle as well as any user owner of the vehicle. Data were given in a CSV file in which each row provides the intermediate records of the trip extracted by the device (GPS) in the vehicle during each trip. Only positions linked to significant events of guide (e.g. acceleration, braking) were provided. Moreover, at least one position per kilometre was provided. Data were available as described in figure 3:

<table>
<tr><th>Field</th><th>Description</th><th>Type and format</th><th>Notes</th></tr>
<tr><td>ID vehicle</td><td>alphanumeric, kept costant for all the analysis period</td><td>Long</td><td></td></tr>
<tr><td>ID trip</td><td>Numeric</td><td>Long</td><td></td></tr>
<tr><td>Latittude</td><td>WGS84</td><td>decimal, with at least 6 significant decimals, decimal separator "."</td><td></td></tr>
<tr><td>Longitude</td><td>WGS84</td><td>decimal, with at least 6 significant decimals, decimal separator "."</td><td></td></tr>
<tr><td>Date and time of the collection</td><td>Date and Time</td><td>yyyy-MM-dd HH:mm:ss</td><td>Local time</td></tr>
<tr><td>Speed</td><td>Number</td><td>Integer</td><td>[km/h]</td></tr>
<tr><td>Travelling direction</td><td>Compared to North</td><td>Integer</td><td>it varies from 0° to 360°</td></tr>
<tr><td>Travelling direction</td><td>4 possible values</td><td>String</td><td>"North", "East", "West", "South"</td></tr>
<tr><td>Type of event</td><td>beginning of the trip, intermediate collection, end of the trip</td><td>Integer</td><td>2=start;
1=end;
9=intermediate</td></tr>
<tr><td>Address</td><td>String made by two sections: geographic data, census information</td><td>Country-County-Province-Municipality-address-ISTAT code-ACE code</td><td>e.g.
'ITALIA|PUGLIA|BA|PUTIGNANO|VIA PALVISINO#72036|1'</td></tr>
<tr><td>Type of road</td><td>Road classification</td><td>Char</td><td>U=urban;
E=rural;
A=motorway;
L=unknown</td></tr>
<tr><td>Driving attitude</td><td>Driver's behaviour</td><td>String</td><td>NA: not available (proper attitude, vehicle power on/off);
C: dangerous turn;
F: braking;
A: acceleration;
LV: speed limit exceeded</td></tr>
<tr><td>Vehicle type</td><td>Vehile classification</td><td>Integer</td><td>1=private vehicle
2=commercial vehicle</td></tr>
<tr><td>Travelled distance</td><td>Number</td><td>Integer</td><td>[km]</td></tr>
</table>

Figure 3. Data mining (TIM, Olivetti).

An example of the data provided can be seen in figure 4. An extract of 10 rows is shown:

<table>
<tr><th>vehID</th><th>tripID</th><th>lat</th><th>long</th><th>datetime</th><th>speed</th><th>direction</th><th>direction</th><th>event</th><th>address</th><th>road type</th><th>attitude</th><th>veh type</th><th>T distance</th></tr>
<tr><td>3262016</td><td>6591582416</td><td>44.879543</td><td>7.35708</td><td>01/11/2019 00:21</td><td>39</td><td>86</td><td>EST</td><td>9</td><td>ITALIA|PIEMONTE|TO|PINEROLO|SENZA NOME#1191|0</td><td>E</td><td></td><td>1</td><td>20</td></tr>
<tr><td>3262016</td><td>6591582416</td><td>44.888439</td><td>7.354612</td><td>01/11/2019 00:23</td><td>29</td><td>226</td><td>OVEST</td><td>9</td><td>ITALIA|PIEMONTE|TO|PINEROLO|SENZA NOME#1191|1</td><td>U</td><td></td><td>1</td><td>20</td></tr>
<tr><td>3262016</td><td>6591582416</td><td>44.891834</td><td>7.341539</td><td>01/11/2019 00:25</td><td>17</td><td>342</td><td>NORD</td><td>9</td><td>ITALIA|PIEMONTE|TO|PINEROLO|VIA DELLA REPUBBLICA|1-39#1191|2</td><td>U</td><td></td><td>1</td><td>20</td></tr>
<tr><td>3262016</td><td>6591582416</td><td>44.891907</td><td>7.339632</td><td>01/11/2019 00:27</td><td>0</td><td>0</td><td>NORD</td><td>1</td><td>ITALIA|PIEMONTE|TO|PINEROLO|VIA SCOLA|20-20#1191|2</td><td>U</td><td></td><td>1</td><td>20</td></tr>
<tr><td>4378930</td><td>6592086300</td><td>45.073376</td><td>7.637328</td><td>01/11/2019 00:00</td><td>0</td><td>0</td><td>NORD</td><td>2</td><td>ITALIA|PIEMONTE|TO|TORINO|VIA MATTIE|1-10#1272|37</td><td>U</td><td></td><td>1</td><td>2.4</td></tr>
<tr><td>4378930</td><td>6592086300</td><td>45.066883</td><td>7.63177</td><td>01/11/2019 00:02</td><td>55</td><td>196</td><td>SUD</td><td>9</td><td>ITALIA|PIEMONTE|TO|TORINO|CORSO MONTE CUCCO|78-86#1272|119</td><td>U</td><td>LV</td><td>1</td><td>2.4</td></tr>
<tr><td>4378930</td><td>6592086300</td><td>45.061275</td><td>7.629564</td><td>01/11/2019 00:05</td><td>42</td><td>196</td><td>SUD</td><td>9</td><td>ITALIA|PIEMONTE|TO|TORINO|CORSO MONTE CUCCO|139-155#1272|119</td><td>U</td><td></td><td>1</td><td>2.4</td></tr>
<tr><td>4378930</td><td>6592086300</td><td>45.062344</td><td>7.630187</td><td>01/11/2019 00:06</td><td>0</td><td>0</td><td>NORD</td><td>1</td><td>ITALIA|PIEMONTE|TO|TORINO|CORSO MONTE CUCCO|135-137#1272|119</td><td>U</td><td></td><td>1</td><td>2.4</td></tr>
<tr><td>5214403</td><td>6591697580</td><td>45.083305</td><td>7.686835</td><td>01/11/2019 00:00</td><td>0</td><td>0</td><td>NORD</td><td>2</td><td>ITALIA|PIEMONTE|TO|TORINO|CORSO EMILIA|1-11#1272|70</td><td>U</td><td></td><td>1</td><td>8.2</td></tr>
<tr><td>5214403</td><td>6591697580</td><td>45.091969</td><td>7.677853</td><td>01/11/2019 00:04</td><td>1</td><td>0</td><td>NORD</td><td>9</td><td>ITALIA|PIEMONTE|TO|TORINO|VIA STRADELLA|17-32#1272|138</td><td>U</td><td></td><td>1</td><td>8.2</td></tr>
</table>

Figure 4. Example of data mining.

2.2 Sample analysis

Data provided were analysed using the software Python. The total observations collected were 24.289.443, describing 2.991.358 trips made by 35.535 vehicles (private and light commercial vehicles) in one month (November 2019). The dataset was divided in 2 sub datasets based on the type of vehicle – these two datasets will be called *private dataset* and *commercial dataset* -. Although the trips made by light commercial vehicles (LCV) represented only 4,47 % of the total trips, the two types of vehicles were studied individually to obtain more reliable and disaggregated results. Therefore, the two subsets obtained were studied singularly, cleaned from errors and then regrouped as one dataset to make the Origin-Destination matrices.

Overall, there were errors manly linked to the position provided by the GPS. All the observations considered as errors were removed, thus the trips related to them were removed from the dataset. Since the position of the vehicle (during the trip) was collected in a range between 2 and 5 minutes, the "type of event" was the key feature to process the dataset. In each row, type of event might have three values:

- 2: beginning of the trip;
- 9: intermediate position collection;
- 1: end of the trip.

Nor duplicates, nor rows/observations missing "type of event" were found in the dataset. The "cleaning" process was conducted by steps:

1) Data geolocalised in a position in which latitude and/or longitude was equal to 0.00 were removed:

vehID	tripID	lat	long	datetime	speed	...	road type	attitude	veh type	T distance
5906045	6593162067	0	0	01/11/2019 15:16	0	...	E		1	13.6
5903954	6593160309	0	0	01/11/2019 15:34	0	...	U		1	6.2
5908245	6593833480	0	0	01/11/2019 17:17	0	...	U		1	1.6
5910517	6594234987	0	0	01/11/2019 21:54	0	...	E		1	8.7
5403550	6595117268	0	0	02/11/2019 10:24	0	...	U		1	1.2

Figure 5. Example of Latitude - Longitude errors.

187 rows had this error. All the trips described by those rows were removed from the dataset.

2) Analysis on the *type of event* feature:

- Trips containing more than one Origin point were removed. Hence, all the trips containing more than one '2' in the *type of event* feature were removed;
- Trips containing more than one Destination point were removed. Hence, all the trips containing more than one '1' in the *type of event* feature were removed;
- Trips containing nor Origin point, nor Destination point, or only one within them were removed. Hence, all the trips containing nor 1, nor 2, or containing only 1 or only 2 in the *type of event* feature were removed.

Grouping all the trips it was possible to study them as a list made by 2, 9, 1 and remove the ones described in the previous page. 864 trips were removed from the private sub dataset, 135 trips were removed from the commercial sub dataset.

Index	tripID	event
0	6591407407	2,9,9,9,9,1
1	6591413972	2,9,9,9,9,9,1
2	6591427772	2,9,9,9,1
3	6591428400	2,9,1
4	6591453064	2,1
5	6591464987	2,9,1
6	6591489499	2,1
7	6591493875	2,1
8	6591495376	2,1

vehID	tripID	event
5932513	6599443141	2
5932513	6599443141	9
5932513	6599443141	9
5932513	6599443141	9
5932513	6599443141	9
5932513	6599443141	2
5932513	6599443141	9
5932513	6599443141	1

Figure 6. Extract of the tripID analysis.

At this point, the travel time for each trip was calculated as the difference between the observation occurred at the end of the trip (event=1) and the observation occurred at the beginning of the trip (event=2).

$$Travel\ time = Time\ (event = 1) - Time\ (event = 2)$$

Knowing the travelled distance and the travel time, the mean speed for each trip was calculated:

$$Mean\ speed = \frac{travelled\ distance}{travel\ time}$$

Moreover, the trip gap between two consecutive trips (*trip i* and *trip i-1*) in the same day was calculated:

$$Trip\ gap = Time_i\ (event = 2) - Time_{i-1}(event = 1)$$

All these features were used to deeply analyse the datasets and find other errors. Analysis on the speed and distances were conducted. Regarding the *mean speed*, 22 trips were removed from the *commercial dataset* because the mean speed obtained for those trips tended to infinite. In the same way, 493 trips were removed from the *private dataset*.

Exploiting the mean speed, it was possible to obtain the distribution of the speeds for all the trips in the datasets. The distribution was computed to remove potential outliers and to keep only significant trips:

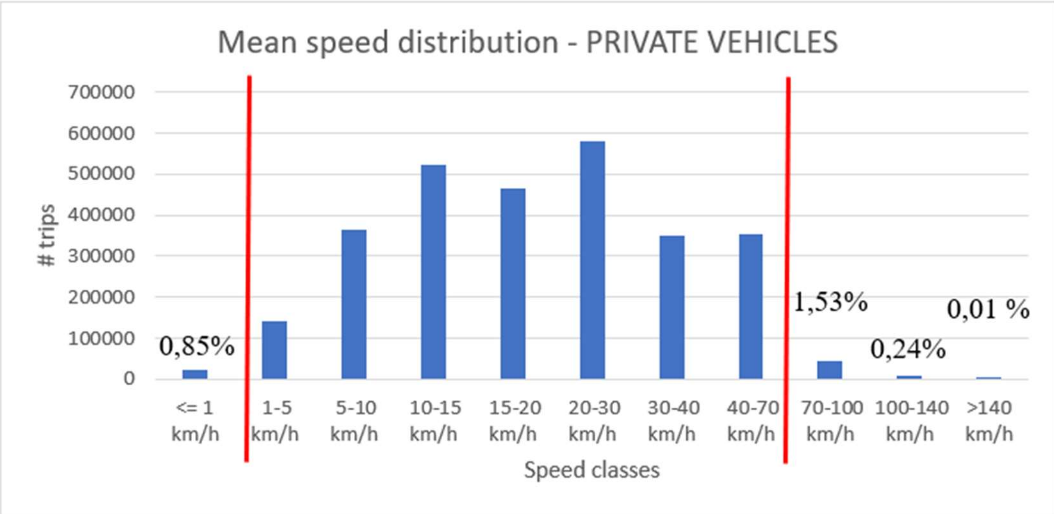


Figure 7. Mean speed distribution for private vehicles.

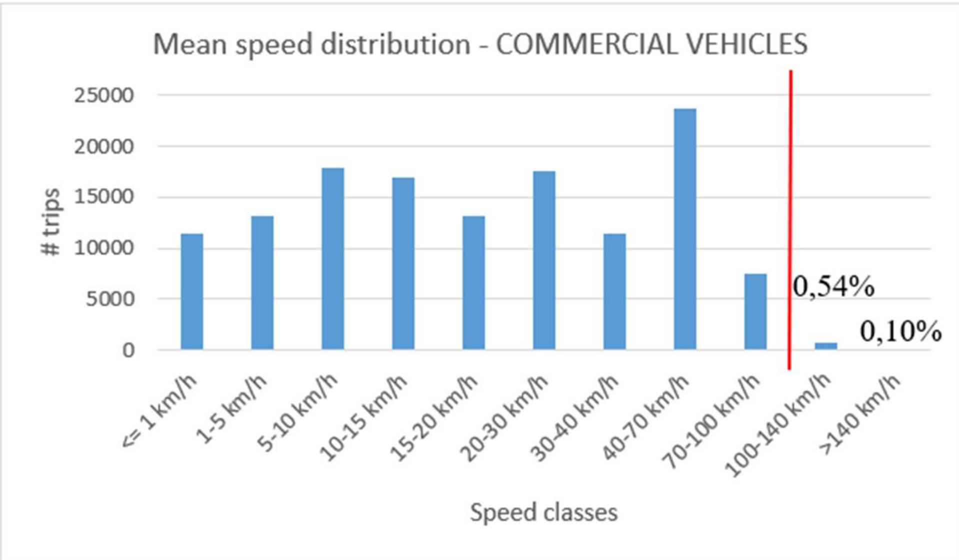


Figure 8. Mean speed distribution for LCVs.

3) According to the mean speed distribution of the dataset, 75.160 trips with a mean travelled speed higher than 70 km/h or lower-equal than 1 km/h were removed from the *private* dataset because they represented less than 3% of the total trips, and 1211 trips with a mean travelled speed higher than 100 km/h were removed from the *commercial* dataset because they represented less than 1% of the total trips. This process allows also to remove observations collected in a wrong way: according to the dataset some vehicles travelled more than 10.000 km in less than 15 minutes.

vehID	tripID	lat_O	long_O	datetime_O	event	lat_D	long_D	datetime_D	trip_duration	mean_speed	ip_ga	foll_event	distance_km	time_t	time_	gap	ed_cl
2748...	6600...	44.9519	7.71712	2019-11-04 14:11:02	2	-60.6007	-105.821	2019-11-04 15:10:02	0.983333	15697	8.5	1	15435.5	14	4	1	11
5029...	6629...	-3.21877	106.696	2019-11-13 12:23:04	2	45.04	6.8417	2019-11-13 12:37:51	0.246389	44806	16.35	1	11039.8	12	13	2	11
3137...	6627...	18.8256	129.527	2019-11-12 05:40:52	2	45.0696	7.70544	2019-11-12 06:10:16	0.49	22116	58.95	1	10837.1	5	12	6	11
4217...	6598...	27.8154	103.115	2019-11-03 11:22:11	2	44.7705	8.00874	2019-11-03 12:18:42	0.941944	8838	510....	1	8325.65	11	3	13	11
3317...	6683...	16.6416	-50.4707	2019-11-30 09:44:06	2	44.9885	7.14428	2019-11-30 10:10:08	0.433889	14313	10.6...	1	6210.37	9	30	2	11
3250...	6651...	12.8856	-29.7911	2019-11-20 07:44:48	2	45.0129	7.82397	2019-11-20 08:02:44	0.298889	16840	13.85	1	5033.54	7	20	2	11
2748...	6658...	45.0716	6.89395	2019-11-22 19:05:19	2	40.7924	-31.0615	2019-11-22 20:26:23	1.35111	2298	nan	1	3105.48	19	22	nan	11

Figure 9. Mean speed dataset errors.

For example, the circled trip in the previous figure (Python layout) has a very high probability to be an error due to the wrong data mining. According to the data collected, the vehicle travelled 11.039 km in less than 15 minutes. A brief research on google maps showed that the trip started in Turin and ended in Indonesia.

Figure 10. Example of error due to wrong data mining

It is reasonable to assume that the trip showed above and many others are data mining errors.

4) The travelled distance distribution was computed to understand how much distance is travelled by each vehicle for every trip.

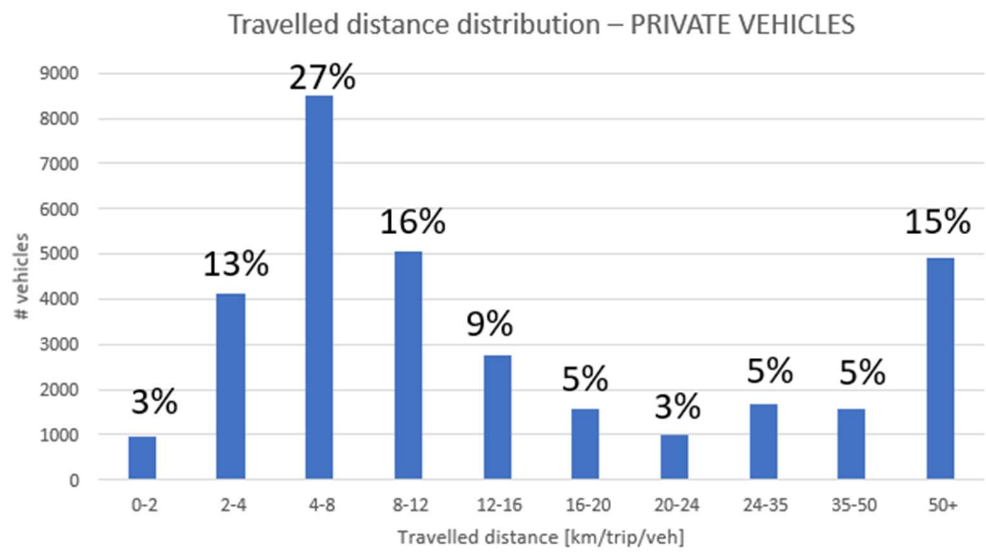


Figure 11. Travelled distance distribution for private vehicles.

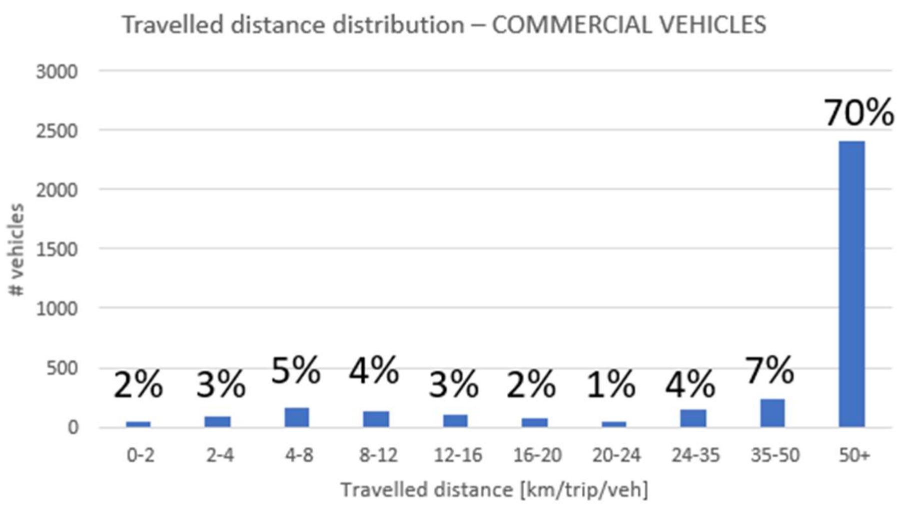


Figure 12. Travelled distance distribution for LCVs.

70% of the commercial vehicles travelled more than 50 kilometres in a single trip. Studying deeply the dataset and the data collected, trips in which the travelled distance might be considered unreal were found. 75 trips with a travelled distance higher equal than 1500 kilometres were removed from the commercial dataset. In some of these trips, the distance covered between the origin and the destination points was higher than 1M kilometres. For example, the vehicle 2751717 travelled 1.683.118 km in the trip 6676585347, in less than 1 hour. This must be an error linked to the data mining and collection.

vehID	tripID	datetime_O	lat_O	long_O	datetime_D	lat_D	long_D	T distance
2751717	6676585347	28/11/2019 16:17	45.239402	7.961088	28/11/2019 17:10	45.010038	7.570622	1683118
2746701	6665402395	25/11/2019 12:00	45.00635	7.672322	25/11/2019 12:15	44.977588	7.64136	917124
2751973	6676096876	28/11/2019 13:07	45.026625	7.853138	28/11/2019 14:04	44.975933	7.65891	855353
2748473	6675054836	27/11/2019 17:53	45.003208	8.943402	28/11/2019 07:15	44.942703	7.724942	842846
2748473	6670234886	26/11/2019 16:30	45.23259	7.591395	26/11/2019 18:15	45.495672	8.932382	842135

Figure 13. Errors linked to the travelled distance.

Moreover, all the trips with a travelled distance lower than 1 km (20.548 trips) were removed from the commercial dataset because they were considered not relevant to the aim of this work: the origin-destination matrices were built to be compared with 5T matrices that are based on macro-trips, therefore all the trips characterized by a travelled distance lower than 1 km were considered unnecessary to the aim of this work.

The datasets obtained after all the "cleaning" process were made by:

- PRIVATE VEHICLES: 2.781.850 trips, described by 18.996.568 observations;
- LIGHT COMMERCIAL VEHICLES: 117.093 trips, described by 2.640.898 observations.

5% of the trips were removed from the original dataset during this preliminary phase because they were considered errors, outliers, or not significant to the analysis.

It must be pointed out that in the private dataset, the distance travelled in almost 39% of the trips (1.076.935 trips) was lower than 1 km. Unlike to what was done in the commercial dataset, in which those trips were removed, in this case it was chosen not to drop them because many of them might be considered only a small part of a bigger trip. Therefore, according to the considerations made for LCVs, trips shorter than 1 km in the private dataset were removed in another phase.

The result from the preliminary study of the dataset showed that:

- 95% of the vehicles in the dataset were '*private vehicles*'; 5% of the vehicles in the dataset were '*light commercial vehicles'*;
- 88% of the total distance travelled by all the vehicles was travelled by '*private vehicles*'; 12% of the total distance travelled by all the vehicles was travelled by '*light commercial vehicles*';

Since the resizing/adaption to the universe had to be done according to 5T (company in Turin that works in transport sector) matrices, only the macro-trips were considered. Therefore, for the private dataset it was chosen to concatenate all the trips occurred in the same day with an interval of 15 minutes or less. On the other hand, trips made by light commercial vehicles were not modified or concatenated due to their minor amount in terms of *number of trips occurred over the day*.

Thus, the chapter below refers only to the private dataset and it describes how consecutive trips were concatenated and why.

2.3 Trips concatenation

5T in its matrices considers only the macro-trips occurring in a single day. The dataset provided by TIM analysed also all the micro-trips. In order to be able to compare and analyse the results with 5T matrices, some trips were joined to the following ones. Using the software Python, it was possible to concatenate consecutive trips, done by the same vehicle and occurred in the same day. A 15 minutes parameter was chosen to concatenate the trips. Most of the trips (32% of the total) occurred in an interval lower than 15 minutes:

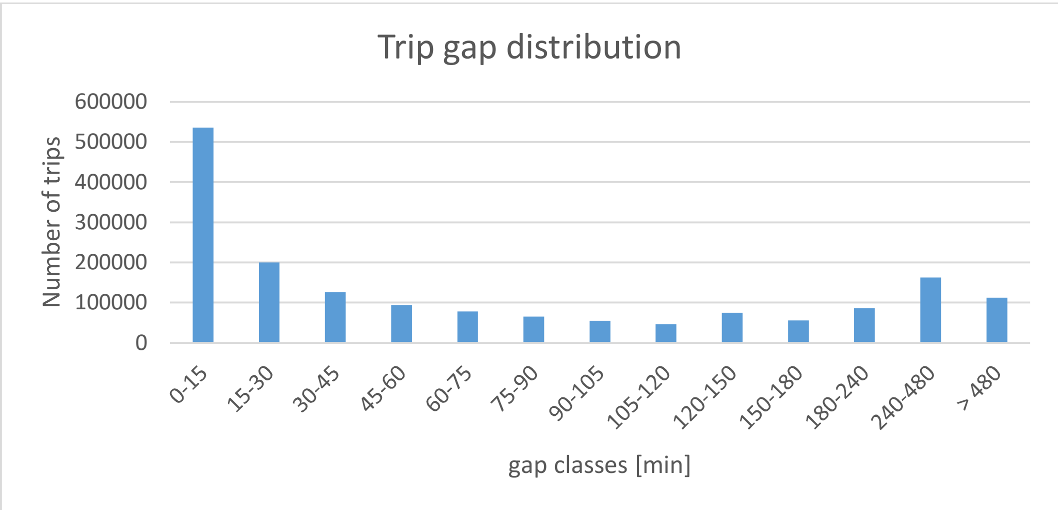


Figure 14. Trip gap distribution.

It is reasonable to assume that all the trips made between an interval lower than 15 minutes are micro-trips and not significant to the scope of this analysis. Therefore, the feature "event" was exploited to concatenate them. The code written in Python works as follow:

- If two consecutive trips have an interval higher than 15 minutes, nothing changes;
- If two consecutive trips have an interval lower or equal to 15 minutes, the same ID identifier of the first trip is assigned to the following one; thus, the feature *event* 1 (end of the trip) of the first trip becomes 9 (intermediate

detection), whereas the feature *event* 2 (beginning of the trip) of the second trip becomes 9;

- Even three or more consecutive trips may merge in one.

The example below is an extract of the dataset in which two consecutive trips have been concatenated. Since the interval between the trips was equal to 3 minutes, the second trip was joined to the first one.

The feature *TripID_real* replaced *tripID* for all the trips identifiers.

vehID	tripID_real	datetime	event	event_old
1203426	6605033821	05/11/2019 14:01	2	2
1203426	6605033821	05/11/2019 14:03	9	9
1203426	6605033821	05/11/2019 14:06	9	9
1203426	6605033821	05/11/2019 14:07	9	1
1203426	6605033821	05/11/2019 14:10	9	2
1203426	6605033821	05/11/2019 14:17	9	9
1203426	6605033821	05/11/2019 14:18	9	9
1203426	6605033821	05/11/2019 14:20	9	9
1203426	6605033821	05/11/2019 14:21	1	1

vehID	tripID	datetime	event
1203426	6605033821	05/11/2019 14:01	2
1203426	6605033821	05/11/2019 14:03	9
1203426	6605033821	05/11/2019 14:06	9
1203426	6605033821	05/11/2019 14:07	1
1203426	6605033831	05/11/2019 14:10	2
1203426	6605033831	05/11/2019 14:17	9
1203426	6605033831	05/11/2019 14:18	9
1203426	6605033831	05/11/2019 14:20	9
1203426	6605033831	05/11/2019 14:21	1

Figure 15. Example of concatenated trips.

Starting from 2.781.850 trips, running the algorithm in Python the total number of trips decreased to 2.003.402.

2.4 Trips evaluation

The cleaning process of the datasets continued after the trips were joined to each other. As it was done with the original data frame, the mean speed and the travelled distance were considered as filter:

- Private dataset:
  - trips with a mean speed lower-equal to 1 km/h or higher than 70 km/h were removed (9.762 trips);
  - trips with a travelled distance lower than 1 km were removed (305.356 trips);
- Commercial dataset:
  - Trips with a mean speed lower-equal to 1 km/h or higher than 100 km/h were removed (56 trips);
  - As already written, trips with a travelled distance lower than 1 km were removed (20.548 trips).

Since it was not indicated in which way the travelled distance provided by TIM was calculated, a new feature *distance* was assigned to each trip as the sum of all the intermediate positions collected during each trip. Knowing the latitude and the longitude it was possible to recreate the path followed by each vehicle in every trip, and then obtain the total distance travelled as the sum of the lines connecting all the points collected. Although the result obtained is an air-line distance made by different segments, it is reasonable to consider it very similar to the measured distance because all the points were provided every 2-5 minutes, hence the air-line distance can be compared with the distance provided by TIM:

$$
\begin{aligned}
&Distance = \\
&distance\ [point(2)\&point(9)] + distance\ [point_i(9)\&point_{i+1}(9)] + \cdots \\
&\qquad\qquad + distance\ [point_{i+n}(9)\&point(1)]
\end{aligned}
$$

The two distances were compared introducing the feature *deviation* defined as:

$$deviation = \frac{|measured\ distance - provided\ distance|}{measured\_distance} \cdot 100$$

In both private and commercial datasets, the *provided distance* was higher (more than 90% of the trips). In order to obtain a precise dataset to study, the deviation feature was exploited to clean once more the dataset from possible errors. The distribution of the deviation for every trip was calculated for the two datasets, and then it was used as a filter to remove possible errors.

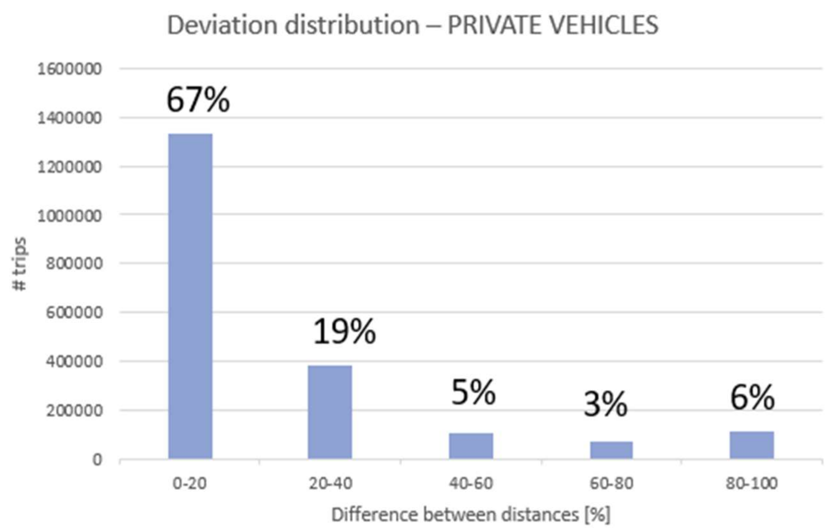


Figure 16. Deviation distribution for private vehicles.

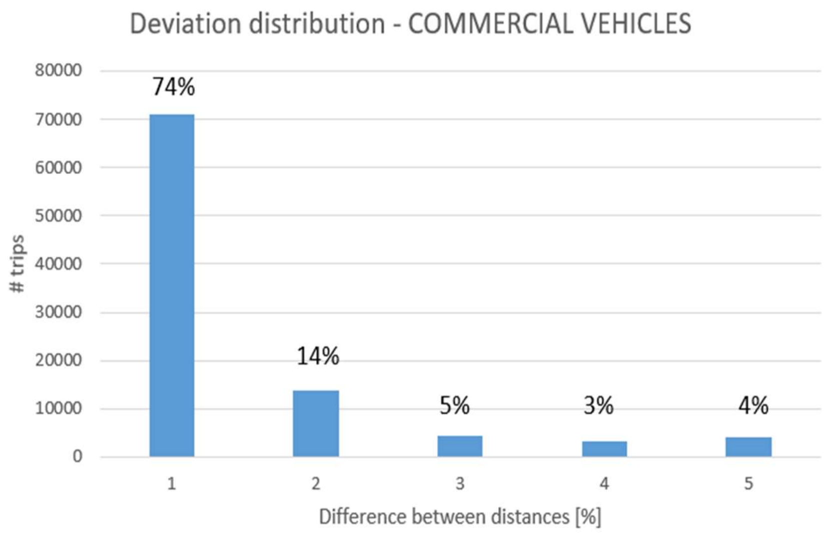


Figure 17. Deviation distribution for LCVs.

All the trips characterized by a deviation higher than 60% were removed:

- 65.288 trips in the private dataset;
- 7.398 trips in the commercial dataset.

The final datasets obtained were:

- PRIVATE DATASET: 1.623.106 trips;
- COMMERCIAL DATASET: 89.091 trips.

Although some of the merged trips, for private vehicles only, might be result in a journey having the origin point coincident to the destination point – e.g. the driver travelled from home to the cigarette shop, and after 10 minutes he drove again from the cigarette shop to home – they cannot be removed because they influence the flows. Moreover, the only issue related to them might be in the origin-destination matrices. However, since they would be treated as intrazonal trips, they would not affect the aim of this work that is focused on the interzonal trips.

At the end of the cleaning process, less than 40% of the trips were removed compared to the original TIM dataset. These trips were used to study the drivers' behaviours and habits. It must be pointed out that only 5,20 % of the trips are recorded by light commercial vehicles. However, the total distance travelled by LCVs is equal to 18,45 % of the total distance travelled by both commercial and private vehicles. Thus, it cannot be excluded from the analysis.

2.5 Data screening

All the trips recorded deal manly with Turin metropolitan area, but they also include external zones and cities, such as Milan, especially for LCVs records. Based on latitude and longitude, origin and destination zones were assigned to each trip. The zoning was provided by 5T and it is made by 356 zones.

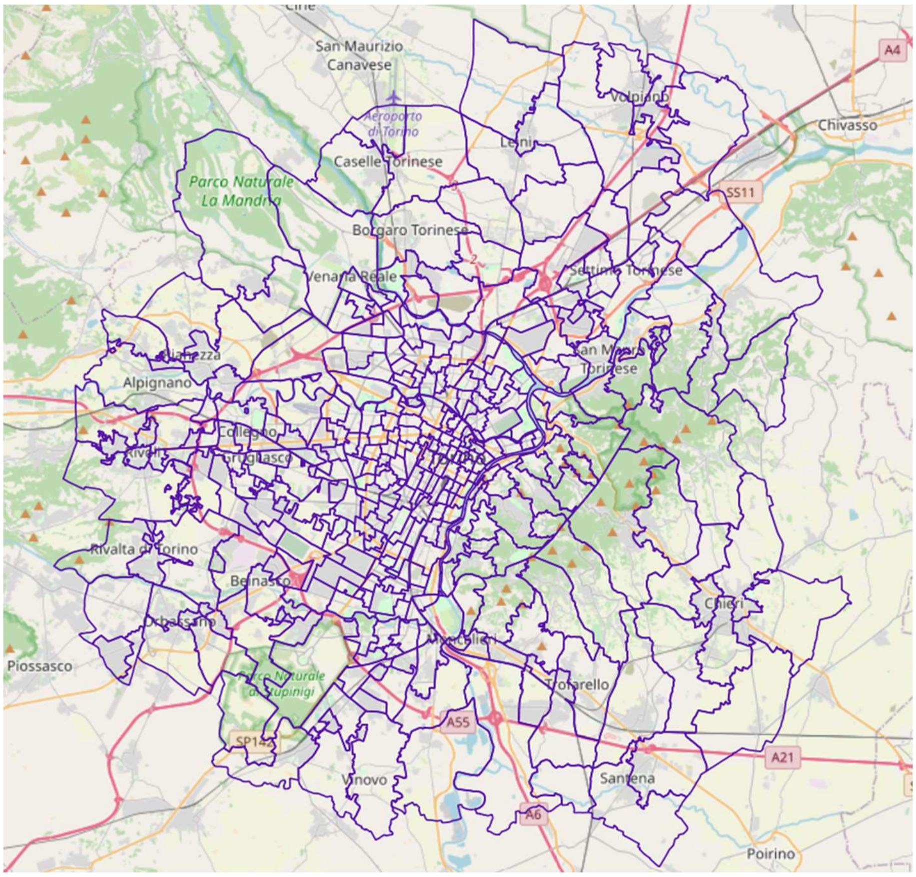


Figure 18. QGIS image representing the 5T zoning.

The zones outside the metropolitan area were indicated with the integer 0. Therefore, the total zones analysed were 357.

Data were grouped by type of day and types of trip. Three types of day were considered:

- *Weekdays*: trips occurred on Tuesdays, Wednesdays and Thursdays;
- *Saturdays:* trips occurred on Saturdays;
- *Sundays*: trips occurred on Sundays.

For each of the three day-types, three macro-trip-types were considered:

- *Internal trips:* trips in which both Origin and Destination fell inside the Turin metropolitan area;
- *Crossing trips*: trips in which both Origin and Destination did not fall inside the Turin metropolitan area, but the vehicle travelled inside it;
- *External trips*: trips in which or the Origin or the Destination fell inside the Turin metropolitan area.

305.662 trips out of 1.712.197 total trips (18%) occurred outside the Turin metropolitan area. Therefore, they haven't been processed. Crossing total trips were 16.920. Due to this low number, it was chosen to process all the crossing trips regardless the fact they were made by private or light commercial vehicles (82% by private vehicles, 18% by LCVs).

However, 18% of the total trips recorded (trips occurred outside the study area) is a significant number, which suggests that most of the people do not actually live in the metropolitan area. Very likely, most of the owners of the vehicles belonging to the dataset live and surely work outside the study area.

This disaggregation aimed to get precise information about the mobility patterns for private and commercial vehicles. Daily individual statistics were averaged over the entire observation period, separating weekdays from Saturdays and Sundays to limit the effect of the trips performed by commuters.

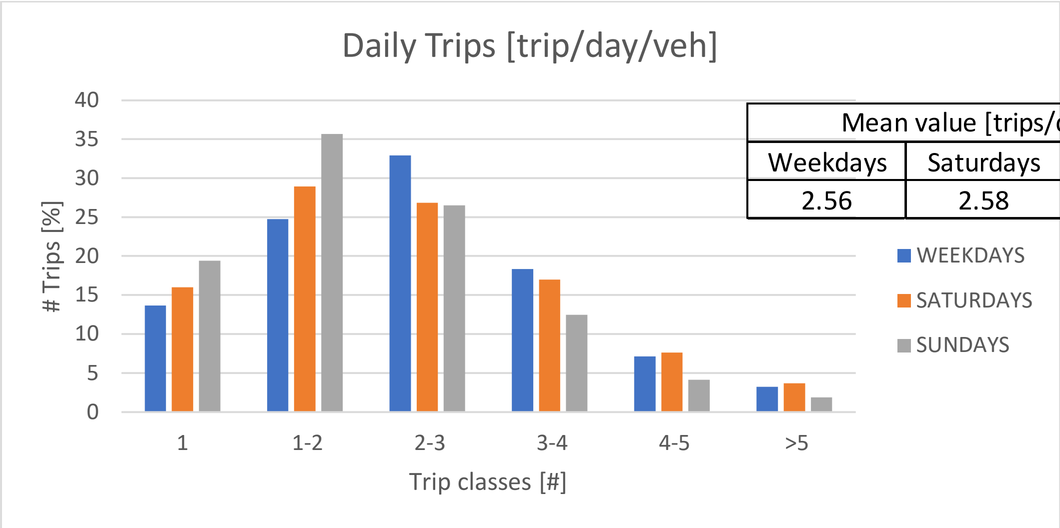
Quantities analysed and plotted have been:

- Mean number of trips: mean number of trips in a single day-type;
- Daily trips: trips done per day by each vehicle;
- Travelled distance per trip: distance travelled per trip by each vehicle;
- Daily travelled distance: total distance travelled per day by each vehicle;
- Travel time per trip: time spent travelling per trip by each vehicle;
- Daily travel time: total time spent travelling per day by each vehicle;
- Mean speed per trip: mean speed per trip travelled by each vehicle;
- Idle time: idle time between consecutive trips occurred in the same day.

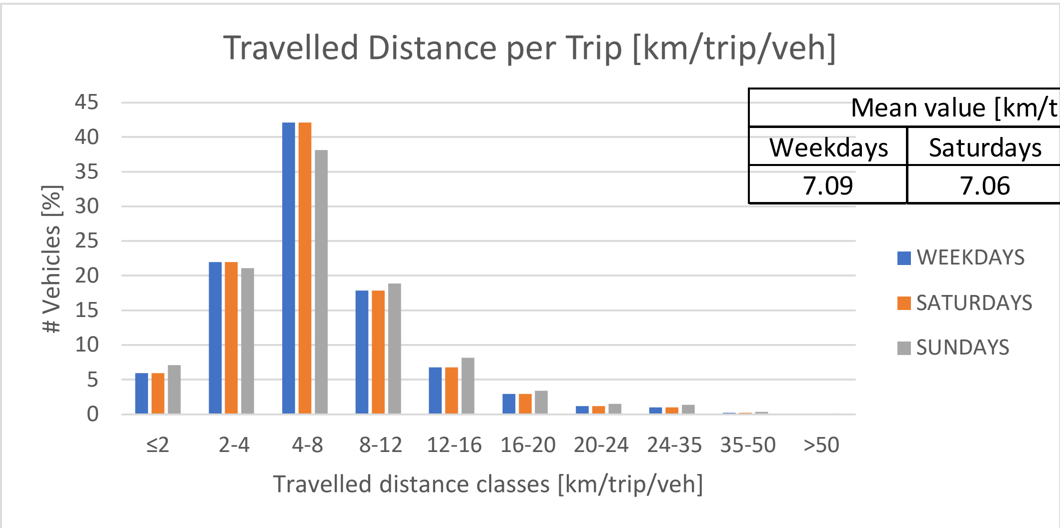
To make the plots as much clear as possible, the results of the analysis were plotted comparing in each graph the three day-type. Nevertheless, the parting between the trip-type was kept. Class intervals in the plots are the same for both private and light commercial vehicles. Although trips made by light commercial vehicles are longer than the ones made by private vehicles, the intervals were not changed to allow a fast comparison between the two types of vehicles. Moreover, as already indicated, trips made by light commercial vehicles are few compared to the private ones, in terms of absolute numbers.

The results are shown in three different groups (internal trips, external trips, crossing trips). To facilitate the analysis and the comprehension of the results, bar graphs were used to plot all the data. Percentage quantities are represented to easy compare quantities among the days considered. As an example, in the next pages only the results obtained for the private dataset and for the trips occurred inside the study area (internal trips) are represented. All the other graphs and results can be found in appendix A. Due to the low number of crossing trips, bar graphs are provided only for internal and external trips.

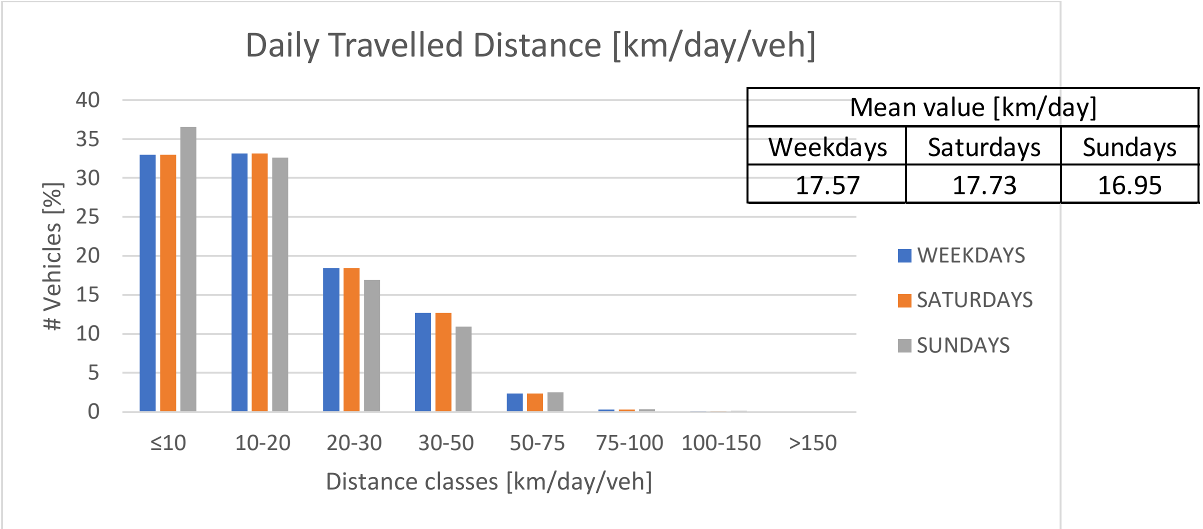
Mean number of total trips		
WEEKDAYS	SATURDAYS	SUNDAYS
34498	28224	20254

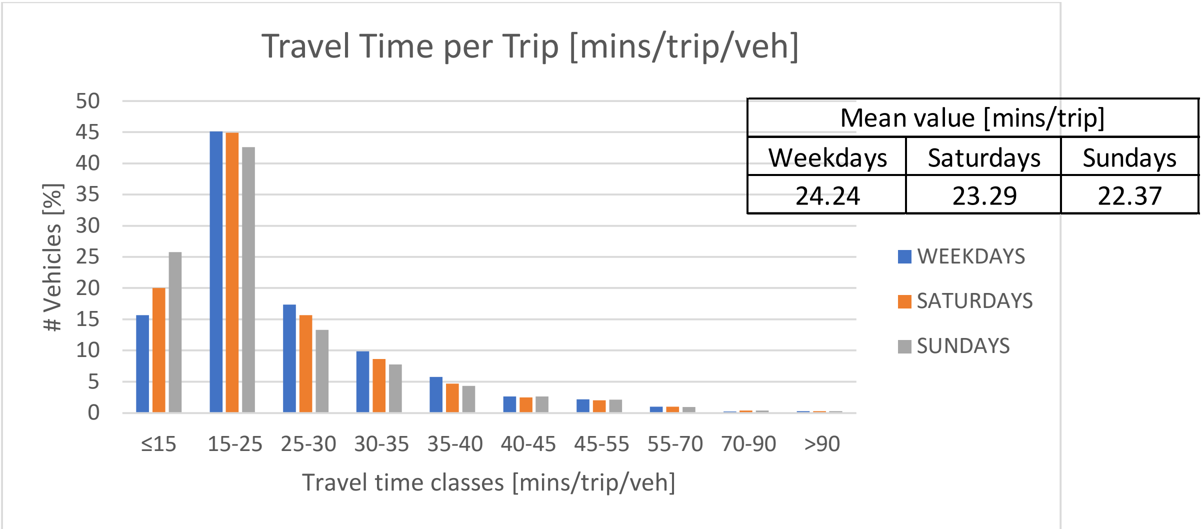


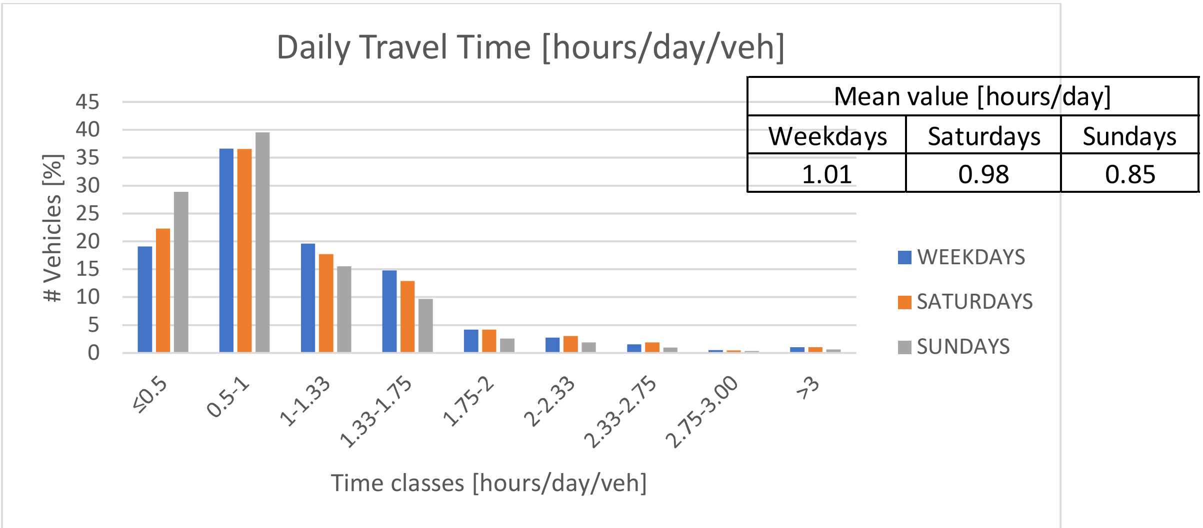
Mean value [trips/day]		
Weekdays	Saturdays	Sundays
2.56	2.58	2.32

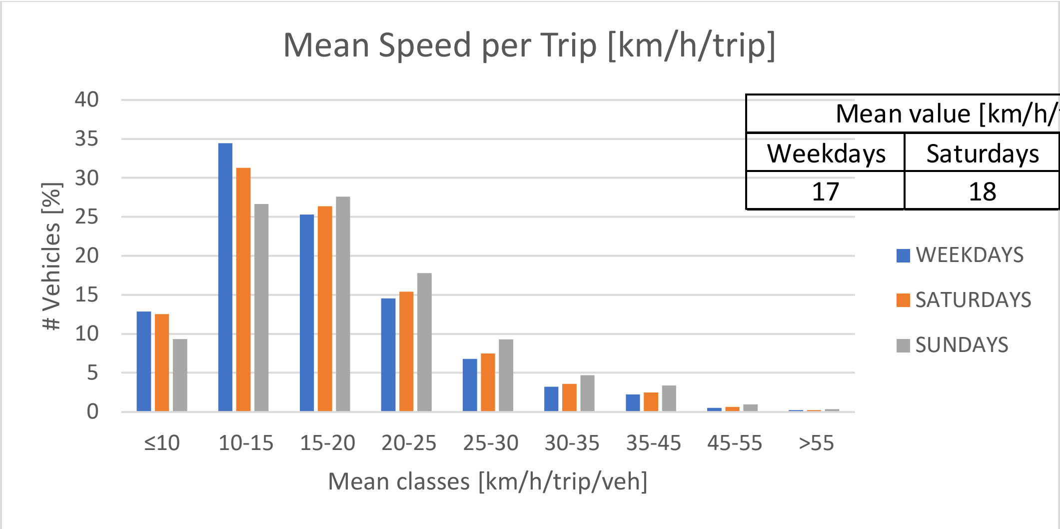


Mean value [km/trip]		
Weekdays	Saturdays	Sundays
7.09	7.06	7.45

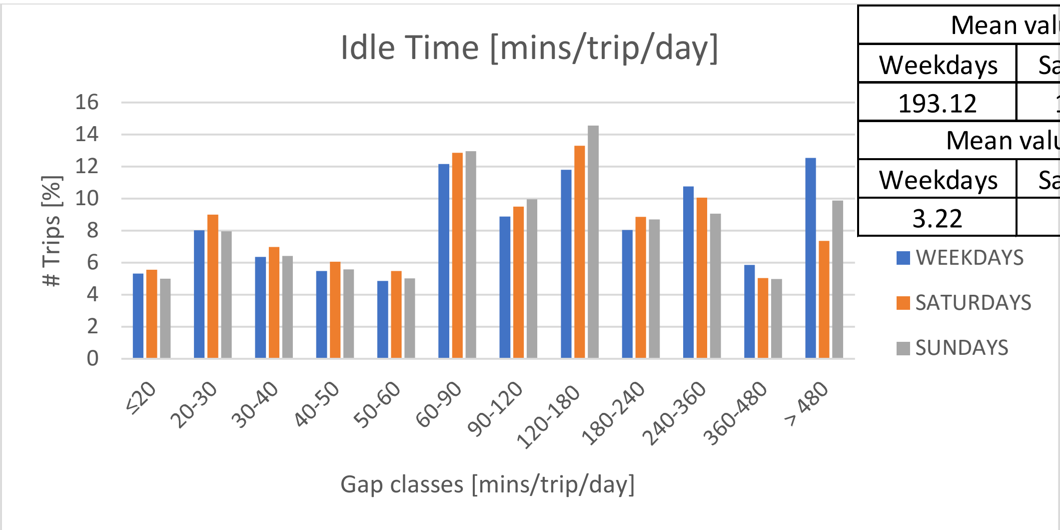

Daily Travelled Distance [km/day/veh]
Mean value [km/day]
Weekdays
Saturdays
Sundays
17.57
17.73
16.95
Vehicles [%]
40
35
30
25
20
15
10
5
0
≤10
10-20
20-30
30-50
50-75
75-100
100-150
>150
Distance classes [km/day/veh]
WEEKDAYS
SATURDAYS
SUNDAYS


Travel Time per Trip [mins/trip/veh]
Mean value [mins/trip]
Weekdays
Saturdays
Sundays
24.24
23.29
22.37
Vehicles [%]
50
45
40
35
30
25
20
15
10
5
0
≤15
15-25
25-30
30-35
35-40
40-45
45-55
55-70
70-90
>90
Travel time classes [mins/trip/veh]
WEEKDAYS
SATURDAYS
SUNDAYS


Daily Travel Time [hours/day/veh]
Mean value [hours/day]
Weekdays
Saturdays
Sundays
1.01
0.98
0.85
Vehicles [%]
45
40
35
30
25
20
15
10
5
0
≤0.5
0.5-1
1-1.33
1.33-1.75
1.75-2
2-2.33
2.33-2.75
2.75-3.00
>3
Time classes [hours/day/veh]
WEEKDAYS
SATURDAYS
SUNDAYS



Mean value [km/h/trip]		
Weekdays	Saturdays	Sundays
17	18	19



Mean value [mins/trip]		
Weekdays	Saturdays	Sundays
193.12	168.44	186.45
Mean value [hours/trip]		
Weekdays	Saturdays	Sundays
3.22	2.81	3.11

Figure 19. Bar graphs for internal trips (private vehicles).

2.5.1 Private vehicles

The private dataset was made by trips recorded by 30.369 vehicles. The table below shows the mean values obtained for each type of trip for the three days analysed. Private and commercial crossing trips have been studied jointly and they are represented in chapter 2.5.3.

PRIVATE VEHICLES						
Mean Values						
	Internal Trips			External Trips		
	Weekdays	Saturdays	Sundays	Weekdays	Saturdays	Sundays
Mean Number of Trips [#]	34498	28224	20254	8632	7347	6067
Daily Trips [trips/day]	2.56	2.58	2.32	1.88	1.8	1.75
Travelled Distance per Trip [km/trip]	7.09	7.06	7.45	31.5	31.48	34.04
Daily Travelled Distance [km/day]	17.57	17.73	16.95	53.22	50.99	54.02
Travel Time per Trip [mins/trip]	24.24	23.29	22.37	47.13	45.84	46.18
Daily Travel Time [hours/day]	1.01	0.98	0.85	1.38	1.28	1.26
Mean Speed per Trip [km/h/trip]	17	18	19	38	40	42
Idle Time [hours/trip/day]	3.22	2.81	3.11	5.06	3.69	3.92

Table 3. Mean values obtained for Private Vehicles.

As it could be expected, most of the trips occurred are categorized as internal trips. Since the dataset referred to a group of people living in the Turin metropolitan area, it was predictable. In terms of numbers, external trips are only the 15% of the total trips.

Overall, weekdays are the busiest days, followed by Saturdays and Sundays. This could be justified by the fact that many Italians tend to spend weekends at home with their families. For example, the number of trips occurred on a typical weekly day is almost 30% higher than Saturdays trips, and more than 50% higher than Sunday trips.

In terms of daily trips, the trend is very similar in all the three categories of trips: daily trips performed during weekdays, Saturdays and Sundays of the same category are comparable. It can be noticed that the fewest number of daily trips occurred for external trips. This result can be explained looking at distances and times: external trips are longer than all the others. Travelling more than 50 kilometres in a single day may justify this result. The smallest distances and the shortest times are travelled and spent for the internal trips. Traffic congestion and busy roads may act as deterrent to force drivers to travel less.

Mean speed increases proportionally to the reduction of congestion. In fact, vehicles travelled faster during weekends. The highest speeds were recorded for external trips.

Interesting results concern the idle times. Overall, the highest temporal gap between two consecutive trips happen on weekdays, probably linked to job duties. Concerning external trips, 30% of the vehicles made one trip every 8+ hours on weekdays. This result is perfectly in line with the results obtained for the travelled distances because people usually make long trips to reach far destinations, and as they park the vehicle, they tend to spend profitable time there. Therefore, it is reasonable to have such big idle times.

2.5.2 Light commercial vehicles

The commercial dataset was made by trips recorded by 3.398 vehicles. The table below shows the mean values obtained for each type of trips for the two days analysed. As already argued, private and commercial crossing trips have been studied jointly and they are represented in chapter 2.5.3.

COMMERCIAL VEHICLES						
Mean Values						
	Internal Trips			External Trips		
	Weekdays	Saturdays	Sundays	Weekdays	Saturdays	Sundays
Mean Number of Trips [#]	1957	853	371	1049	296	153
Daily Trips [trips/day]	2.68	2.91	2.43	1.92	1.72	1.68
Travelled Distance per Trip [km/trip]	13.23	9.72	7.82	100.16	84.68	99.18
Daily Travelled Distance [km/day]	28.71	25.17	18.54	182.51	127.42	134.3
Travel Time per Trip [mins/trip]	31.46	26.77	20.86	101.66	82.62	46.18
Daily Travel Time [hours/day]	1.21	1.18	0.8	3.1	2.11	2.39
Mean Speed per Trip [km/h/trip]	25	23	23	56	57	57
Idle Time [hours/trip/day]	1.65	1.66	2.30	3.25	2.70	3.35

Table 4. Mean values obtained for LCVs.

As it was for the private datasets, the largest number of trips occurred for internal trips. The proportion of trips made for each day is approximately the same for each category. Weekdays are the most travelled followed by Saturdays and Sundays.

Travelled distances and travel times for internal trips are by far lower than distances and times obtained for external trips. Despite this, internal trips involved more daily trips: almost 3 per days for trips occurred on weekdays.

As already pointed out for private vehicles, mean speeds are higher for external trips, probably due to the minor impact of congestion on extra urban roads. Outside the study area, vehicles travel twice as fast as they do inside the study area.

Overall, idle times for external trips are almost double compared to internal trips. It seems that light commercial vehicles that made internal trips tended to spend less time parked than vehicles that made external trips. However, in both trips categories idle times are much shorter than private vehicles. This can be justified by the fact that many light commercial vehicles may include delivery vans.

A strange value obtained from the analysis concerns the travel time per trips for external trips on Sundays. Although the mean daily travel time is 2.39 hours, results shows that the mean travel time per trip is only 46,18 minutes with a mean value of daily trips per vehicle equal to 1,68. However, commercial dataset is too small to be considered very reliable. In this work results about LCVs were given just to have an overall viewpoint of the difference between trips made by privates and commercials. Therefore, even though results for both datasets are reliable according to the analysis conducted, data obtained for light commercial vehicles may not reflect the universe behaviour due to the small amount of records provided.

To improve the analysis for commercial vehicles, more data would be needed. To have a better understanding of the differences between private and commercial vehicles, the same number of vehicles for both categories should be analysed. Moreover, information about commercial vehicles were not provided. It was not possible to label these vehicles considering the aim of the trips; e.g. delivery vans trips are surely different from passenger carrier vehicles trips.

2.5.3 Crossing trips

Crossing trips involved both private and commercial trips. Although only 16.920 trips (only 1,20% of the entire dataset) cross the study area, they were analysed and represented to give a complete viewpoint of the statistics about everything that potentially can influence the mobility inside the study area.

	Crossing Trips		
	Weekdays	Saturdays	Sundays
Mean Number of Trips [#]	934	681	578
Daily Trips [trips/day]	1.22	1.21	1.24
Travelled Distance per Trip [km/trip]	75.79	53.29	46.93
Daily Travelled Distance [km/day]	89.48	61.56	55.68
Travel Time per Trip [mins/trip]	92.94	75.39	64.89
Daily Travel Time [hours/day]	1.82	1.44	1.28
Mean Speed per Trip [km/h/trip]	43	40	40
Idle Time [hours/trip/day]	4.80	4.00	4.58

Table 5. Crossing trips (both private and commercial vehicles).

Overall, there is not such difference between the three types of day. As it happened for internal and external trips, weekdays are the most congested and busiest. Moreover, on weekdays vehicles travel more both in terms of time and distance. Travelled distances and travel times recorded are quite similar between trips occurring on Saturdays and Sundays. Concerning the mean speed values, it is almost the same in all the three type of days, around 40 km/h.

2.6 Zoning and Origin – Destination Matrices

A zoning system is used to aggregate the individual user and premises into manageable chunk for modelling purpose. The main two dimensions of a zoning system are the number of zones and their size. The greater the number of zones is, the smaller they can be to cover the same study area. Zones are represented in the computer models as if all their attributes and properties were concentrated in a single point called *zone centroid*. This notional spot is best thought of as floating space and not physically on any location on a map. Centroids are attached to the network through *centroid connectors* representing the average costs (time, distance) of joining the transport system for trips with origin or destination in that zone. Some of the zoning criteria concern that:

- zoning size must be such that the aggregation error caused by the assumption that all activities are concentrated at the centroid is not too large. It might be convenient to start postulating a system with many small zones, as this may be aggregated in various ways later depending on the nature of the projects to be evaluated.
- the zoning system must be compatible with other administrative divisions, particularly with census zones; this is probably the fundamental criterion and the rest should be followed if they do not lead to inconsistencies with it.
- Zones should be as homogeneous as possible in their land use and/or population composition; census zones with clear differences in this respect (i.e. residential sectors with vastly different income levels) should not be aggregated, even if they are very small.
- Zone boundaries must be compatible with cordons and screen lines and with those of previous zoning systems. However, it has been found in practice that the use of main roads as zone boundaries should be avoided, because this increases considerably the difficulty of assigning trips to zones, when these originate or end at the boundary between two or more zones.
- The shape of the zones should allow an easy determination of their centroid connectors; this is particularly important for later estimation of intra-zonal characteristics. A zone should represent the natural catchment area of the

transport networks and its centroid connector(s) identifies so as to represent the average costs to access them.

- Zones do not have to be of equal size; if anything, they could be of similar dimensions in travel time units, therefore generating smaller zones in congested than in uncongested areas.

(*Source: Juan de Dios Ortuzar – Modelling Transport*)

Zoning can be assumed as a simplified representation of the reality that can be used to understand how people influence the system. In transport planning subject, the main inputs to study people's influence are the trips made by each city user during the day. Knowing the number of trips produced and attracted by each zone, it is possible to make the Origin-Destination matrices.

2.6.1 5T zoning

As already discussed in chapter 2.5, 5T provided the zoning for the city of Turin and its metropolitan area, made by 356 zones:

- 183 zones represent the *City of Turin*;
- 173 zones represent neighbourhoods and municipalities outside the City of Turin.

The study area covers a surface of 636,42 km^2 inhabited by 1.427.361 people. The smallest zones are in the City Centre, placed between the two main railway stations of *Porta Nuova* and *Porta Susa*, whereas the largest ones are out of the border of the City, more specifically at the border of the study area. Overall, the 173 zones representing the municipalities outside the city of Turin area are bigger than the others. In terms of surface, the smallest zone is about 0,040 km^2 wide, the largest zone is about 28,126 km^2 wide.

Municipalities included in the metropolitan area are:

Municipality	Area [km^2]	Inhabitants	Municipality	Area [km^2]	Inhabitants	Municipality	Area [km^2]	Inhabitants
Alpignano	12.0	16683	Druento	27.7	8940	Pianezza	16.5	15504
Baldissero Torinese	15.5	3653	Grugliasco	13.1	37466	Pino Torinese	21.9	8388
Beinasco	6.8	17687	Leini	31.9	16433	Rivalta di Torino	25.3	20278
Borgaro Torinese	11.2	11891	Mappano	9.7	7446	Rivoli	29.5	48315
Cambiano	14.2	5955	Moncalieri	47.0	57170	San Mauro Torinese	12.0	18744
Caselle Torinese	23.6	13963	Nichelino	20.6	47327	Settimo Torinese	31.5	46691
Chieri	54.3	36470	Orbassano	22.1	23278	Torino	130.2	867620
Collegno	18.1	49432	Pecetto Torinese	9.2	4103	Trofarello	12.3	10790
						Venaria Reale	20.3	33134

Table 6. Turin Metropolitan Area Municipalities.

2.6.2. OD Matrices

Using the software Python, origin-destination matrices were obtained from the private and commercial sub datasets. The first step was to join, as in the original sample, all the trips made in one dataset. Then, according to the starting zone and the ending zone of each trip, 24 hourly matrices for each type of day analysed (weekday, Saturday, Sunday) were obtained, dividing the total number of trips between zones by the number of days considered belonging to the type of day:

- Weekdays: 12 days;
- Saturdays: 5 days;
- Sundays: 4 days.

The result of each cell was rounded up.

Therefore, 72 matrices made by 357 rows and 357 columns (356 zones belonging to the study area and one zone concerning all the points not belonging to the study area) were obtained. The hourly matrices are based on the departure time, hence if a vehicle left at 13.30 and ended the trip at 14.30, it was included in 13-14 matrix.

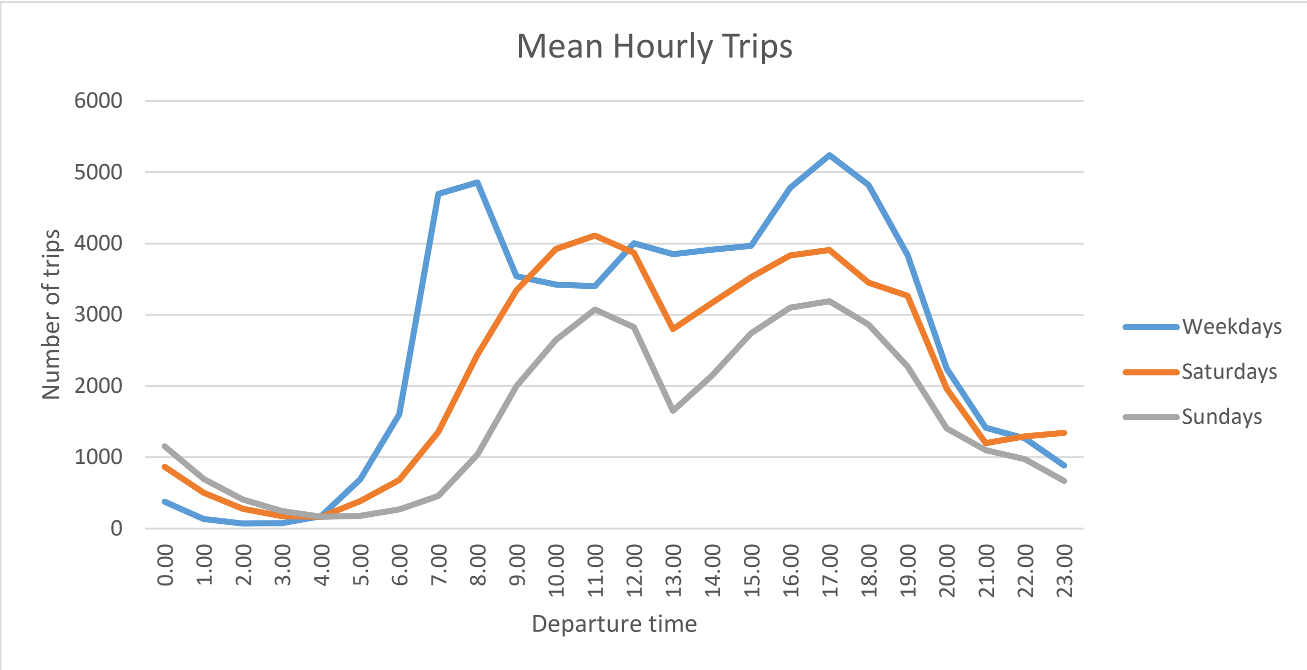


Figure 20. Mean hourly trips distribution.

Looking at the hourly distribution of the trips it is possible to notice the peak-hours during the day:

- Weekdays: the morning peak-hour is between 07.00 and 09.00; the evening peak-hour is between 16.00 and 19.00. According to the data, the largest number of trips recorded is in the evening peak (5.242 is the maximum number of trips between 17.00 and 18.00).
- Saturdays: the morning peak-hour is shifted to the right and it occurs between 10.00 and 13.00 but it is less important than the peak acquired for weekdays. Even though from 13.00 to 20.00 the variation of the number of trips is not so significant, it is possible to define an evening peak hour between 16.00 and 18.00 (4.114 is the maximum number of trips between 11.00 and 12.00).

- Sundays: it is very similar to the Saturdays trend. However, the number of trips is significantly smaller than the others. 3.194 is the largest number of trips recorded between 17.00 and 18.00.

Interesting data are the ones related to night trips. Usually for most of the people, weekends are the days off. For this reason, many of them usually spend their leisure time out until late at night. This is detectable from the hourly trips distribution where the number of trips recorded at night for the weekdays are significantly lower than the trips occurred in the same hours recorded on Saturdays and Sundays.

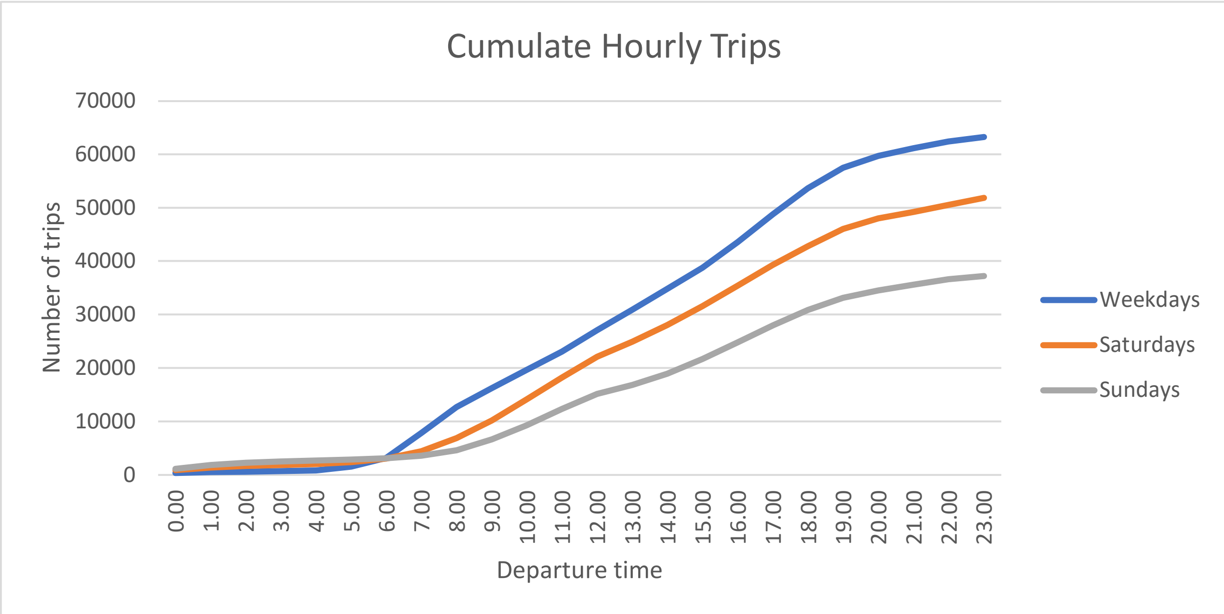


Figure 21. Cumulate hourly trips.

As it can be seen from the cumulate hourly trips graph, the slope of the curve is maximum during the peak-hours. In support of what exposed above about night trips, the cumulate curve for Saturdays and Sundays stand higher than weekdays curve until morning hours.

Due to the large number of zones belonging to the study area, showing all the matrices was assumed to be chaotic and unclear, hence it was voluntarily chosen not to present the 72 matrices in this thesis. As a demonstration of what was done, the following figures graphically represent the trips produced and attracted by each zone. All the graphs refer to trips recorded during weekdays. Three times of the day were chosen to be represented: morning peak-hour (08.00-09.00), evening peak-hour (17.00-18.00), and evening off-peak-hour (21.00-22.00). To better understand and study trips between zones, intrazonal trips haven't been considered.

- Morning Peak-Hour (08.00).

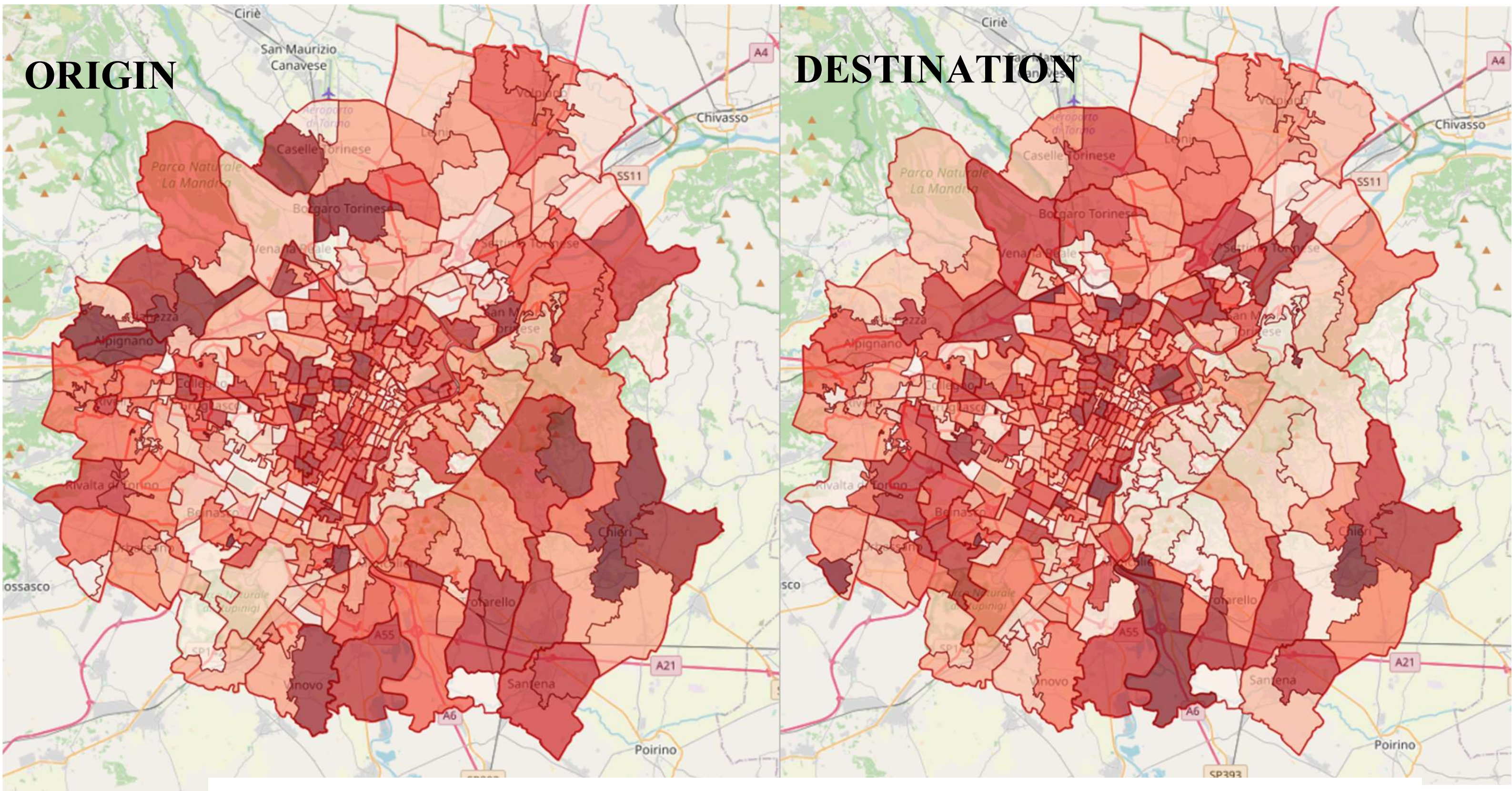


Figure 22. Mean number of trips produced (left) and attracted (right) during morning peak-hour.

Overall, the busiest zones are the ones placed in the city centre and at the border of the study area. Chieri municipality is surely the busiest with a total number of produced trips equal to 43, and a total number of attracted trips equal to 41. However, according to the dataset, during the morning peak most of the people move towards the area placed around the city centre. This is clear looking at the different number of trips produced and attracted by those zones: attracted trips are significantly higher than produced ones. Although some zones in the City centre get busier during the morning peak, they are not as much congested as the suburban areas. Noteworthy fact concerns all the area around Mirafiori that is almost empty of produced trips, but extremely brim-full of attracted trips, confirming its importance in Turin business and as jobs provider. South-East and North directions are the most congested.

- Evening Peak Hour (17.00).

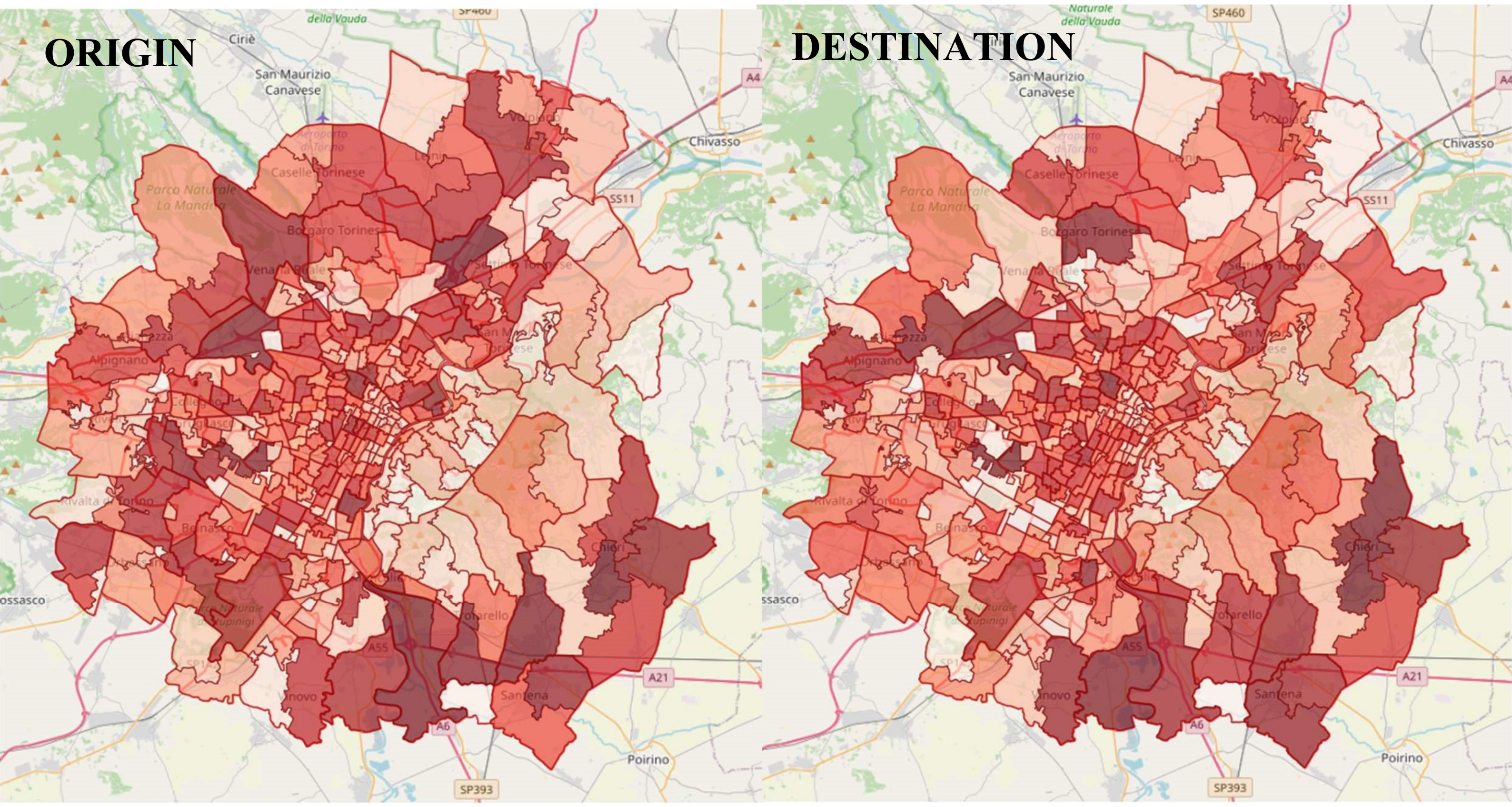


Figure 23. Mean number of trips produced (left) and attracted (right) during evening peak-hour.

For the evening peak, the results are almost mirrored compared to the matrix 08.00-09.00. This means that most of the trips are linked to job activities and people leave home in the morning to come back in the evening. Even though intrazonal trips haven't been considered in these representations, many of the suburban zones maintain a constant number of trips, hence most of the vehicles of the dataset belonged to people living in the suburban area of Turin. However, it is also reasonable to find such a vast number of trips for those zones, since they are dramatically bigger compared to the zones around the city centre. Considering Chieri municipality for example, its zones (6-7 zones) are more than one third of all the city of Turin area.

- Evening Off-Peak-Hour (21.00).

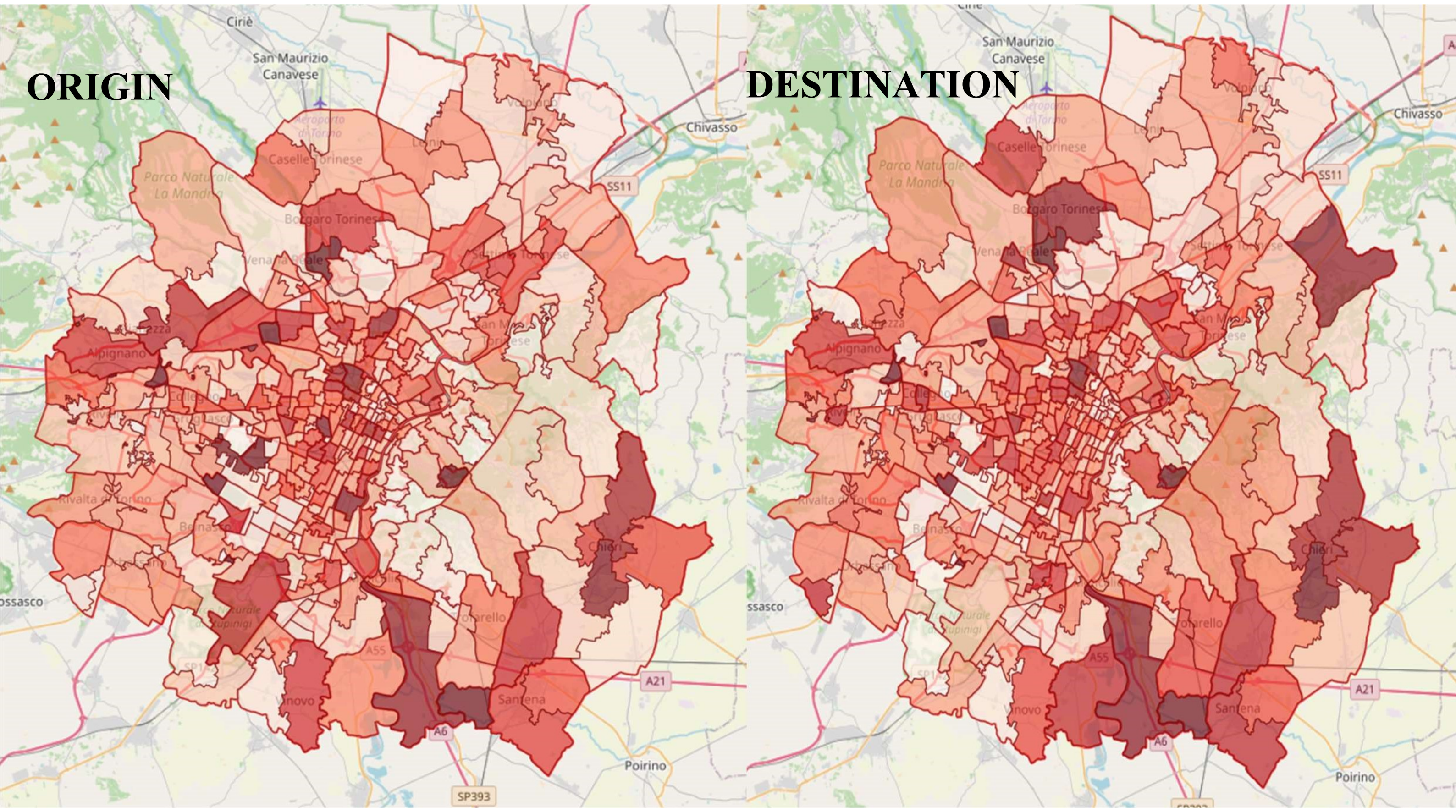


Figure 24. Mean number of trips produced (left) and attracted (right) during evening off-peak-hour.

Also for the off-peak-hour, the border zones are the busiest but with a significant low number of trips. As already argued, these results strengthen the fact that is reasonable to assume that most of the people, from whom records were taken, live at the border of the study area. This is perfectly in line with the results related to the external and crossing trips. It is likely to assume that if people did not live so far from the centre of the study area, trips towards external areas would have been less.

Chapter 3: Sample resizing to the universe

The Origin-Destination matrices obtained referred to the sample provided by TIM, that contained data recorded by little more than 35.000 vehicles. Therefore, they should be resized to the universe (reality) to be purposeful. To adapt the matrices to real mobility in Turin, 5T matrices were studied and analysed. 5T provided daily matrices for the three day-types (Weekdays, Saturdays, Sundays). Its matrices are representative of the mean trips occurring in Turin metropolitan area throughout the day.

3.1 Trips weights

In order to expand the size of the FCD matrices to the size of the universe, trips attracted and produced in each zone, obtained from the FCD analysis, must be compared with the trips produced and attracted in the same zones referring to 5T matrices. Hence, the first step was to sum all the hourly matrices to obtain the three day-type daily matrices. 24 hourly matrices for each day-type were transformed into one and only matrix: one daily matrix per day-type. Using the software Python, the ratios/weights between 5T and FCD produced trips - and the same for the attracted trips - were acquired:

$$Weight = \frac{5T_{trips}}{FCD_{trips}}$$

Those weights are function of the zone and the day considered. Knowing the weights, it is possible to size the matrices to the universe: the total number of daily trips attracted and/or produced by each zone can be obtained multiplying the trips and the related weight.

For example, the total number of trips attracted by zone 12 (destination) will be equal to:

$$trips(12 = D)_{universe} = weight(12) \cdot trips(12 = D)_{FCD}$$

Where:

- 12 is the destination (zone);
- Weight(12) is the weight referred to zone 12 obtained as the ratio between 5T trips attracted in that zone (12), and FCD trips attracted in the same zone.

Zone	Trips_D_5T	Trips_D_FCD	Weight	Trips_D_Universe
12	18752	2983	6.29	18752
13	90	15	6.00	90
14	7465	849	8.79	7465
15	9419	1002	9.40	9419
28	3059	977	3.13	3059
29	447	110	4.06	447
38	7044	1856	3.80	7044
39	5798	808	7.18	5798
40	14146	1605	8.81	14146
41	1955	46	42.50	1955
42	6727	1773	3.79	6727

Table 7. Example of trips resizing on weekday.

The same method was adopted for the origins (productions).

Since it wasn’t possible to get the number of vehicles produced/attracted by and from every zone, it was assumed that the *weight* referred to the trips was equal to the weight referred to the vehicles. Therefore, if the weight assigned to one zone is x, the generic vehicle leaving and/or arriving in that same zone represent a number of vehicles equal to the weight assigned to the zone (x). Knowing the number of vehicles representative of the reality can make possible to understand how many vehicles start and/or end their trips in each zone belonging to Turin metropolitan area. The total number of vehicles has been used in chapter 5 to estimate and forecast the energy consumption of the future circulating EVs.

Similarly to what was done in chapter 2.6.2, the following figures graphically represent the daily matrices, resized to the universe.

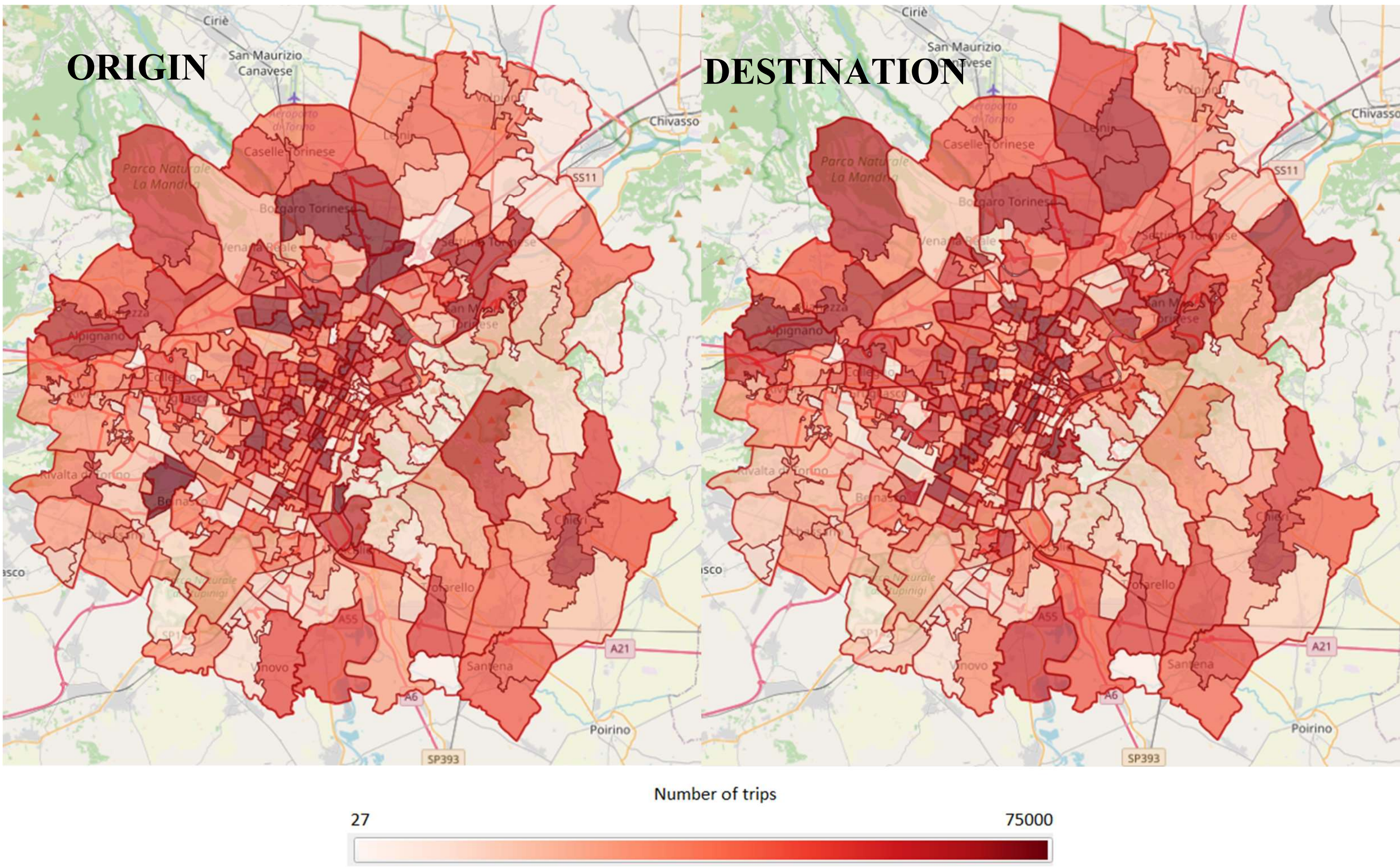


Figure 25. Weekdays daily matrix.

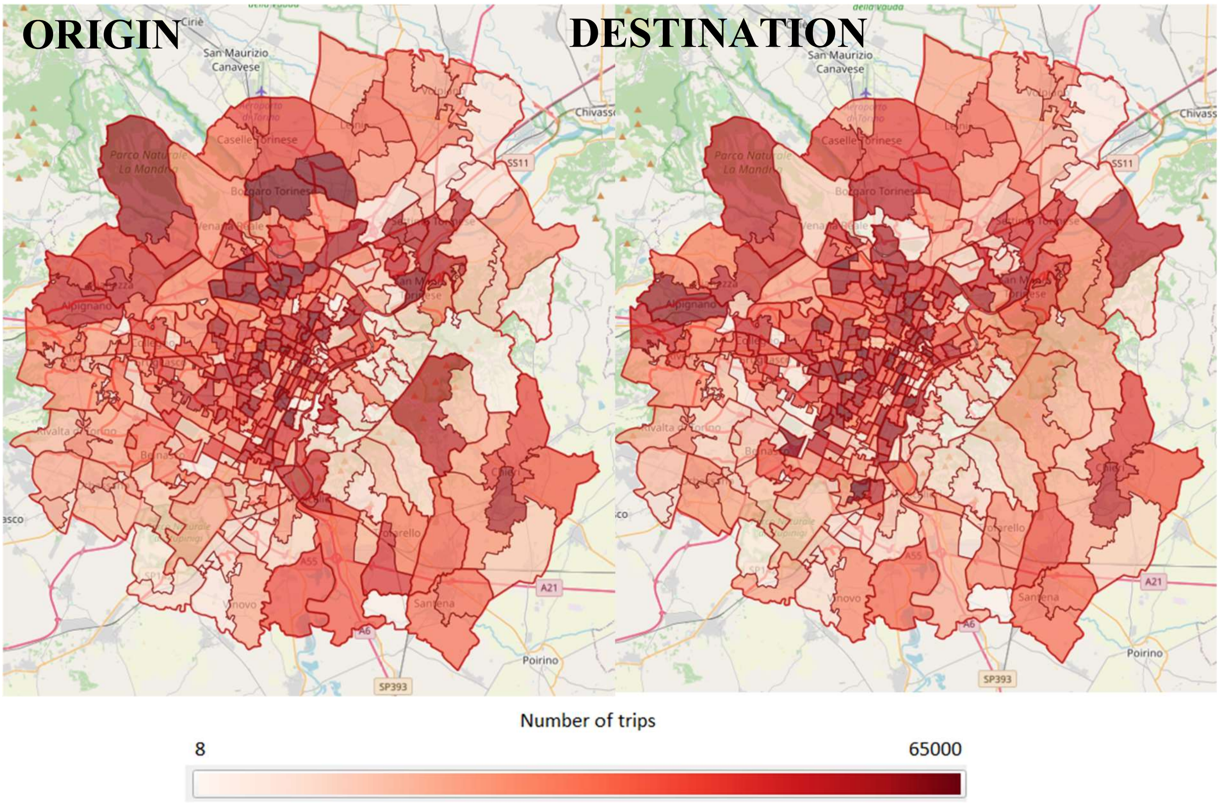


Figure 26. Saturdays daily matrix.

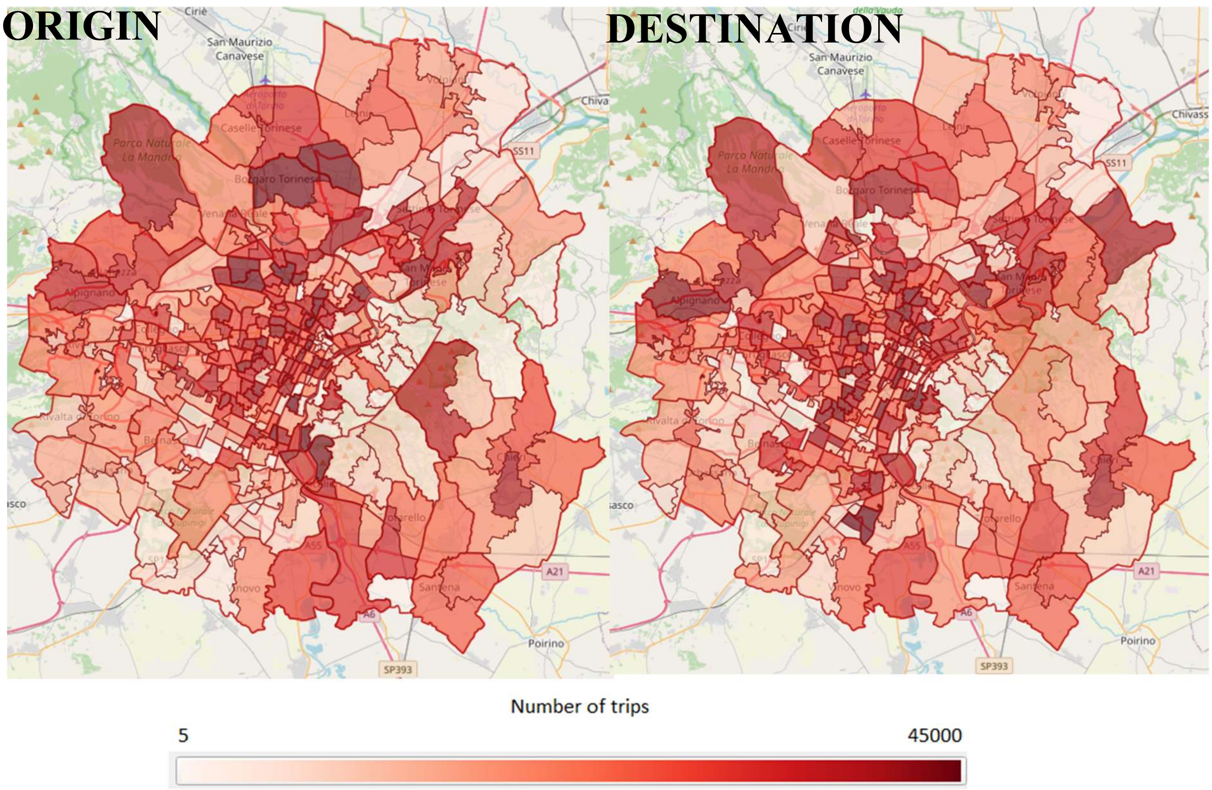


Figure 27. Sundays daily matrix.

3.2 Trips comparison

Although hourly matrices weren't provided, 5T sent an Excel file containing the percentage (weights) of the trips made every 15 minutes for each day. Those weights have been transformed in hourly percentages and compared with the ones obtained from the matrices obtained from FCD analysis.

Weekdays			Saturdays			Sundays		
Departure Time	5T WGHT	TIM WGHT	Departure Time	5T WGHT	TIM WGHT	Departure Time	5T WGHT	TIM WGHT
0	1.40	0.59	0	2.67	1.67	0	4.12	3.09
1	0.72	0.21	1	1.79	0.96	1	3.10	1.86
2	0.41	0.12	2	1.18	0.53	2	2.12	1.09
3	0.31	0.12	3	0.87	0.33	3	1.54	0.66
4	0.37	0.27	4	0.75	0.32	4	1.16	0.44
5	1.07	1.09	5	1.08	0.74	5	1.03	0.48
6	2.30	2.54	6	1.75	1.31	6	1.19	0.72
7	6.22	7.42	7	2.98	2.62	7	1.51	1.22
8	7.50	7.68	8	4.15	4.70	8	2.38	2.78
9	6.15	5.59	9	5.24	6.45	9	3.91	5.36
10	5.63	5.41	10	6.09	7.56	10	5.21	7.11
11	5.49	5.38	11	6.37	7.94	11	5.90	8.26
12	5.58	6.33	12	6.53	7.46	12	5.97	7.59
13	5.25	6.09	13	5.17	5.40	13	4.07	4.43
14	5.82	6.18	14	5.38	6.11	14	4.65	5.76
15	6.03	6.27	15	6.16	6.80	15	6.05	7.36
16	6.49	7.56	16	6.36	7.40	16	6.61	8.32
17	7.36	8.28	17	6.60	7.54	17	7.38	8.58
18	7.40	7.62	18	6.56	6.66	18	7.78	7.68
19	6.39	6.07	19	6.55	6.30	19	7.51	6.11
20	4.46	3.55	20	5.22	3.79	20	5.55	3.77
21	2.90	2.23	21	3.54	2.31	21	4.21	2.95
22	2.58	2.00	22	3.34	2.49	22	3.81	2.61
23	2.17	1.40	23	3.65	2.59	23	3.24	1.79

Table 8. Weights comparison (TIM FCD vs 5T).

Despite the low number of vehicles belonging to the sample, results obtained from FCD shows that the distribution of the trips in Turin metropolitan area is very similar to the 5T universe. Percentage of trips occurred during the morning and evening peak-hours are comparable with a maximum difference in relative terms around 1%, except for Sundays (FCD seems to slightly overestimate the number of trips). The most interesting result is that the peak-hours coincide in the two analysis:

- Weekdays: 08.00 – 09.00 and 17.00 – 18.00 are respectively the morning and the evening rush hours;
- Saturdays: 11.00 – 12.00 and 17.00 – 18.00 are respectively the morning and the evening rush hours;
- Sundays: peak hours are not precisely the same, but it can be noticed that for both analysis the busiest hours are between 17.00 and 19.00.

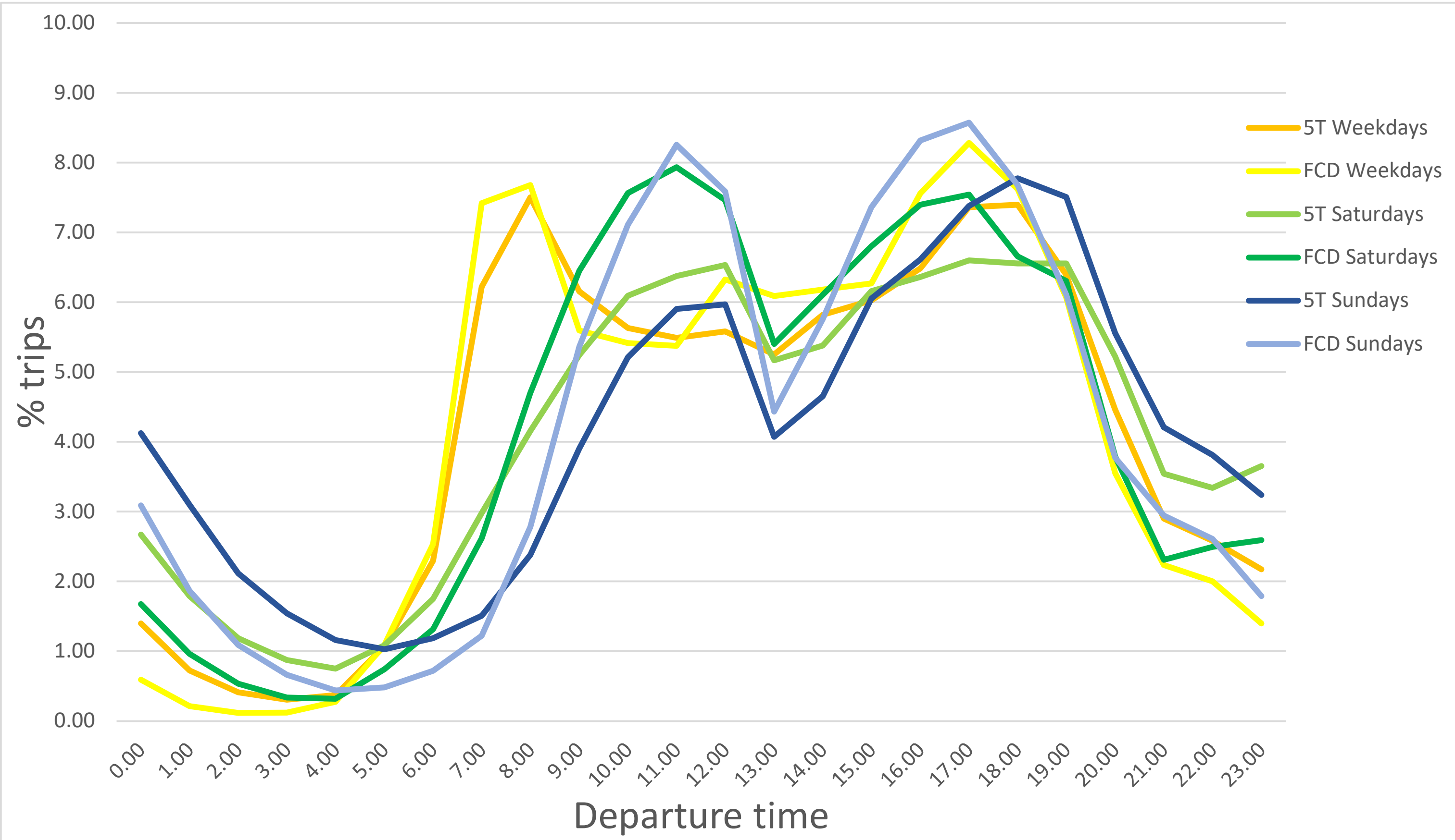


Figure 28. Trips distribution (FCD TIM vs 5T).

Overall, FCD slightly overestimate the percentage of trips occurred throughout the day, especially during peak hours. However, it can be noticed that the two trends (FCD and 5T for each day) of the distributions are comparable. Hence, FCD provided by TIM and processed in this work may be considered reliable.

Chapter 4: Electric Vehicles diffusion in Turin

This part of the thesis is focused on the estimation of the Electric Vehicle diffusion in Turin metropolitan area. With the increasing popularity of EVs among policy makers and the general public, economists have been called to design convincing methods for forecasting the development of this market. Bass model is a good starting point for forecasting the long-term penetration pattern of new technologies and products under two types of conditions:

1. A product has recently been introduced and the penetration has been observed for a few time periods;
2. The product has not yet been introduced, but it is similar in some way to existing products or technologies with a known diffusion history.

These conditions are required to estimate the unknown coefficients in the Bass model. Studies state that data must be available for at least four periods to allow the estimation of the parameters. If no such data is available, parameters estimated for historical innovations that are similar to the innovation being studied are often used instead. Due to these reasons, the estimation of the EVs penetration in Turin was conducted adopting the Bass model.

4.1 Bass Model

Bass Model (1969) is a tool to predict the adoption of innovative products. Over time, this diffusion model has proved to be very efficient in marketing for sales forecasts and analysis of new products. It is the most widely applied new-product diffusion model and it has been tested in many industries concerning different products (including services) and technologies. The model is mainly used for forecasts made prior to product launch when there are no sales data upon which the prediction is based. The adoption of new technologies has often been found to follow an S-shaped curve. In this setting, cumulated purchases of innovative products can be characterised by three different growth phases: a slow take-up phase, followed by a phase of more rapid growth as the technology becomes widespread and, finally, slowing growth when the 'not so new' technology approaches saturation. Diffusion theories try to explain or model the actual shape of diffusion curves: they try to model the speed and the shape of the cumulative adoption of an innovation among a set of prospective buyers.

Bass Model consists of a simple differential equation that describes the process of how new products get adopted in a population. The model presents a rationale of how current adopters and potential adopters of a new product interact. According to Bass, the adopters of an innovation can be divided into two groups according to when they buy the product:

- Innovators: people who buy the product first and are influenced only by 'external communication' e.g. mass media or advertisement;
- Imitators: individuals who, in contrast, buy if others have already bought the product since they are influenced by word of mouth or so-called 'internal communication'.

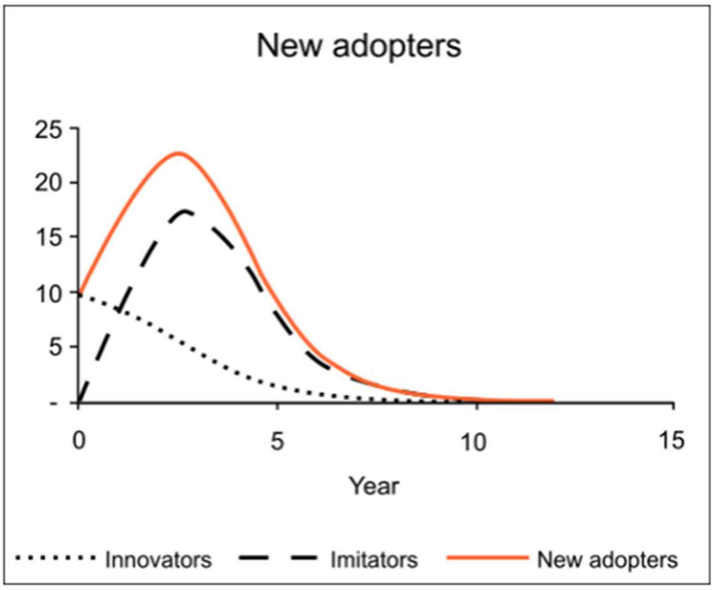


Figure 29. New adopters class according to Bass

The behavioural theory behind the model foresees that the innovation is first adopted by a small group of innovators who will then influence the group of imitators who will buy the product due to a purely imitative character. One of the greatest advantages of this model is the possibility to illustrate the diffusion starting phase of the product through the presence of the innovators. Clearly, the diffusion does not take place with a constant rate, but it assumes a typical trend of empirical models.

Based on this, Bass computed the probability of being adopted, at a given time t (or *hazard-rate*) as:

$$P(t) = p + q\frac{N(t-1)}{M}$$

With:

p: coefficient of innovation;
q: coefficient of imitation;
N(t-1): cumulative number of adoptions before the time t;
M: maximum potential adopters.

The coefficient p captures the intrinsic tendency to adopt; the coefficient q captures the fact that the adoption probability of customers increases with the proportion of eventual adopters who have already adopted.

Therefore, it is possible to state that the number of new adopters at period t is defined as:

$$n(t) = \left[p + q\frac{N(t-1)}{M}\right][M - N(t-1)]$$

an important characteristic of the Bass model is that it is symmetric around the inflection point. Moreover, in the Bass model the interpretation of the coefficients p and q can be directly associated with innovators and imitators.

Assuming N(0)=0, the following solutions are obtained:

$$N(t) = M\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}$$

$$\frac{dN(t)}{dt} = n(t) = M\frac{p(p+q)^2 e^{-(p+q)t}}{(p + qe^{-(p+q)t})^2}$$

Deriving the last expression and placing it equal to zero it is possible to derive the time t* (year-to-peak-sales) in which the peak of the sales is forecasted:

$$t^* = \frac{1}{p+q}\ln\frac{q}{p}$$

$$n(t^*) = \frac{M(p+q)^2}{4q}$$

$$N(t*) = \frac{M(q-p)}{2q}$$

At this point, forecasted sales according to Bass model are directly linked to the estimation of parameters *p, q, M*.

4.1.1 Bass model parameters estimation

Several methods can be adopted to estimate the parameters of the Bass model. These models can be classified based on whether they rely on historical sales data or judgment for calibrating the model. Linear and nonlinear regression can be used if historical sales data for the new product for a few period (years) are provided. Judgmental methods include using analogs or conducting surveys to determine customer purchase intentions. Usually, the potential market estimation (M) is left to managerial intuition, trying to give it a likely size, whereas the parameters *p* and *q* are estimated following one of the following methods:

- **Econometric estimation:** starting from historical sales data it is possible to calibrate the model using NLLS (nonlinear least squares) according to which knowing historical sales at time t, it is possible to estimate p and q minimizing the error, through the least squares, of the following equation:

$$\boldsymbol{n(t) = M\left[\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}} - \frac{1 - e^{-(p+q)(t-1)}}{1 + \frac{q}{p}e^{-(p+q)(t-1)}}\right]}$$

- **Research by 'analog':** if data are not available or the diffusion of the technology has not started yet, the parameters are estimated relying on similar products, hence the same p and q of the similar products are adopted.

4.1.2 Generalized Bass Diffusion Model

The Bass diffusion model cannot consider the external factors that may affect the diffusion of the technologies, such as the price and the communication. For this reason, the Bass Diffusion Model (GBDM) was developed to overcome the limitation of Bass model. The GBDM is expressed as:

$$n(t) = \left[p + q\frac{N(t-1)}{M}\right][M - N(t-1-)]X(t)$$

with:

$$X(t) = M\left[\frac{1 - e^{(-(p+q)(t+\beta_1 \ln(Pr(t))+\beta_2 \ln(ADV(t))))}}{1 + \frac{q}{p}e^{(-(p+q)(t+\beta_1 \ln(Pr(t))+\beta_2 \ln(ADV(t))))}}\right]$$

And year-to-peak-sales t* equal to:

$$t^* = \frac{\ln\left(\frac{q}{p}\right)}{p+q} - (\beta_1 \ln(Pr) + \beta_2 \ln(ADV))$$

In the formulae above, the two factors that may influence the model are the *price Pr(t)* and the *advertising ADV(t)*. β_1 and β_2 are two variables directly proportional to the impact of the price variation and the impact of the advertising on the adoption of the technology. In GBDM X(t) may move up or down the diffusion curve referred to the studied technology that means that decisional factors can accelerate or decelerate the adoption process. Referring to price and advertising, β_1 is usually comprised between 1 and 2, whereas β_2 is usually comprised between 0,3 and 1.

The Bass model has been used for understanding how successful innovations have diffused through the population. However, it is important to recognize its limitations. Most past data (from analog) describe how successful innovations have diffused through the population, but do not account for their chances of success. Thus, such data would predict favourable forecasts for any new product, resulting in a success bias in the forecasts. To minimize such a bias, one must incorporate the probability of product failure in the model. Unfortunately, the sales patterns of innovations that failed are not easily available or provided. Another limitation of the Bass model is that it is possible to estimate its parameters well from data only after making several observations of actual sales. However, by this time the firm has already made critical investment decisions. While the use of analogs can help firm make forecasts before introducing an innovation into the market, the choice of a suitable analog is critical and requires careful judgment.

4.2 Case of studies

Since the Bass model is the most used to predict the diffusion of new products, many countries adopted it to try to forecast the diffusion of the electric vehicles. In literature, it is possible to find interval values for p and q coefficients. Many studies estimate parameters for one market to apply them for estimations for another market. This can relate to technologies but also geographically (from one country to another). In 2008, Lamberson forecasted the diffusion of Hybrid Electric Vehicles (HEV) in USA based on monthly vehicle registrations from February 2001 to October 2007. In 2011, Park et al estimated a diffusion model for Korea based on HEV in Japan between 1997 and 2006. Then, they converted the estimated imitation factor to the Korean context. In 2014, Jensen and Cherchi used numbers of new EV car registrations in Norway to implement them in a calibrated model for Denmark. In 2019 Soumia and Maaroufi estimated a GBDM for Moroccan EVs analysing the France EVs sales from 2011 to 2017. However, the results of these works showed that there is a wide discrepancy among p and q values for modelling the market diffusion. In the Figure 30, a summary of the main results about Bass coefficients for new propulsion technologies found in the literature is shown:

Source Technology	Method	Innovation coefficient p	Imitation coefficient q	Market Potential
Becker, Sidhu et al. (2009) Electric cars	Authoritative sources	0.01 0.02 0.025	0.4	Exogenous: 70% or 90% of the light-vehicle market in each year.
Davidson et al. (2013) Electric cars	Authoritative sources, but eventually refers to Becker (2009)	Idem	Idem	Exogenous : Number of Household are "0.03, 0.25, and 0.7 in the low, medium, and high growth scenarios"
Gross (2008)	Authoritative sources	0.01	0.1	
Li (nd) Electric cars	Based on "a statistic model of EVs in US from 1999 to 2008"	0.0000365	0.447	Exogenous: "At most half of the vehicles in market can be EVs, the ultimate market potential is calculated as 2.5 million".
Cordill (2012) Prius Hybrid Civic Hybrid Ford Escape Hybrid	Calibration on US market data 2000-2010	 0.0016 0.00343 0.036	 1.45 0.631 0.432	Estimated 2.87 million 3.68 million 0.36 million
Steffens (2003) - Conventional cars	First car purchase (not specifically AFV) in Australia 1966-1996	0.0076	0.0905	Exogenous: 91% of the population would finally purchase the technology.
Shoemaker (2012)* Passenger vehicles Utility vehicles	Calibration on AFV monthly sales in the US Dec 1995 (oct 2004 for utility AFV) dec 2011 in the US	 0.0912 0.008124	 0.4692 0.4632	Estimated 436 000 2 300 000
Lamberson (2008)* HEV	Calibration on US monthly sales (Feb. 2001 - Oct. 2007)	0.000618	0.8736	Estimated 1.6 million veh.
Park et al (2011) HEV	HEV sales in Japan (1997 - 2006) parameterized to Korea[7]	0.0037	0.3454	10,2 million veh.
Jensen et al. (2014) Electric cars	Norwegian new electric car registration data from (Jan. 2003 – Jun. 2013)	0.002	0.23	Exogenous: Result of a Discrete Choice Model
MacManus (2009) HEV	HEV annual Data in the US. (1999-2008)	0.0026 (0.00124 generalised Bass)	0.709 (0.77922 gen.ed bass)	Estimated: 1.9 million veh.
Cao (2004) E85 CNG Hybrids	Calibration on annual sales in the US 1993-2002	 0.00441 0.0210 0.000446	 0.491 0.265 0.4788	 E85: 245 971 CNG : 100 000 Hybrid: Exogenous. Based on EIA scenario of 19 million HEV sold until 2025, subsequently varies in function of HEV awareness and (lagged) fuel price

Figure 30. Summary of available estimates for p, q, M (Massiani, Gohs).

4.3 EV Diffusion model in Turin

The diffusion of the electric vehicles in Turin and its metropolitan area was estimated through the adoption of the Bass model. As discussed in the previous sections, the coefficients of the diffusion model can be estimated on historical data for a similar product. Since the electric mobility in the City is still too low, the analog approach was followed to obtain the circulating EVs forecast. Initially, it was assumed that the number of EVs in Turin would increase similarly to how the Hybrid-Electric cars developed in Italy. Therefore, the diffusion of the circulating Hybrid cars in Italy was used as analog. Based on the same hypothesis, Hybrid Fuel and Compressed Natural Gas vehicles (CNGs) diffusion in Italy was also used as analog. Finally, to have a third result to compare, the EVs diffusion forecast was conducted adopting Bass parameters obtained from a project in Norway, which is the first project in Europe that adopted the Bass model method to forecast the diffusion of EVs (*Predicting the potential market for electric vehicles, Jensen et al.)*.

4.3.1 Hybrid-Electric cars as analog

Hybrid Electric Vehicles (HEV) market in Italy started in 1997 when the Toyota introduced the Prius in the Italian market. HEVs diffusion was slow in the first years and it was only after 2005 that this new type of vehicles really began to make their appearance on the Italian road networks. The increased focus on the environmental impacts and the incentives promoted by the Government to whom who bought and drove HEVs were the main reasons of the diffusion. In order to make this new market competitive, HEVs owner got many benefits such as subsidized insurance policies and the possibility of free movement in ZTLs. Starting from 2009, circulating HEVs number raised dramatically.

ACI website provides historical data of all the vehicles circulating in Italy, grouping them by geographic zone and engine supply. Using historical data of circulating HEVs from 2000 to 2018 it was possible to get the Bass coefficients p and q that describe the diffusion of the HEVs in Italy. Although it was possible to find data for circulating HEVs only from 2013 to 2018, data from 2000 to 2013 were estimated in the following way:

- Data from 2000 to 2008. In these years few data about HEVs are available but purchases and circulating data are missing. However, *UNRAE* association provided all the HEV registrations since 2000. These values were considered as HEV purchases. Therefore, circulating HEVs in the i^{th} year were assumed to be equal to the circulating HEVs in the $i\text{-}1^{th}$ year plus HEVs registrations in the i^{th} year. Considering these values is extremely important to reach a value close to 0 in order to adopt the Bass model.

- Data from 2009 to 2013. *GreenStart website* provides car purchases in Italy year by year. HEVs circulating number was obtained assuming that the number of the circulating HEVs in the i^{th} year is equal to the difference between the number of the circulating HEVs and the HEVs purchases in the $i+1^{th}$. For example, in 2013 circulating HEVs were 45.404 and the purchases were 14.685. it was assumed that in 2012 the circulating HEVs were $45.404 - 14.685 = 30.719\ vehicles$.

The estimations were conducted in order to get as close as possible to the value zero, i.e. to get close to the year in which the diffusion of the HEVs began. Non Linear Least Square Method (NLLS) was used to estimate the coefficients p and q.

Data used for the estimation of p and q parameters are shown in the following table. Data taken from ACI are shown in green; data taken and estimated from GreenStart are shown in pink; data taken from UNRAE are shown in yellow.

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Circulating HEVs	5	23	15	11	495	1110	2179	3450	3337	7607	4570	5061	6577	14685	20499	25331	38060	66041	81657
HEVs purchases	5	28	43	54	549	1659	3838	7288	10625	14511	19081	24142	30719	45404	65840	89932	126508	185052	256640
Δ	0	5	28	43	54	549	1659	3838	7288	6904	14511	19081	24142	30719	45341	64601	88448	119011	174983

Table 9. Historical Data for HEVs.

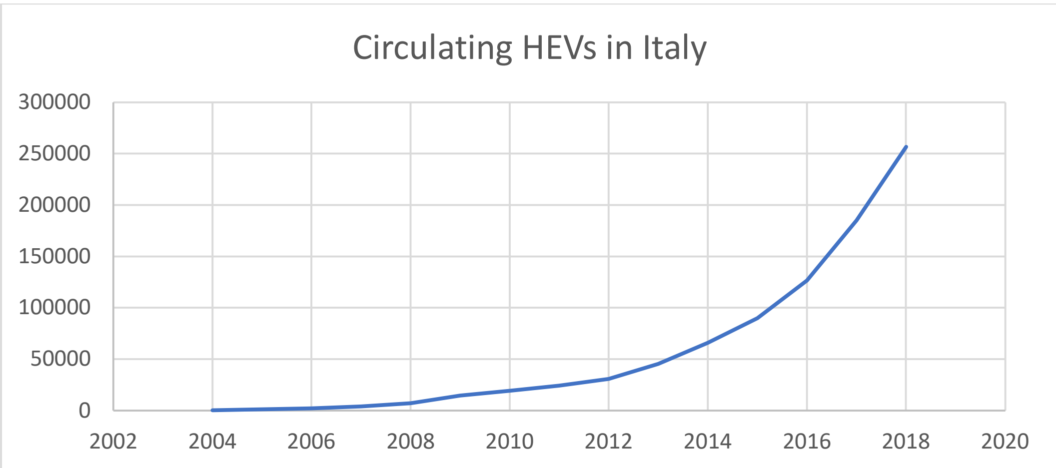


Figure 31. Actual number of circulating HEVs in Italy.

Adopting the Bass diffusion model, the coefficient of innovation p and the coefficient of imitation q were obtained:

HEVs Bass coefficients	
p	0.0000014
q	0.3063771

Table 10. Bass coefficients from HEVs historical data.

Since HEVs diffusion was used as analog, the same coefficients were adopted to forecast the circulating number of EVs in the future. Assuming that p and q - obtained considering all the circulating HEVs in Italy - can be used as the diffusion of the EVs in the city of Turin is a strong assumption. However, considering that automotive industries are pushing heavily on the EV market and that citizens in recent years seem to be much more aware than the past about topics concerning environmental impacts and climate change, it can be assumed and hoped that in next years EVs diffusion will skyrocket. Moreover, as it can be seen below, the number of circulating EVs has dramatically increased since 2015. Although in 2019 EVs represented only 0,12 % of the total vehicles, in absolute numbers they scaled up by six times in 5 years. Due to these reasons, adopting the same diffusion coefficients obtained for the HEVs in Italy was considered reliable.

Number of circulating EVs in Turin				
Year	City	EV	Total	% EV
2015	TORINO	88	551419	0.02
2016	TORINO	95	566831	0.02
2017	TORINO	197	597551	0.03
2018	TORINO	385	576571	0.07
2019	TORINO	658	554422	0.12

Table 11. Number of circulating EVs in Turin.

The analysis started from the cumulative value of the circulating electric vehicles in the year 2019. The M value, the potential market, was set to 500.000 vehicles, that is almost equal to the number of the total vehicles currently circulating in Turin.

According to the results obtained in this work, the value M will be reached in 40 years starting from now. However, if the number of circulating vehicles would keep constant in time, attractive and significant number of circulating EVs will be reached soon after 2035 when the estimation number will get close to 10% of the total vehicles. By those years, Turin will need appropriate infrastructures and suitable supplies for the Electric Vehicle market.

HEV ANALOG											
Year	Adopters	Cumulative Adopters	%	Year	Adopters	Cumulative Adopters	%	Year	Adopters	Cumulative Adopters	%
2015	-	88	0.018	2037	15354	71853	14.371	2059	893	497962	99.592
2016	-	95	0.019	2038	18851	90703	18.141	2060	622	498584	99.717
2017	-	197	0.039	2039	22748	113452	22.690	2061	433	499016	99.803
2018	-	385	0.077	2040	26872	140324	28.065	2062	301	499317	99.863
2019	-	658	0.132	2041	30926	171250	34.250	2063	209	499526	99.905
2020	201	859	0.172	2042	34497	205747	41.149	2064	145	499671	99.934
2021	263	1122	0.224	2043	37097	242844	48.569	2065	101	499772	99.954
2022	343	1465	0.293	2044	38266	281110	56.222	2066	70	499842	99.968
2023	448	1913	0.383	2045	37704	318814	63.763	2067	48	499890	99.978
2024	584	2497	0.499	2046	35396	354210	70.842	2068	34	499924	99.985
2025	761	3258	0.652	2047	31643	385853	77.171	2069	23	499947	99.989
2026	992	4249	0.850	2048	26988	412841	82.568	2070	16	499963	99.993
2027	1291	5540	1.108	2049	22049	434889	86.978	2071	11	499975	99.995
2028	1679	7219	1.444	2050	17351	452240	90.448	2072	8	499982	99.996
2029	2180	9398	1.880	2051	13235	465475	93.095	2073	5	499988	99.998
2030	2825	12223	2.445	2052	9847	475322	95.064	2074	4	499992	99.998
2031	3653	15877	3.175	2053	7188	482510	96.502	2075	3	499994	99.999
2032	4710	20587	4.117	2054	5171	487681	97.536	2076	2	499996	99.999
2033	6048	26634	5.327	2055	3681	491362	98.272				
2034	7725	34360	6.872	2056	2601	493963	98.793				
2035	9804	44163	8.833	2057	1827	495790	99.158				
2036	12336	56499	11.300	2058	1279	497069	99.414				

Table 12. Estimated number of circulating EVs in Turin (HEV analog).

4.3.2 CNG cars as analog

The diffusion of the Hybrid Fuel and Compressed Natural Gas vehicles (CNG) was used as analog to compare EV diffusion with vehicles that, at the beginning of their diffusion, hardly find gas stations to supply. As it happened for CNG vehicles, EVs might deal with the same problem. In fact, it is not easy to currently find charging stations along Italian infrastructures. Therefore, supply difficulties may decelerate EVs diffusion in Turin city. As for the HEVs, it was assumed that EVs vehicles diffusion in Turin city will be the same that CNGs had in Italy. *ACI* website provided data about circulating CNGs from 2005 to 2019. Reports before 2005 are scarce and many data are missing. *Unrae book 2019* provided data for the years between 1991 and 2000 about circulating CNGs. Although interesting results were obtained from this analysis, due to the not negligible amount of missing data, this forecast cannot be considered very reliable.

CNG data															
Year	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Circulating CNGs	14184	27062	-	-	-	45884	-	-	-	53419	-	-	-	-	344734
Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	
Circulating CNGs	375351	423358	506341	612275	660174	680994	719685	773539	833668	883190	911246	926704	945184	965340	

Table 13. Data about circulating CNG vehicles.

Data in table 14 were used to predict Bass coefficients through NLLS method:

CNGs Bass coefficients	
p	0.01076
q	0.41240

Table 14. Bass coefficients from CNGs historical data.

As it was done for the HEV vehicles, Bass coefficients obtained for the CNGs diffusion in Italy were used to predict the diffusion of the EVs in Turin. The analysis started from the cumulative value of the circulating electric vehicles in the year

2019. The M value, the potential market, was set to 500.000 vehicles, that is almost equal to the number of the total vehicles currently circulating in Turin.

CNG ANALOG											
Year	Adopters	Cumulative Adopters	%	Year	Adopters	Cumulative Adopters	%	Year	Adopters	Cumulative Adopters	%
2015	-	88	0.018	2037	46683	219864	43.973	2059	6	499991	99.998
2016	-	95	0.019	2038	50801	270665	54.133	2060	4	499995	99.999
2017	-	197	0.039	2039	51198	321863	64.373	2061	2	499997	99.999
2018	-	385	0.077	2040	47290	369153	73.831	2062	1	499998	100.000
2019	-	658	0.132	2041	39840	408993	81.799	2063	1	499999	100.000
2020	271	929	0.186	2042	30700	439693	87.939	2064	0	499999	100.000
2021	382	1311	0.262	2043	21871	461564	92.313	2065	0	500000	100.000
2022	539	1851	0.370	2044	14633	476196	95.239	2066	0	500000	100.000
2023	760	2611	0.522	2045	9349	485546	97.109	2067	0	500000	100.000
2024	1071	3683	0.737	2046	5789	491334	98.267	2068	0	500000	100.000
2025	1508	5190	1.038	2047	3512	494846	98.969	2069	0	500000	100.000
2026	2118	7308	1.462	2048	2104	496950	99.390	2070	0	500000	100.000
2027	2970	10278	2.056	2049	1250	498200	99.640	2071	0	500000	100.000
2028	4152	14430	2.886	2050	740	498940	99.788	2072	0	500000	100.000
2029	5779	20209	4.042	2051	436	499376	99.875	2073	0	500000	100.000
2030	7997	28206	5.641	2052	257	499633	99.927	2074	0	500000	100.000
2031	10976	39183	7.837	2053	151	499784	99.957	2075	0	500000	100.000
2032	14893	54075	10.815	2054	89	499873	99.975	2076	0	500000	100.000
2033	19889	73964	14.793	2055	52	499925	99.985				
2034	25990	99954	19.991	2056	31	499956	99.991				
2035	32981	132935	26.587	2057	18	499974	99.995				
2036	40247	173182	34.636	2058	11	499985	99.997				

Table 15. Estimated number of circulating EVs in Turin (CNG analog).

4.3.3 Forecast adopting Jensen's coefficients

In 2015, Jensen A., Cherchi E., Mabit S. and others published "*Predicting the potential market for electric vehicles*". This work aimed to predict the EV car registrations in Denmark adopting the Bass model. Since the number of EVs in Denmark was scarce in those years, the model was implemented using the EV car registrations in Norway between January 2003 and June 2013. Norway was the country with the highest share of EV in Europe and was quickly reaching a share of total registrations equal to 1%. Moreover, both Denmark and Norway had "fairly high registration taxes on cars and in both countries battery electric vehicles were exempted from those taxes". According to the paper, "the time horizon of 2020 is a long enough period to appreciate the curve of the typical diffusion process", therefore, assuming that the number of EV sales in a time period is equal to the number of EV adopters in that period, the diffusion of the EVs in Denmark was estimated, using non-linear least squares estimation. Although in the paper is told that the parameter for the potential market M was insignificant (in terms of confidence) because there was not enough data to estimate the overall market, it was assumed that the method could still be used to describe the evolution of the market. The potential market was set to half of the car owning families in 2013 (877.000 families).

HEVs Bass coefficients	
p	0.0020
q	0.2300

Table 16. Bass coefficients provided by Jensen's et al. analysis.

Comparing the actual Danish EV market in 2020 with the forecast made 6 years ago, it can be assessed that the trend forecasted for the diffusion of the EVs was close to the current result.

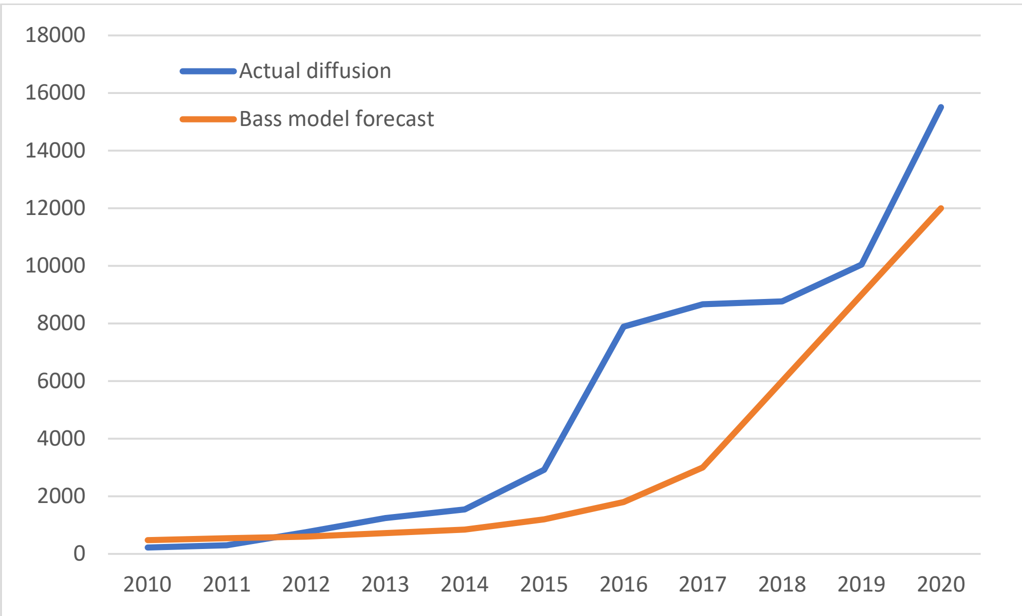


Figure 32. Comparison between EVs current market and its forecast.

As it can be seen, the curve that describes the prediction of the EVs diffusion seems to underestimate the actual diffusion (it is always below the real curve). Although in 2016 EVs new registrations almost tripled the registrations of the 2015, the forecast made by Jensen et al. seems to underestimate the EVs diffusion. This is not necessarily a drawback, because nowadays the need of electric vehicles and the necessity to reduce pollution has assumed a key role for everyday life. Therefore, assuming that EVs diffusion in Turin will have the same trend of the Danish forecast, may be very convenient and desirable. Hence, the same coefficients were used as analog to forecast the EVs diffusion in Turin:

FORECAST ADOPTING JENSEN'S COEFFICIENTS											
Year	Adopters	Cumulative Adopters	%	Year	Adopters	Cumulative Adopters	%	Year	Adopters	Cumulative Adopters	%
2015	-	88	0.018	2037	4724	26182	5.236	2059	13670	444731	88.946
2016	-	95	0.019	2038	5707	31889	6.378	2060	11307	456038	91.208
2017	-	197	0.039	2039	6867	38756	7.751	2061	9222	465260	93.052
2018	-	385	0.077	2040	8223	46978	9.396	2062	7435	472695	94.539
2019	-	658	0.132	2041	9790	56768	11.354	2063	5937	478632	95.726
2020	151	809	0.162	2042	11574	68343	13.669	2064	4705	483337	96.667
2021	186	995	0.199	2043	13570	81913	16.383	2065	3705	487042	97.408
2022	228	1223	0.245	2044	15753	97666	19.533	2066	2903	489945	97.989
2023	281	1504	0.301	2045	18075	115742	23.148	2067	2266	492211	98.442
2024	345	1849	0.370	2046	20458	136200	27.240	2068	1764	493975	98.795
2025	424	2273	0.455	2047	22793	158993	31.799	2069	1369	495344	99.069
2026	520	2793	0.559	2048	24940	183933	36.787	2070	1061	496405	99.281
2027	639	3432	0.686	2049	26742	210675	42.135	2071	821	497226	99.445
2028	784	4216	0.843	2050	28039	238714	47.743	2072	635	497860	99.572
2029	961	5177	1.035	2051	28691	267405	53.481	2073	490	498350	99.670
2030	1178	6355	1.271	2052	28611	296016	59.203	2074	378	498728	99.746
2031	1443	7798	1.560	2053	27776	323792	64.758	2075	292	499020	99.804
2032	1766	9564	1.913	2054	26245	350037	70.007	2076	225	499245	99.849
2033	2158	11722	2.344	2055	24147	374184	74.837	2077	173	499418	99.884
2034	2633	14355	2.871	2056	21656	395840	79.168	2078	134	499552	99.910
2035	3207	17561	3.512	2057	18966	414806	82.961	2079	103	499655	99.931
2036	3897	21459	4.292	2058	16256	431062	86.212	2080	79	499734	99.947

Table 17. Estimated number of circulating EVs in Turin (Jensen coefficients)

4.3.4 Forecasts results

In this chapter, the three analogs used to predict the circulating EVs in Turin are represented. For all the three forecasts, the market potential M was set equal to 500.000 vehicles that is about the total number of the current circulating vehicles in Turin. The low diffusion scenario corresponds to the Danish (Jensen et al.) curve in which 20% of the potential market is predicted to be reached in 2045. The same value, in the high diffusion scenario (CNG analog) may be reached ten years before, in 2035. According to the HEV analog, which distribution is placed between the other two predictions, the 20% of the total market will be reached in 2038. Overall, the HEV analog trend seems to be the average between the other two distributions. Moreover, as already explained in the previous chapters, CNG analog may be not so reliable due to the amount of missed data. Therefore, HEV analog can be assume as the actual EVs diffusion forecast. In the next chapters, data referred to HEV analog diffusion will be used as reference.

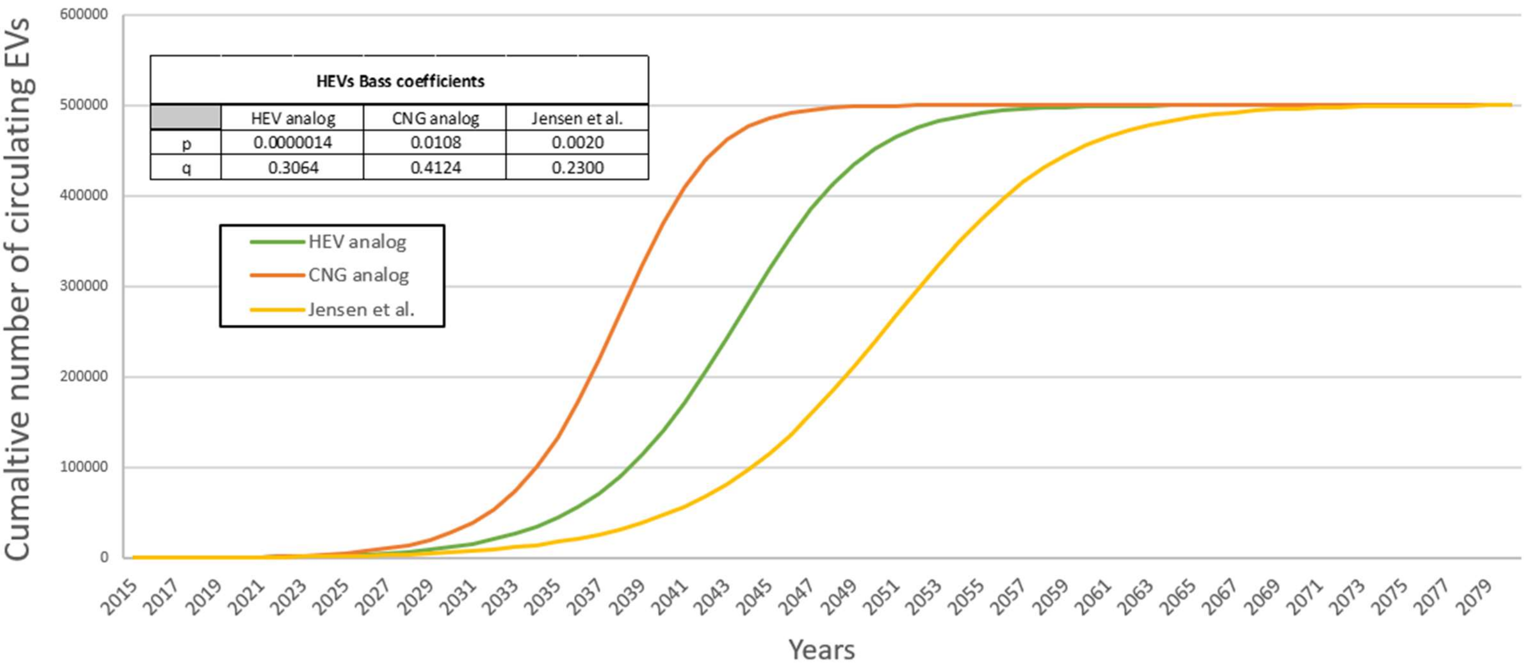


Figure 33. Estimated number of circulating EVs in Turin.

Chapter 5: Charging demand

Although there are many aspects to consider to identify the impact of the electricity distribution in Turin mobility network, the most important and relevant ones are linked to the vehicle charging supplies. Moreover, they are the most interesting because they allow to analyse the interaction between the network and the vehicle, in terms of energy and power. The power required to charge the EVs depends mainly on the construction standards of the vehicles and the type of the charging devices that are currently placed in Turin metropolitan area, but mostly on charging devices that will be installed over the years.

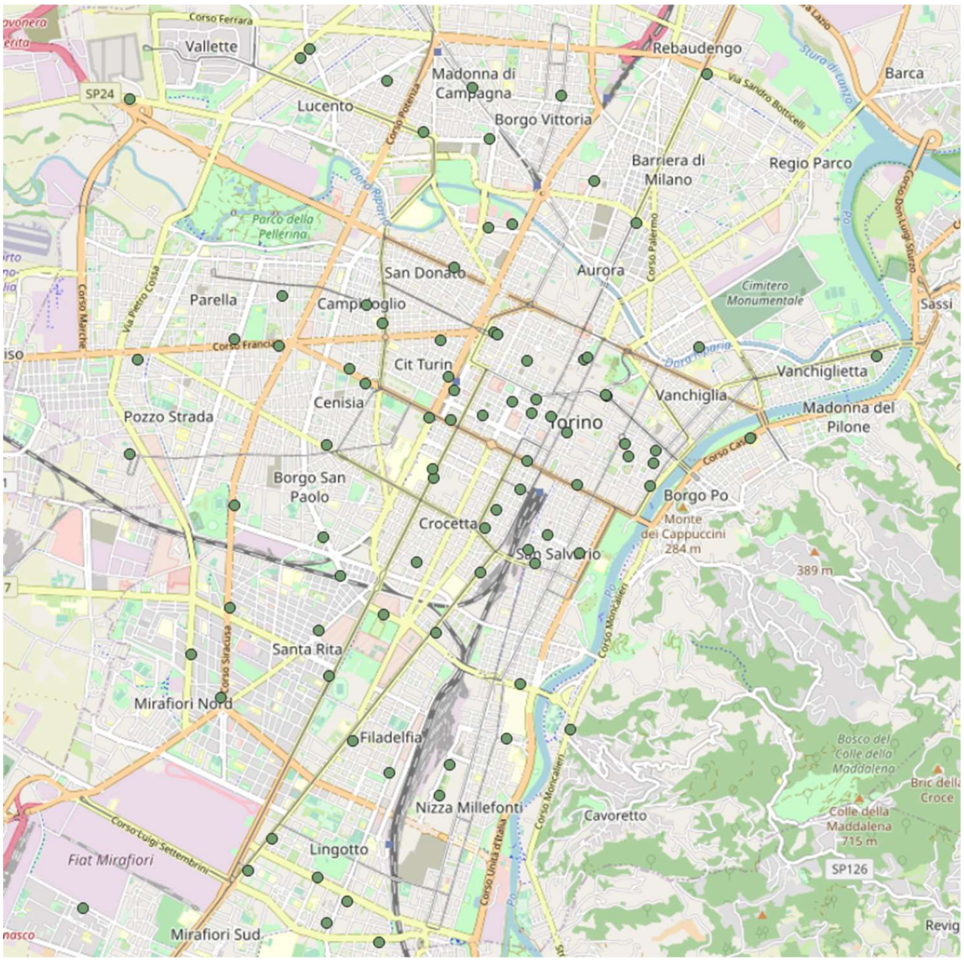


Figure 34. Charging points/stations in City of Turin (Open Charge Map).

Figure 34 (source: *Open Charge Map*) shows the charging stations that are currently installed in the city of Turin, operated by *EVWAY, Tesla Motors, Blue Torino/Leasys and Enel*. Although Blue Torino is a private operator, it was considered in this study because the company allows the access to the service to all the subscribers, whether they are using their own car or a Blue Torino car. The energy focus was referred to only the city of Turin because until now it is the city/municipality with the most widespread charging network in the entire metropolitan area.

Concerning the need to accommodate the use of the EVs, the duration of the recharge is a key element. The energy needed to charge the vehicles depends on other factors besides the power, such as:

- EVs battery capacity [kWh];
- EVs battery consumption [kWh/km].

Knowing the battery capacity and the number of trips made by the vehicle in a typical day, it is possible to estimate the energy consumed and the state of charge (SoC) after the trips. In other terms, it is possible to calculate the reduction of the battery charge occurred in the day. Therefore, based on the SoC by the time the vehicle will arrive at a charging point, and the power available by the station itself, the recharge duration can be determined. Consequently, the energy exchanged with the transport network can be determined, assuming that all the recharges will occur at constant power. The availability of those information for all the zones and for all the circulating EVs allows to evaluate the impact of the charging stations on the mobility network. In next chapters, two types of recharge points have been considered:

- Recharge at home: it regards all the people owning a private box. In this case the power of the recharge was set equal to 4 kW;
- Recharge in city of Turin: it regards all the people who do not own a private box and are constrained to charge the vehicle using the public charging points. In this case the power of the recharge was set equal to 22 kW.

5.1 EVs energy consumption

Referring to *"EV Database (2020)"*, mean values concerning the electric capacity of the batteries and the EVs consumption were obtained.

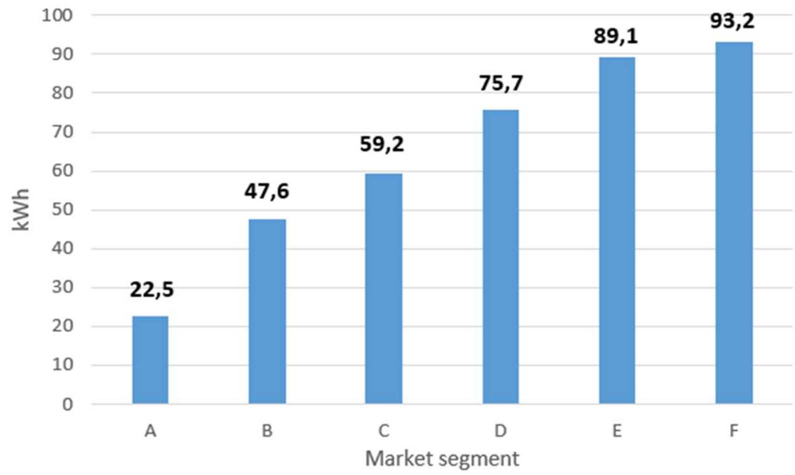


Figure 35. Mean battery capacity for different market segments.

Overall, mean battery capacities increase proportionally with the market segment (higher segments, larger capacities). The lowest capacity is equal to 22,5 kWh for A segment (mini car), the highest one is close to 95 kWh for F segment. Increasing the capacity of the battery, the electric range of the vehicle increases as well.

The same increasing trend concerns the energy consumptions.

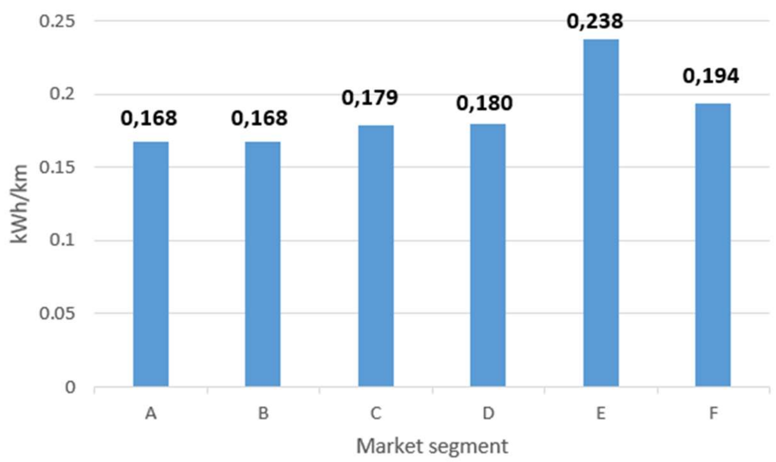


Figure 36. Mean energy consumption for different market segments.

Regarding the energy consumptions, small cars consumption is close to 0,170 kWh/km, whereas cars belonging to E and F segments (executive and luxury cars) reach values close to or higher than 0,200 kWh/km. However, all the values represented refer to what declared by the manufacturers.

In this work, future EVs were considered as vehicles belonging to the segment B (small cars). Therefore, in the next pages all the vehicles analysed in the samples are characterized by battery capacities equal to 47,6 kWh and mean energy consumptions equal to 0,168 kWh/km.

5.2 Power needed forecast

The forecast of the power distribution needed to recharge the increasing EVs demand was the last task of this thesis. The energetic focus was set for the city of Turin. The main achievement was to obtain an estimation of the mean power distribution within all the zones. Therefore, from the FCD analysis described in chapter 2, the busiest day was chosen as sample/day-type. According to the analysis results, the busiest day was Thursday 28th November 2019: 64.368 total trips made by 7.441 vehicles occurred in that day. Starting from those trips, a sample made by the following features was obtained:

- VehID: it is the vehicle identifier;
- First origin (Oi): it is the first origin of the day analysed; hence it is the zone from which the vehicle started its first trip of the day;
- Arrive time Oi: it is the date and time the vehicle arrived in Oi; hence it describes the moment the vehicle travelled to Oi the day before;
- Departure time Oi: it is the date and time the vehicle left the first origin;
- Charging destination (Dj): it is the zone in which the vehicle stops the longest time over the day;
- Arrive time Dj: it is the date and time the vehicle arrived in Dj;
- Idle time Dj: it is the parking time of the vehicle in Dj;

- TD to Dj: it is the cumulative Travelled Distance travelled by the vehicle to reach Dj over the day;
- Leg: it indicates the number of trips occurred over the day before reaching Dj (it includes the last trip to reach Dj);
- Weight: it is the weight of the vehID analysed compared to the universe, hence it describes how many vehicles have the same mobility characteristics in the reality. It is based on the first origin: the number of vehicles represented by the vehID leaving from Oi; e.g. if weight is equal to 4 for zone 540, it means that all the vehicles leaving from 540 are representative of 4 vehicles in the Universe. *For more in-depth clarifications, see chapter 3.*

vehID	Oi	Arrive Oi	Departure Oi	Dj	Arrive Dj	Idle time Dj [h]	TD to Dj [km]	Leg	Weight
1221299	716	27/11/2019 22:11	28/11/2019 16:05	47	28/11/2019 21:44	2.11	28.34	3	7.94
2004418	545	27/11/2019 19:28	28/11/2019 07:50	545	28/11/2019 13:38	4.68	3.98	2	3.91
1505156	298	27/11/2019 17:34	28/11/2019 06:32	617	28/11/2019 06:47	6.19	4.79	1	3.71
1231189	472	27/11/2019 20:05	28/11/2019 07:03	549	28/11/2019 07:43	9.38	18.76	1	3.1
2000964	713	27/11/2019 12:05	28/11/2019 11:36	713	28/11/2019 12:27	4.35	3.93	2	5.69
1235845	487	27/11/2019 18:47	28/11/2019 05:18	484	28/11/2019 05:24	6.18	1.89	1	7.12
1238448	47	27/11/2019 20:44	28/11/2019 06:01	640	28/11/2019 06:11	7.84	4.9	1	6.8
1239739	282	27/11/2019 11:35	28/11/2019 06:48	578	28/11/2019 07:24	8.62	11.33	1	4.04
1268375	337	27/11/2019 11:04	28/11/2019 11:04	337	28/11/2019 11:19	3.36	2.16	1	3.17
2011573	747	27/11/2019 11:16	28/11/2019 10:55	747	28/11/2019 11:29	6.35	1.96	1	3.29
1270487	514	27/11/2019 22:31	28/11/2019 09:13	573	28/11/2019 12:29	7.34	8.44	2	7.73
1270962	385	27/11/2019 19:09	28/11/2019 07:43	667	28/11/2019 08:16	7.83	9.89	1	5.43
1271112	405	27/11/2019 20:14	28/11/2019 11:06	164	28/11/2019 11:21	7.95	7.61	1	4.52
1271378	520	27/11/2019 19:42	28/11/2019 07:01	287	28/11/2019 07:25	4.67	6.41	1	2.2
1271808	630	27/11/2019 19:37	28/11/2019 13:57	573	28/11/2019 15:36	3.76	4.79	2	12.39
2018530	607	27/11/2019 21:37	28/11/2019 11:21	636	28/11/2019 11:39	4.47	5.23	1	2.21

Table 18. Extract of the sample related to the busiest day.

It was chosen to forecast the mean power distribution in city of Turin in 15 years from now (2036). According to what was obtained from Bass model forecast, 11,30% of the vehicles will be EVs in 2036. Assuming that the sample related to 28th November 2019 might describe also the mobility patterns in 2036, as a sample describing the total circulating vehicles in Turin, 11,30% of the vehicles belonging to the dataset were randomly considered Electric Vehicles. Therefore, data referred to 3.094 Electric Vehicles were studied and analysed: it is as if 3.094 EVs will travel on the busiest day of the week in Turin in 2036.

Since many people own a private box, the possibility to recharge the vehicle without using the public devices was assigned randomly to half of the sample. The private box was hypothesised to be in Oi. Thus, the sample was subdivided in two datasets:

- Private box owner: 50% of the vehicles recharge in Oi at a constant power equal to 4 kW (recharge at home);
- Private box unavailable: 50% of the vehicles recharge in Dj at a constant power equal to 22 kW (public recharge).

In order to quantify the amount of energy needed to fully recharge the vehicles, the maximum electric range/autonomy of the vehicle was set equal to 300 km, that is the maximum distance that the vehicle can travel without recharging; hence to this value corresponds a State of Charge (SoC) equal to 100%. Moreover, from FCD analysis the mean daily travelled distances of all the vehicles belonging to the dataset were obtained.

The actual SoC of the vehicles was directly linked to the actual electric range available, that can be read as the distance that can still be travelled:

$$electric\ range\ [km] = (max\ electric\ range)\ -\ TD$$

where:

- Max electric range is equal to 300 km;
- TD is the distance travelled by the vehicle at the time of charging.

Knowing the electric range, the state of charge was calculated as the relative ratio between the distance that might still be travelled without recharging and the maximum distance that can be travelled by the vehicle:

$$SoC\ [\%] = \frac{electric\ range}{max\ electric\ range} \cdot 100$$

However, the minimum SoC for the vehicles was set equal to 20%. Hence, for vehicles that according to math travelled longer distances than 1/5 of the maximum electric range, the SoC was forced to be 20% and the electric range to be 1/5 of the maximum electric range. This was done to set a minimum value of SoC supposedly representative of the reality. It was assumed that people would never drive if the vehicle had a state of charge lower than 20%.

vehID	Oi	…	Weight	Mean daily TD [km]	TD [km]	EV 2036	Box	Electric range [km]	SoC [%]
1451337	212	…	9.09	6.62	33.12	1	1	266.88	89
2508610	604		3.54	24.20	121.01	1	0	178.99	60
2526117	588		20.09	9.61	48.03	1	0	251.97	84
2600483	645		3.63	24.95	124.74	1	1	175.26	58
2608966	535		104.25	18.18	90.88	1	0	209.12	70
2629305	635		11.68	19.64	98.19	1	0	201.81	67
2630932	484		5.45	12.70	63.48	1	1	236.52	79
2707853	638		10.14	138.30	691.48	1	1	60.00	20
2738152	598		8.91	18.78	93.89	1	1	206.11	69
2739210	640		8.2	50.39	251.96	1	1	60.00	20
2740959	717		5.41	38.03	190.14	1	1	109.86	37
2740975	403		5.66	35.77	178.86	1	0	121.14	40
2746142	307		2.93	73.49	367.46	1	0	60.00	20
3168076	747		3.29	26.98	134.88	1	0	165.12	55
3233426	160		6.99	22.26	111.28	1	0	188.72	63
3237291	679		4.95	12.97	64.84	1	0	235.16	78

Table 19. Extract of the EV sample.

At this point, the sample containing the EVs mobility patterns related to the busiest day (28th November 2019) was implemented as described below:

1. EVs "owning" a private box (called below as *BOX*) were separated from the ones not owning a private box (called below as *NO_BOX*);
2. As already told the main differences between BOX and NO_BOX are:
   - BOX: EVs recharge from a private charging device at a constant *power* of 4 kW located in Oi;
   - NO_BOX: EVs recharge from a public charging device at a constant *power* of 22 kW located in Dj.
3. The energy consumed was calculated for all the vehicles as:

$$energy\ consumed\ [kWh] = TD \cdot (mean\ energy\ consumption)$$

   Where:
   TD=Travelled Distance
   Mean energy consumption=0,168 kWh/km for a B segment.

4. The charging time required to reach a SoC equal to 100% was calculated for all the vehicles as:

$$charging\ time\ = \frac{energy\ consumed}{power}$$

   However, if the *charging time* obtained was higher than the actual idle time in Oi (BOX) or Dj (NO_BOX) it was set equal to the idle time itself. Therefore, the idle time for BOX vehicles referred to the difference between the times of departure and arriving in Oi, whilst the idle time for NO_BOX vehicles referred to the difference between times of departure and arriving in Dj (called above as *idle time Dj*).

Since the key result was to obtain a distribution of the mean power needed for the EVs aggregated by zones and hours, the actual time spent recharging hour per hour was calculated using the software Python. Particularly, a code that assigned the hour linked to the time the vehicle recharges and the total time spent recharging was written. The total time was divided in intervals equal to 1 minute.

Time Dj	Charging time [min]	Hour	vehID
28/11/2019 07:14	1	7	5446871
28/11/2019 07:15	1	7	5446871
28/11/2019 07:16	1	7	5446871
	…		
28/11/2019 07:59	1	7	5446871
28/11/2019 08:00	1	8	5446871
28/11/2019 08:01	1	8	5446871
28/11/2019 08:02	1	8	5446871
	…		
28/11/2019 08:13	1	8	5446871
28/11/2019 08:14	1	8	5446871
28/11/2019 15:18	1	15	5901765
28/11/2019 15:19	1	15	5901765
28/11/2019 15:20	1	15	5901765
	…		
28/11/2019 15:58	1	15	5901765
28/11/2019 15:59	1	15	5901765
28/11/2019 16:00	1	16	5901765
28/11/2019 16:01	1	16	5901765
28/11/2019 16:02	1	16	5901765
28/11/2019 16:03	1	16	5901765
28/11/2019 16:04	1	16	5901765
28/11/2019 16:05	1	16	5901765
	..		
28/11/2019 07:00	1	7	2366670

Time Dj	Charging time [min]	Hour	vehID
28/11/2019 07:01	1	7	2366670
	…		
28/11/2019 07:58	1	7	2366670
28/11/2019 07:59	1	7	2366670
28/11/2019 08:00	1	8	2366670
28/11/2019 08:01	1	8	2366670
28/11/2019 08:02	1	8	2366670
	…		
28/11/2019 08:48	1	8	2366670
28/11/2019 08:49	1	8	2366670
28/11/2019 12:39	1	12	4182555
28/11/2019 12:40	1	12	4182555
	…		
28/11/2019 12:58	1	12	4182555
28/11/2019 12:59	1	12	4182555
28/11/2019 13:00	1	13	4182555
28/11/2019 13:01	1	13	4182555
28/11/2019 13:02	1	13	4182555
	…		
28/11/2019 13:53	1	13	4182555
28/11/2019 13:54	1	13	4182555
28/11/2019 13:55	1	13	4182555

Table 20. Extract of the charging intervals for all the EVs.

Summing all the intervals, the actual charging time of the vehicles, hour per hour, was finally obtained. This datum was used to get the total energy charged per vehicle hour by hour:

$$energy\ charged\ [kWh/veh] = (charging\ time) \cdot (power)$$

In order to resize all the results to the Universe, the *energy charged* by each vehicle was multiplied for its weight:

$$total\ energy\ charged = (energy\ charged) \cdot (weight)$$

Finally, joining the results achieved for BOX and NO_BOX the definitive and last data frame was obtained. This data frame gives information about:

- Zone: it is the zone where the vehicles recharge;
- Hour: it identifies the hour when vehicles recharge;
- Mean charging time: it is the mean charging time per vehicle in the zone considered;
- # Vehicles: it is the number of vehicles recharging, zone by zone, hour per hour, sized to the universe;
- Mean power: it is the mean hourly power needed by the zone, hour per hour, to meet the demand:

$$Mean\ power\ [kW] = \frac{(total\ energy\ charged)}{1\ h}$$

Zone	Hour	Mean charging time [min/veh]	# Vehicles	Mean power [kW]
38	12	45	3.59	10.75
38	13	60	3.59	14.34
38	14	60	3.59	14.34
38	15	60	3.59	14.34
38	16	60	3.59	14.34
38	17	60	3.59	14.34
38	18	60	3.59	14.34
38	19	60	3.59	14.34
38	20	60	3.59	14.34
38	21	11	3.59	2.63
47	0	60	6.8	27.18
47	1	60	6.8	27.18
47	2	53	6.8	24.01
47	10	26	6.8	11.78
47	11	60	6.8	27.17
47	12	60	6.8	27.17
47	13	60	6.8	27.17
47	14	60	6.8	27.17
47	15	60	6.8	27.17
47	16	60	6.8	27.17
47	17	34	6.8	15.40
47	18	22	6.8	9.97
47	19	60	6.8	27.18

Table 21. Extract of the Mean Power distribution.

From *Open Charge Map* the localization of the *in-use* charging stations was acquired. As already revealed, since the energetic focus regards only the city of Turin, the localization in figure 34 refers only to stations placed inside the border of the city.

The main achievement was to forecast the future need of the mean power within the city of Turin. To graphically represent the results, two scenarios were considered:

- Scenario 1: it was hypothesized that the vehicles travelled for 5 days and then they recharge on the 6th day, but only the vehicles with a SoC lower than 60% would recharge.
- Scenario 2: A random SoC was assigned to all the vehicles and it was assumed that all the vehicles would recharge after travelling a distance equal to the mean daily travelled distance.

For both the scenarios, a bar graph and three heat maps showing the mean power distribution in the city are represented. The bar graphs refer to the mean power distribution within the city over the day. The heat maps show the hour with the highest demand over the day. The first heat map refers to all the vehicles, the second one refers only to the vehicles/people that do not own a private box, the third one only to vehicles/people that own a private box. According to the assumptions made in the chapters above, it is reasonable to assess that only the vehicles that cannot recharge in a private box will use the public charging devices.

5.2.1 Scenario 1 (SoC < 60%)

Since the mean daily travelled distance is not comparable with the maximum electric range, these distances were multiplied by a factor 5 to increase the total distance travelled by the vehicles before recharging: at higher travelled distances usually correspond a greater need of recharging; people recharge the vehicles only after very long trips, when the tank is almost empty. This assumption can be seen as if people have travelled for five days, e.g. from Monday to Friday, and then all would have recharged on Saturday. This was done to have a higher mean power distribution (worst case) within the city, and to make the forecast as close as possible to reality. All the above assumptions aim to make the model similar to what happens to the reality. If more information about people behaviours in each zone were available, the model might be improved. However, according to what was told in previous chapters, if the SoC reached after 5 days would have been higher than 20%, the vehicle would have recharged before the 5th day, as the SoC got equal to 20% (20% is the minimum SoC that people can reach according to the preliminary assumptions).

The mean power distribution over the day shows that according to the results, the higher energy is consumed in the morning. The morning peak is between 8.00 and 10.00. This distribution was obtained from the analysis of 1.348 EVs circulating in Turin (mean daily travelled distance of the dataset equal to 42,4 km/day).

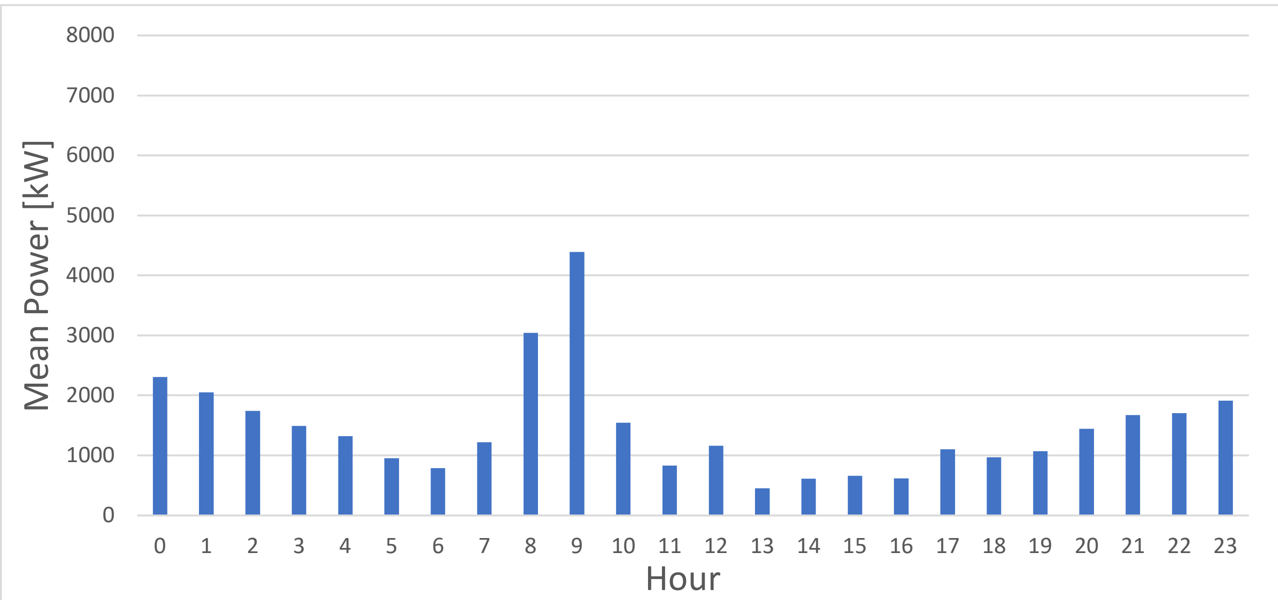
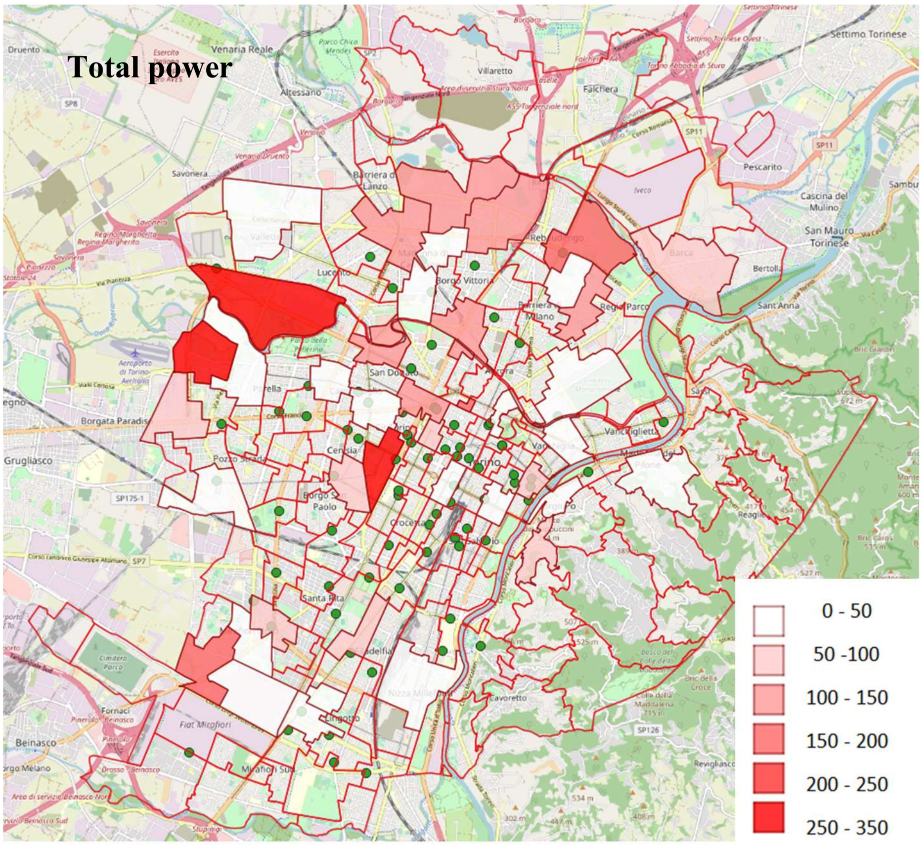


Figure 37. Mean power distribution (scenario 1).

In the afternoon there is an increasing trend of the power distribution. These results are close to the reality since it can be assumed that people arrive at work in the morning and park their own vehicles, and then they will go back home in the evening. Therefore, the increasing trend of power distribution starting from 18.00 to midnight and then the decreasing trend starting from midnight can be justified by the fact that as more people go back home, more power would be needed. Since the power of the charging devices at home is lower than that provided by public charging stations, vehicles recharging at home need much more time to fully recharge.

The morning peak was graphically represented using the software QGIS. The distribution refers to the mean power needed by each zone from 9.00 to 10.00. The first representation refers to all the vehicles. The other two figures refer respectively to vehicles without a private box (left) and with a private box (right). The dots on the figures represent the current charging devices that are located within the city of Turin operated by *EVWAY, Tesla Motors, Blue Torino/Leasys and Enel*.



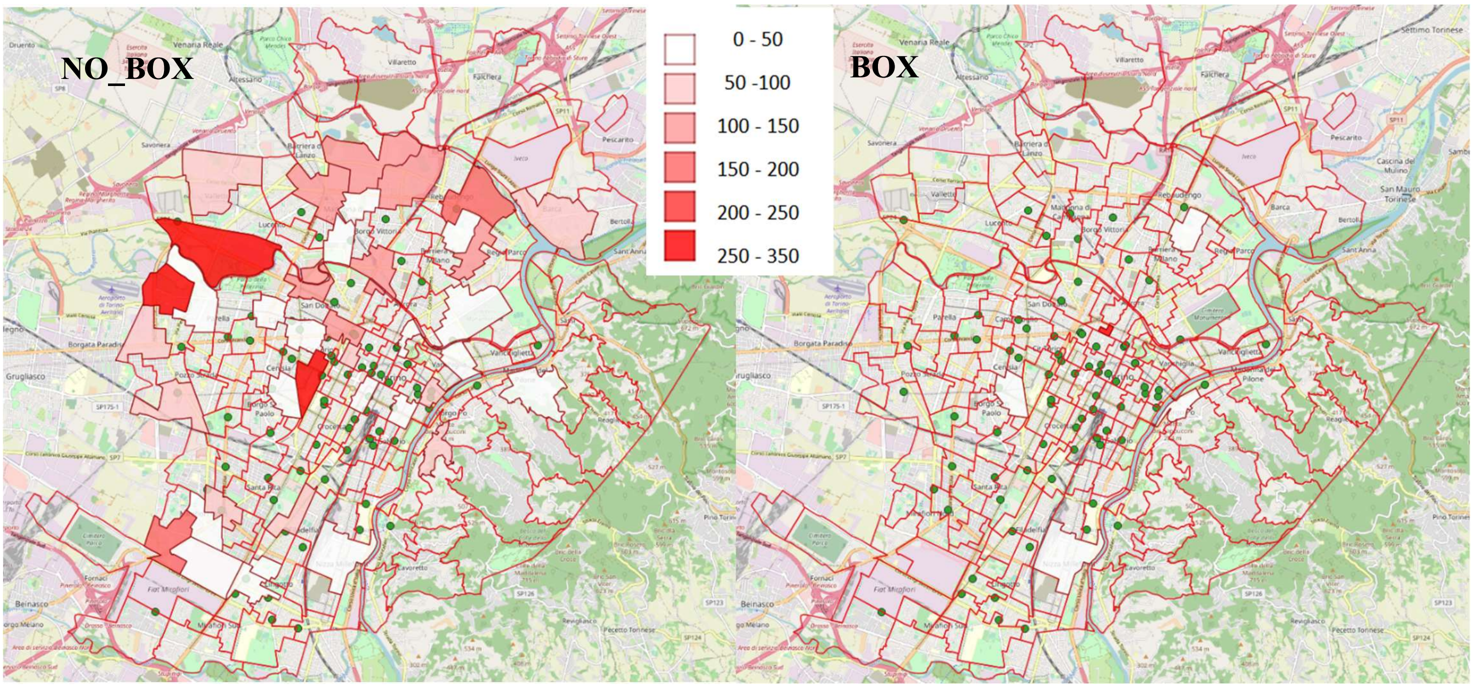


Figure 38. Mean power distribution [kW] at peak hour (scenario 1) according to preliminary assumptions.

Since the representations refer to the morning peak, only few zones are used by vehicles that are supposed to own a private box. In fact, it is reasonable to assess that over the morning peak most of the people work and they would not drive back home. This is also why the largest energetic consumptions regard zones close to the main Turin attraction workplace zones, such as Mirafiori and Politecnico di Torino. Scenario 1 may be considered as representative of a *medium range anxiety*, due to the fact that people would recharge only if SoC would be lower than 60%. According to the results, the electric network should be developed towards northern neighbourhoods where the electric demand was estimated to be relevant. The same concerns may be applied for the zones close to the Parco della Pellerina where a business centre is settled. Currently, there aren't charging stations that serve those zones.

5.2.2 Scenario 2 (SoC < 100%)

In this scenario, an initial SoC between 20% and 100% was randomly assigned to the vehicles. Then, it was assumed that all the vehicles would have travelled a distance equal to their mean daily travelled distance before recharging.

As it was done for the scenario 1, the mean power distribution is shown in figure 39 in a bar graph. This distribution was obtained from the analysis of 3.094 EVs circulating in Turin (mean daily travelled distance of the dataset equal to 27,8 km/day).

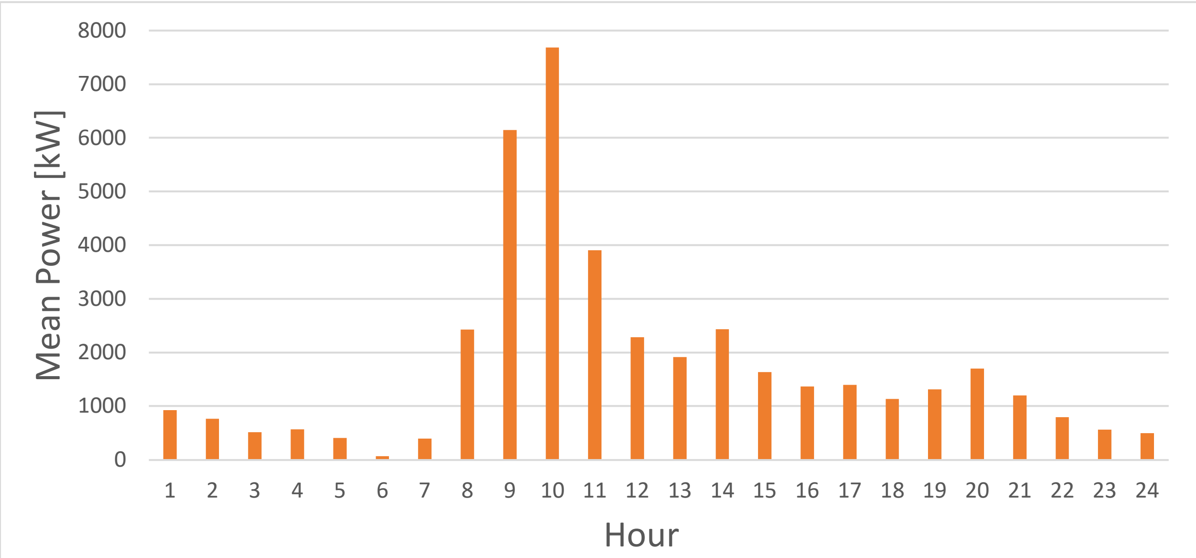


Figure 39. Mean power distribution (scenario 2)

From the graph it is possible to notice the morning peak between 8.00 and 11.00. Since in this scenario all the vehicles recharge, it is reasonable to assess that most of them would recharge as soon as they arrive at the workplace. Therefore, the morning peak is much higher than the other values because, as it would happen in the reality, people would charge the vehicles in the place they would spend most of the time. Supposing that they would travel to workplace at 8.00, they would charge the vehicle as they arrive.

The morning peak was graphically represented using the software QGIS. The distribution refers to the mean power needed by each zone from 9.00 to 10.00 that is also the hour analysed in scenario 1. The first figure refers to all the vehicles. The other two figures refer respectively to vehicles without a private box (left) and with a private box (right). The dots on the figures represent the current charging devices that are located within the city of Turin operated by *EVWAY, Tesla Motors, Blue Torino/Leasys and Enel*.

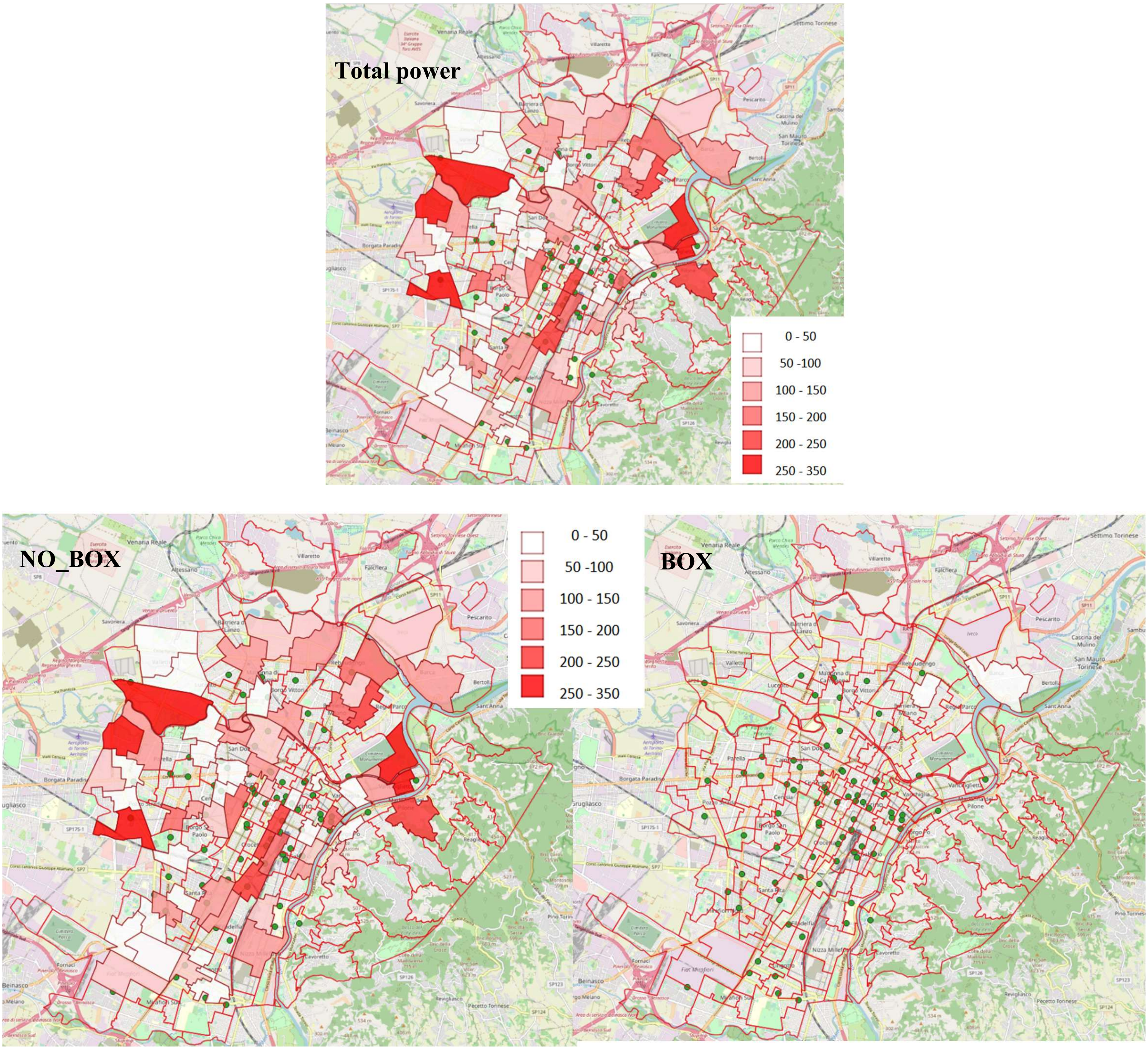


Figure 40. Mean power distribution [kW] at peak hour (scenario 2) according to preliminary assumptions.

As it happened for the scenario 1, most of the vehicles that recharge over the morning peak are the ones without the private box. Only two zones concern the presence of vehicles that "own" a private box. Since all the vehicles recharge regardless their state of charge, in this scenario more zones are affected by the presence of charging vehicles. Attraction poles such as Lingotto and all the zones within Piazza d'Armi would get high energy demand according to these results. Scenario 2 may be considered as representative of a *high range anxiety*, due to the fact that people would always recharge at the end of the day, regardless the distance that the vehicle might still travel. According to the results, northern and western neighbourhoods are the zones in which new charging stations should be settled because they are not currently served by any charging devices.

Although only two scenarios were represented in this thesis, the results obtained could be used as potential indicators suggesting in which places new public charging stations could be placed. These two scenarios were chosen regarding the mean power distribution but changing the input data in the Python algorithm different scenarios may be obtained.

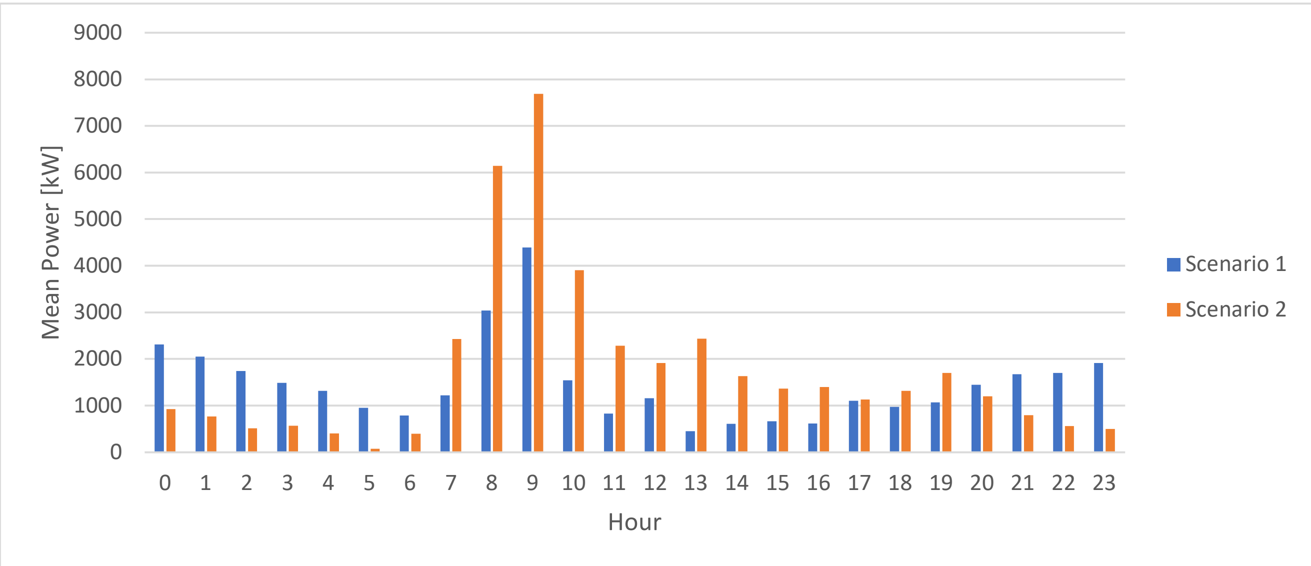


Figure 41. Mean power distribution comparison.

Figure 41 shows the comparison between the mean power distribution between the two scenarios analysed. The largest energetic consumption regards scenario 2. However, it can be noticed that the peak in terms of energetic consumption happen over the same hours.

Chapter 6: Conclusions

The main objective of this thesis was modelling charging activities of electric vehicles for the estimation of the power needed within the city of Turin to accommodate the future electric mobility. Starting from the analysis of the vehicle trips recorded by FCD, it was possible to study the mobility patterns of a sample made by little more than 35.000 vehicles. After the cleaning process and the trips concatenation, the final sample allowed to study separately private and light commercial vehicles trips in order to aggregate them and extract significantly features such as the mean daily travelled distances and the mean travel times. Moreover, the trips were divided into three day-types (Weekdays, Saturdays, Sundays) to get tailored results. Knowing the number of trips per day over the month of November 2019, and the starting and ending point of each trip, the graphical representation and the geolocation of the trips were conducted. Therefore, a deeper classification of the trips was made according to the fact they occurred within the study are (Turin metropolitan area), outside the study area, and/or through the study area. In addition, adding 5T zoning to the representation, the geolocation allowed to get the zone from which and to which the trips started and ended. This made possible the realization of the origin-destination matrices that have been compared to 5T matrices in order to size the sample to the universe/reality. The matrices described the mobility patterns in terms of flows over the day, showing what are the busiest neighbourhoods within the study area according to the data provided by FCD. The results showed that the highest number of trips was concentrated in industrial zones (especially Mirafiori), in the city centre (between Porta Susa and Porta Nuova railway stations) and in the municipalities outside the border of the city of Turin (such as Chieri). The analysis on the mobility patterns allowed also the detection of peak-hours over the day. It was noticed that they occurred in different times depending on the day considered. However, it was possible to identify one morning peak hour and one evening peak hour for all the day-types. Overall, the results obtained matched the reality.

Another important task of this work was to estimate the future number of electric vehicles in Turin metropolitan area in order to have an idea of the potential demand for the power/energy required to face the future demand. The Bass model was used as tool to forecast the demand. The forecast was conducted using the comparison *as analog*, hence the Hybrid-Electric-Vehicles diffusion in Italy was analysed and studied. From that diffusion, the coefficients of adoption and imitation were obtained and used for the EV forecast diffusion in Turin. Results showed that the first significant number of EVs will be reached around 2030 when 2,45% of the total circulating vehicles might be EVs. Another significant target was set to 2040 when EVs might skyrocket to 28,06% and then dramatically increase exponentially. This is why it would be suggested that Turin infrastructures should be ready at least by 2030 to fully accommodate the electric demand. This forecast was exploited to estimate the power distribution within the city of Turin. According to the forecast, in 15 years from now, 11,30% of the circulating vehicles will be EVs. This datum was used as input for the mean electric power estimation. The energy focus was conducted only within the border of the city and not in all the metropolitan area because city of Turin is currently the area with the most widespread charging network in the entire study area. Therefore, starting from the sample containing the mobility patterns of the FCD for the busiest day (28th November 2019), some assumptions were made to forecast the power distribution along the zones. The private boxes owners were estimated randomly to separate vehicles that would have used private recharging (power equal to 4 kW – at home) from the ones that would have used public recharging (power equal to 22 kW – public charge). This final step has consisted to determine the future power distribution needed by all the zones. Although many assumptions were made, the results may be a good starting point to forecast zones in which future electric demand could play a crucial role in Turin road networks. However, some of the conducted analysis can be improved and refined according to data availability. In fact, all the algorithms that were written may be applied to different scenarios only changing the input parameters. If more data were available about Turin mobility, concerning also behaviours about electric mobility, more reliable results might be obtained.

Firstly, to what concern the sample from which electric data were obtained (chapter 5), the boxes assignment for the vehicles might be carried out more precisely. Rather than assign the private box to half of the dataset, looking for data about the number of boxes' owners, and where they are located, would increase the reliability of the results of this study. Similarly, the EVs spread in city of Turin was randomly estimated without analysing the fact that not all the people would buy electric vehicles until their prices become competitive compared to those of city/family cars. Studying, zone per zone, to which extent people are keen to switch to electric mobility would refine the estimation of EVs spread within the study area. Moreover, the Bass model doesn't consider the socio-economic characteristics of the citizens. If this type of data was available for each zone, the model built in this work might be refined.

Finally, knowing the charging behaviours and how people would be affected by the "range anxiety", the estimation of the scenarios related to the mean electric power distribution would be more-close-to-reality.

◊ ◊ ◊ ◊

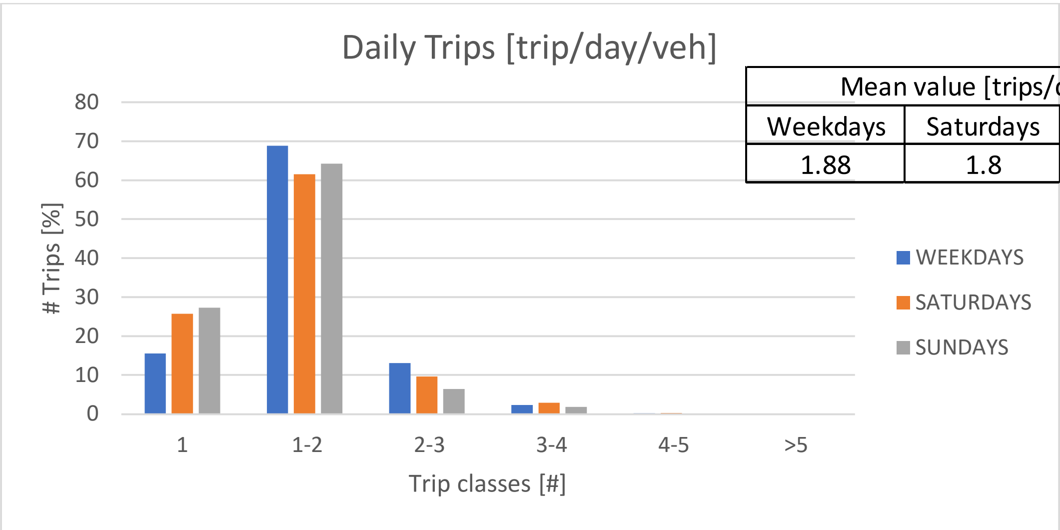
Transport means are steadily changing, and the infrastructures need to keep up with them. Providing new charging stations within the city of Turin may help the spread of electric mobility over the next years. Electric vehicles hold the potential of transforming the way the world moves. They can increase energy security by diversifying the fuel mix and decreasing dependence on petroleum, while also reducing emissions of greenhouse gases and other pollutants. Just as important, EVs can unlock innovation and create new advanced industries that spur job growth and enhance economic prosperity. To accelerate this transition, cities and metropolitan regions around the world are creating EV-friendly ecosystems and building the foundation for widespread adoption. Promoting the realization of projects consistent with long-terms strategies for the reduction of the air pollution and gas emissions, Turin may become an interesting *Smart City* improving the quality of life through the application of effective solutions and protocols. The spread of the sustainable mobility is surely a great starting point to optimize and improve the everyday life of Turin citizens.

APPENDIX A

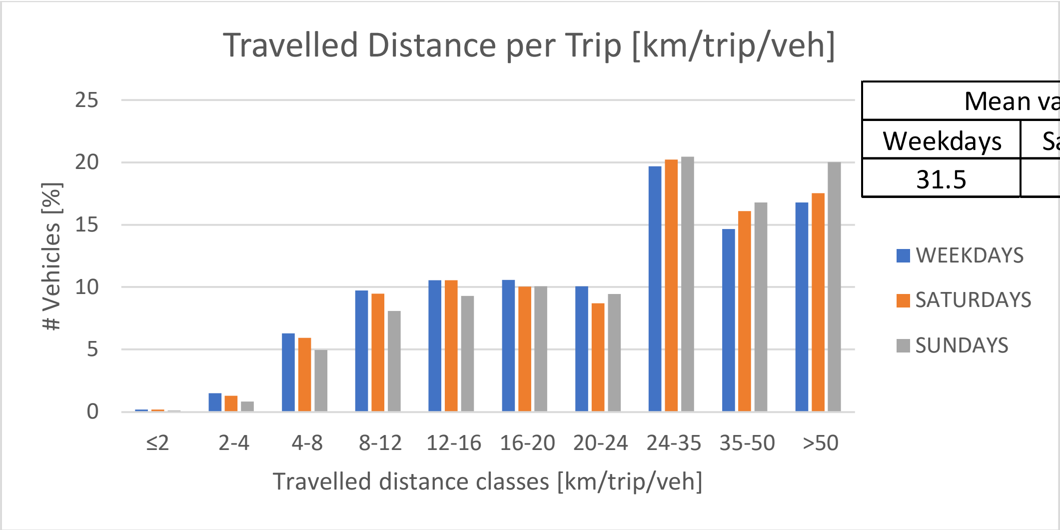
- PRIVATE VEHICLES:

  – <u>external trips</u>:

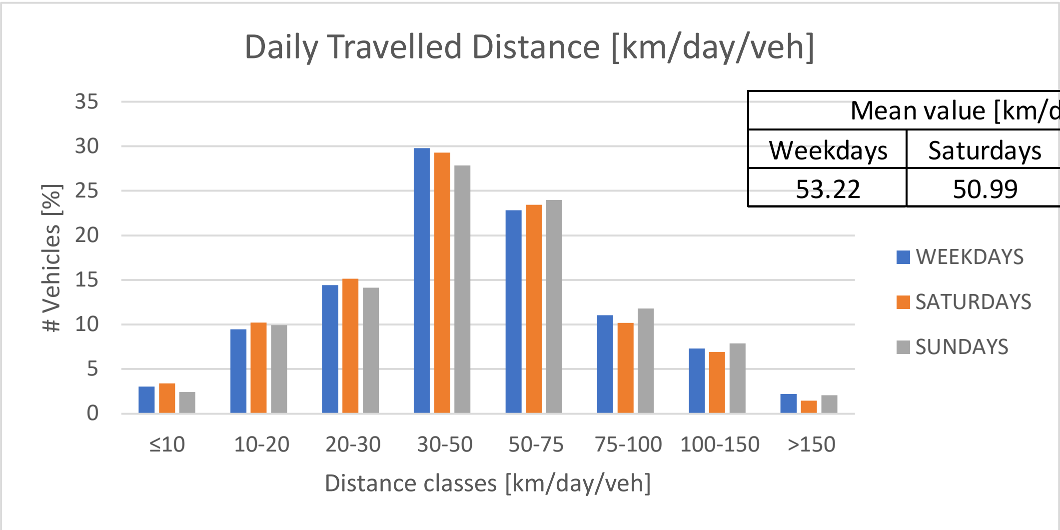
Mean number of total trips		
WEEKDAYS	SATURDAYS	SUNDAYS
8632	7347	6067



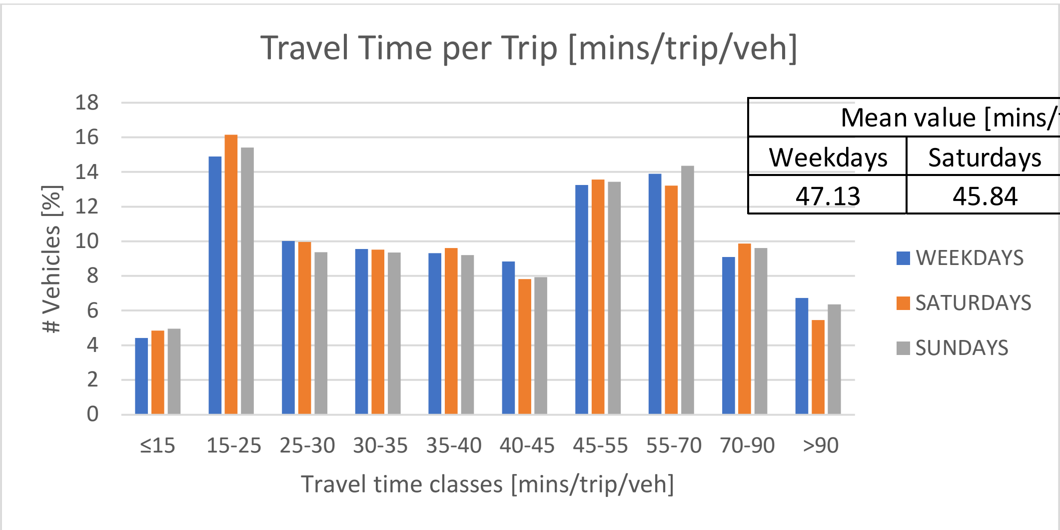
Mean value [trips/day]		
Weekdays	Saturdays	Sundays
1.88	1.8	1.75



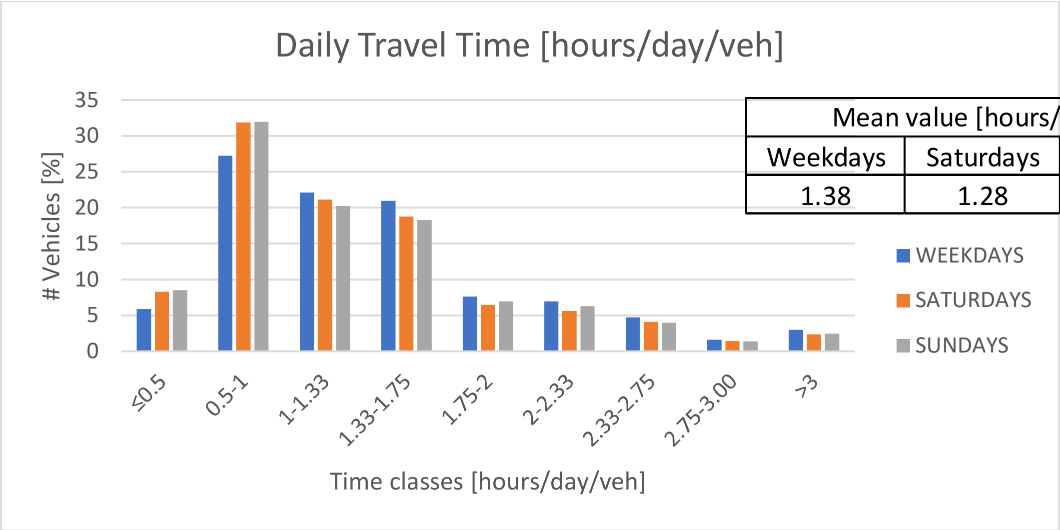
Mean value [km/trip]		
Weekdays	Saturdays	Sundays
31.5	31.48	34.04



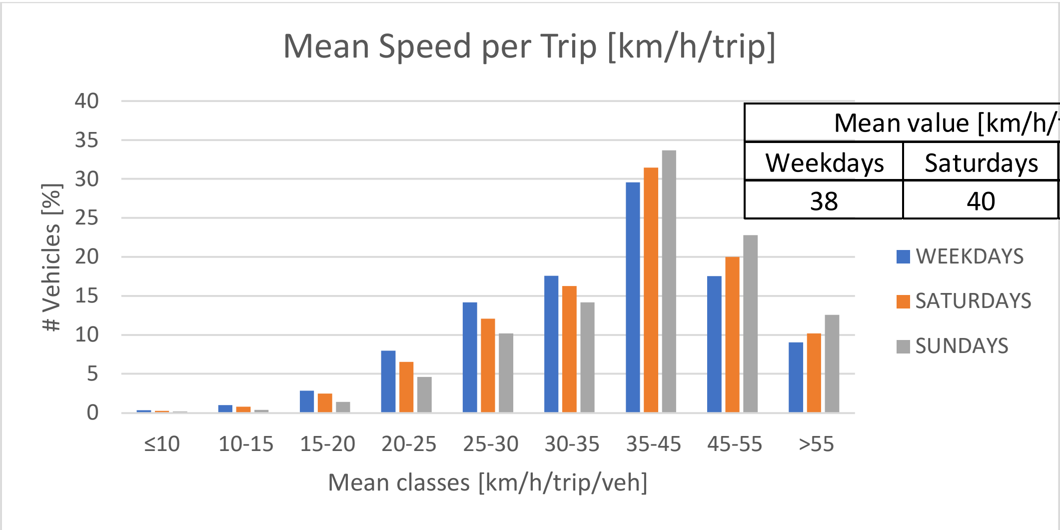
Mean value [km/day]		
Weekdays	Saturdays	Sundays
53.22	50.99	54.02



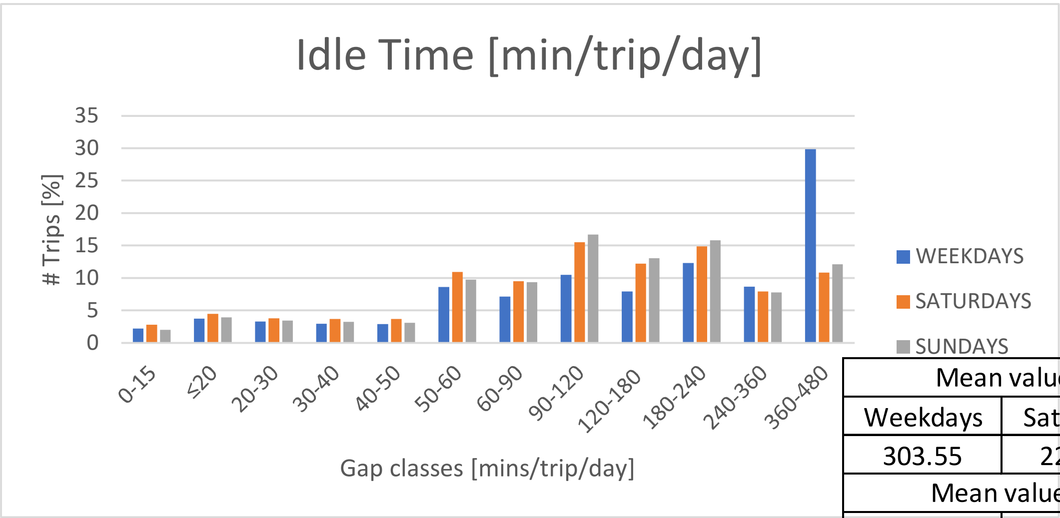
Mean value [mins/trip]		
Weekdays	Saturdays	Sundays
47.13	45.84	46.18



Mean value [hours/day]		
Weekdays	Saturdays	Sundays
1.38	1.28	1.26



Mean value [km/h/trip]		
Weekdays	Saturdays	Sundays
38	40	42

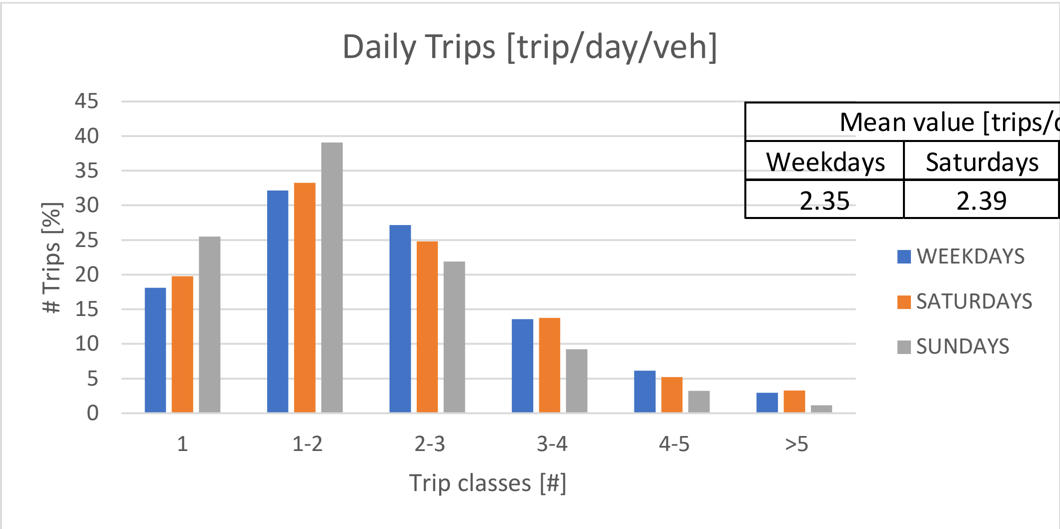


Mean value [mins/trip]		
Weekdays	Saturdays	Sundays
303.55	221.42	235.05
Mean value [hours/trip]		
Weekdays	Saturdays	Sundays
5.06	3.69	3.92

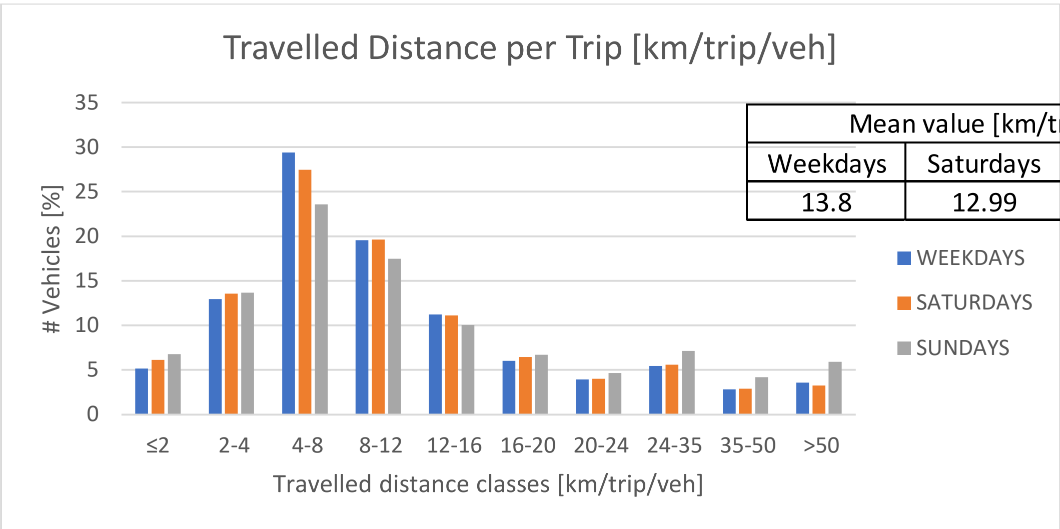
Figure 42. Bar graphs for external trips (private vehicles).

– <u>crossing trips</u>:

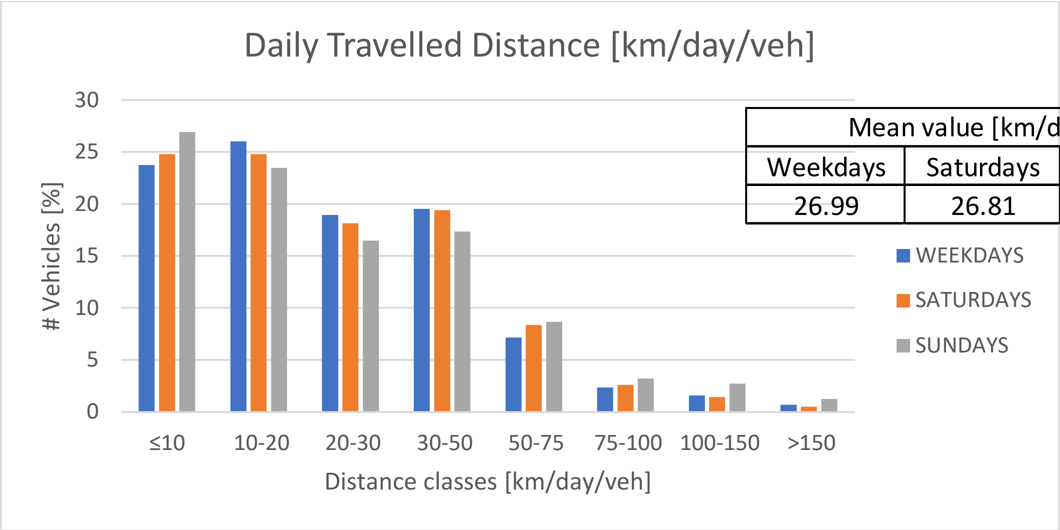
Mean number of total trips		
WEEKDAYS	SATURDAYS	SUNDAYS
16209	14718	10250



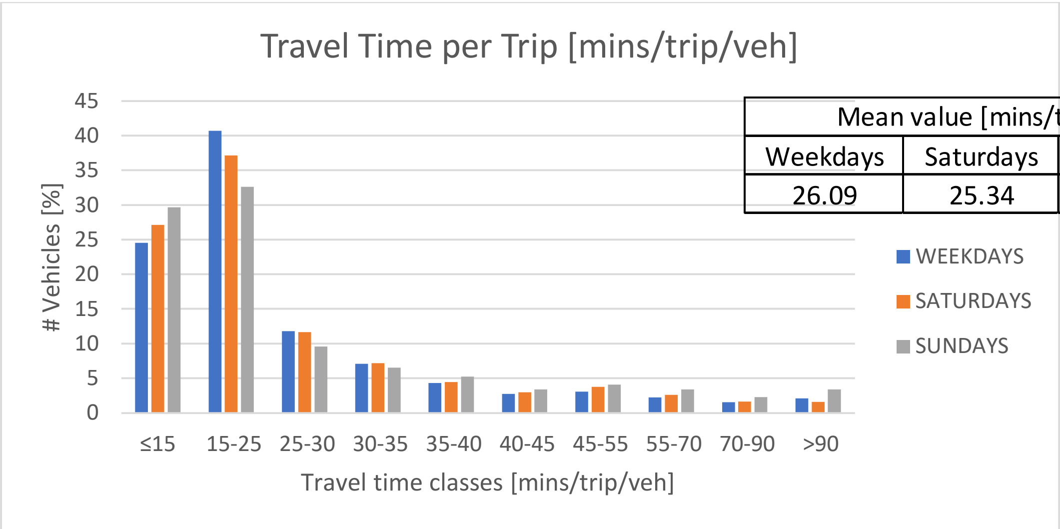
Mean value [trips/day]		
Weekdays	Saturdays	Sundays
2.35	2.39	2.12



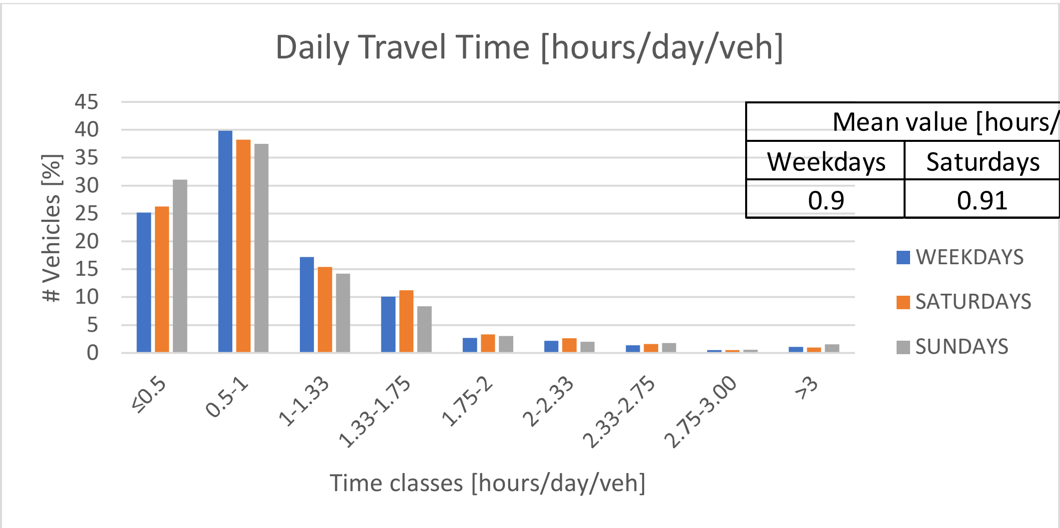
Mean value [km/trip]		
Weekdays	Saturdays	Sundays
13.8	12.99	16.58



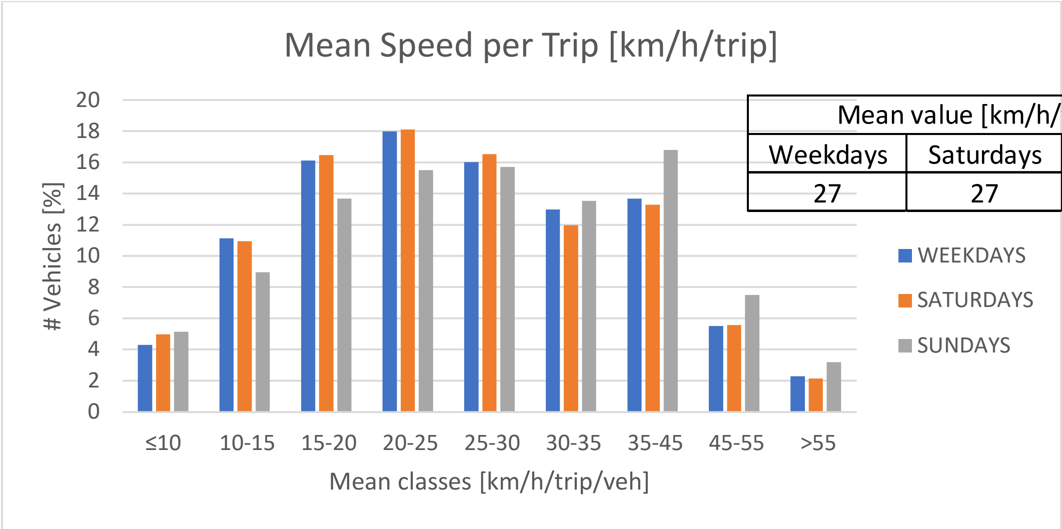
Mean value [km/day]		
Weekdays	Saturdays	Sundays
26.99	26.81	29.33



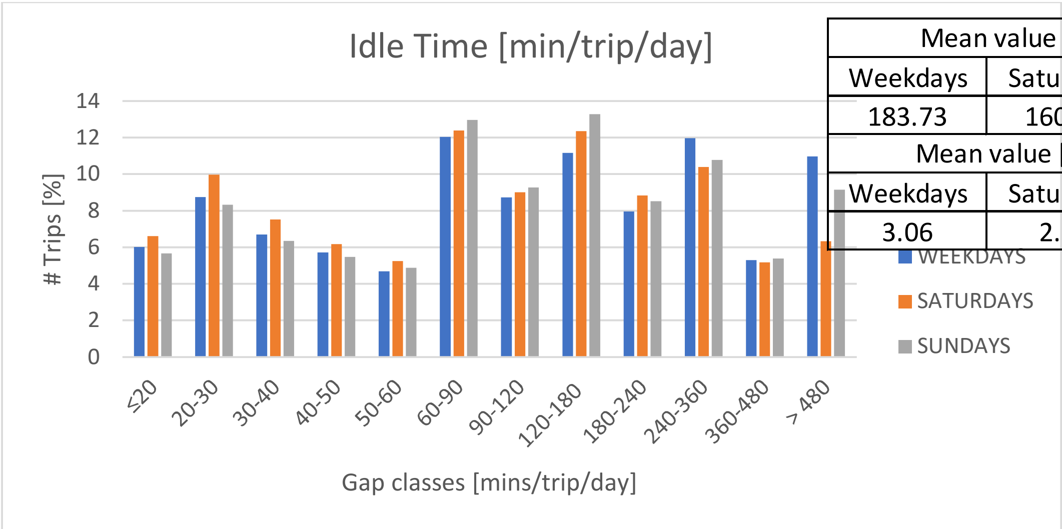
Mean value [mins/trip]		
Weekdays	Saturdays	Sundays
26.09	25.34	28.13



Mean value [hours/day]		
Weekdays	Saturdays	Sundays
0.9	0.91	0.87



Mean value [km/h/trip]		
Weekdays	Saturdays	Sundays
27	27	29



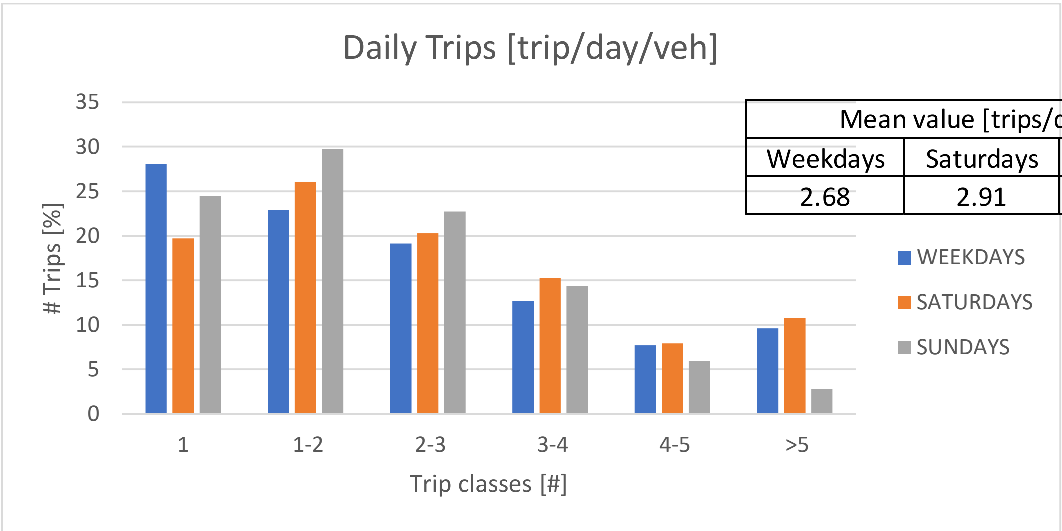
Mean value [mins/trip]		
Weekdays	Saturdays	Sundays
183.73	160.44	183.73
Mean value [hours/trip]		
Weekdays	Saturdays	Sundays
3.06	2.67	3.06

Figure 43. Bar graphs for crossing trips (private vehicles).

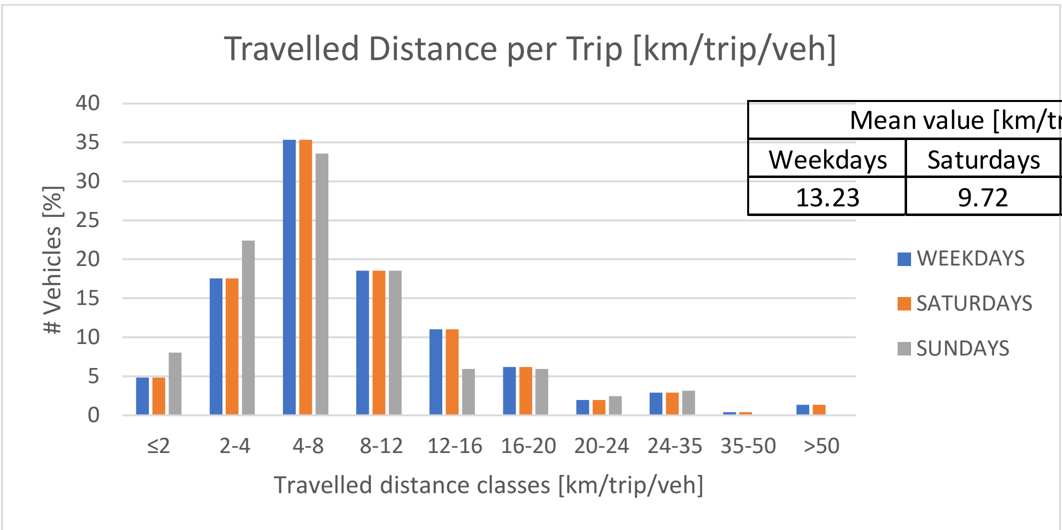
- LIGHT COMMERCIAL VEHICLES:

  – <u>Internal trips</u>:

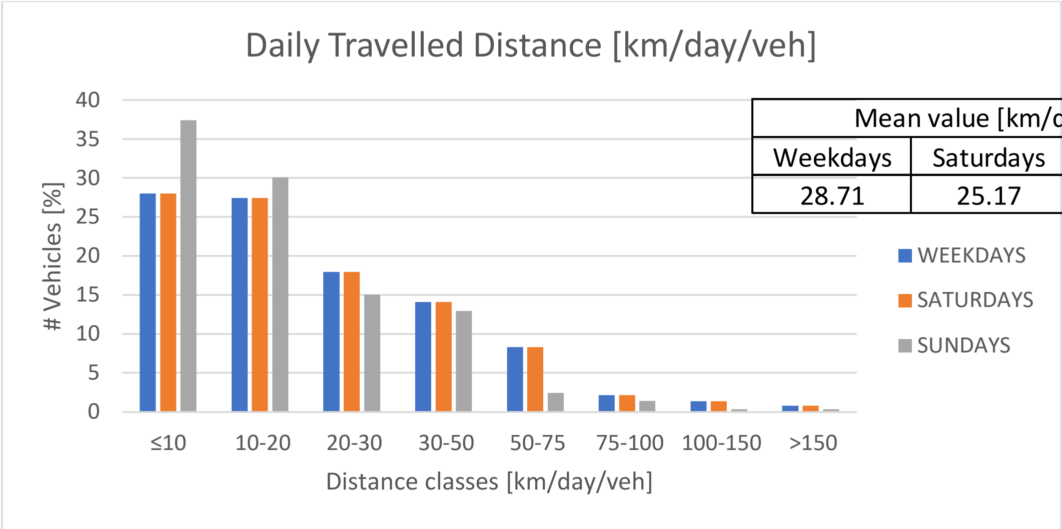
Mean number of total trips		
WEEKDAYS	SATURDAYS	SUNDAYS
1957	853	371



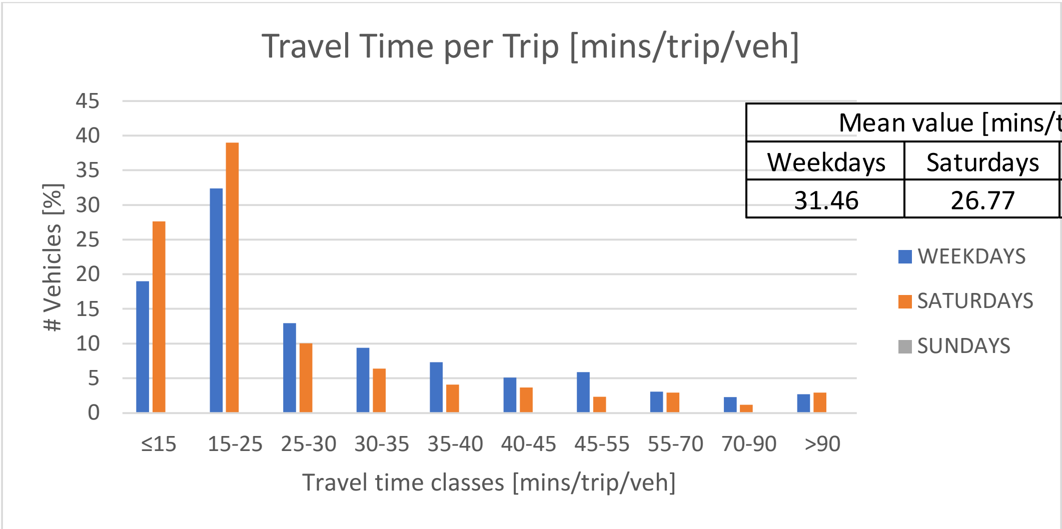
Mean value [trips/day]		
Weekdays	Saturdays	Sundays
2.68	2.91	2.43



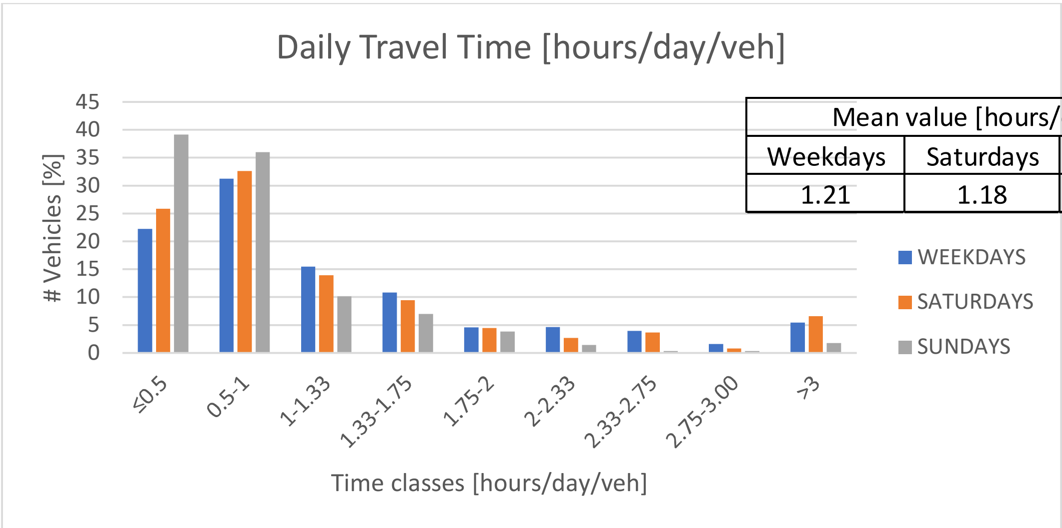
Mean value [km/trip]		
Weekdays	Saturdays	Sundays
13.23	9.72	7.82



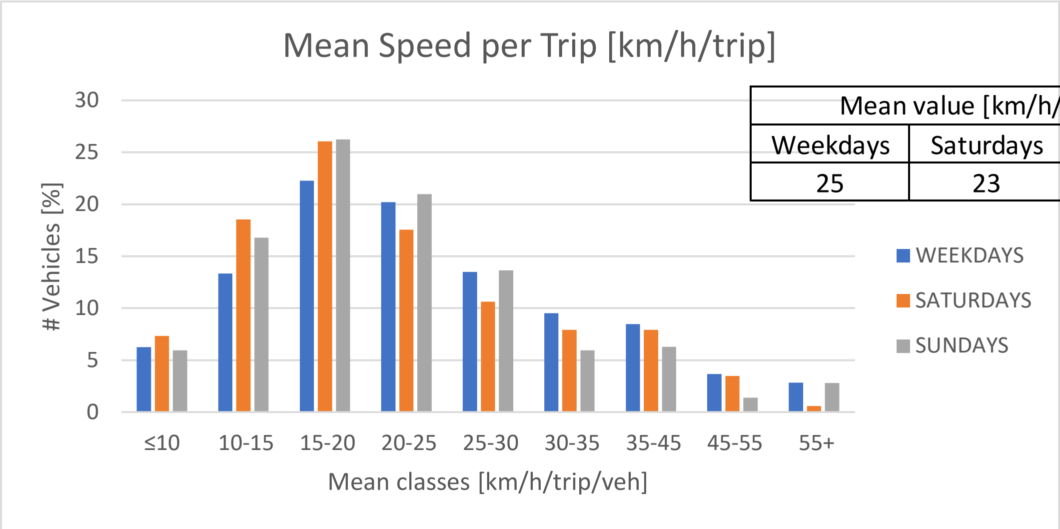
Mean value [km/day]		
Weekdays	Saturdays	Sundays
28.71	25.17	18.54



Mean value [mins/trip]		
Weekdays	Saturdays	Sundays
31.46	26.77	20.86



Mean value [hours/day]		
Weekdays	Saturdays	Sundays
1.21	1.18	0.8



Mean value [km/h/trip]		
Weekdays	Saturdays	Sundays
25	23	23

Mean value [mins/trip]		
Weekdays	Saturdays	Sundays
98.92	99.3	138.05
Mean value [hours/trip]		
Weekdays	Saturdays	Sundays
1.65	1.66	2.30

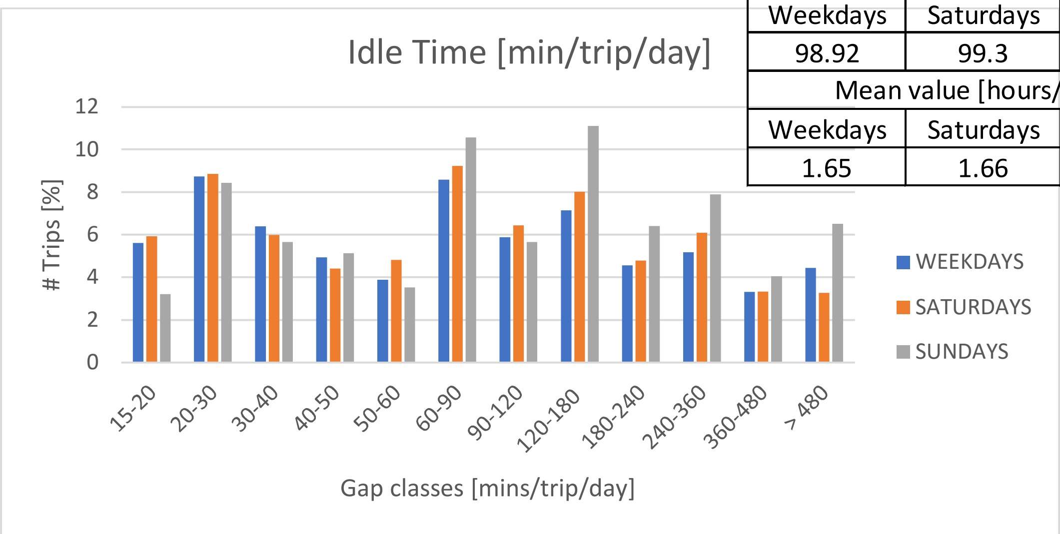
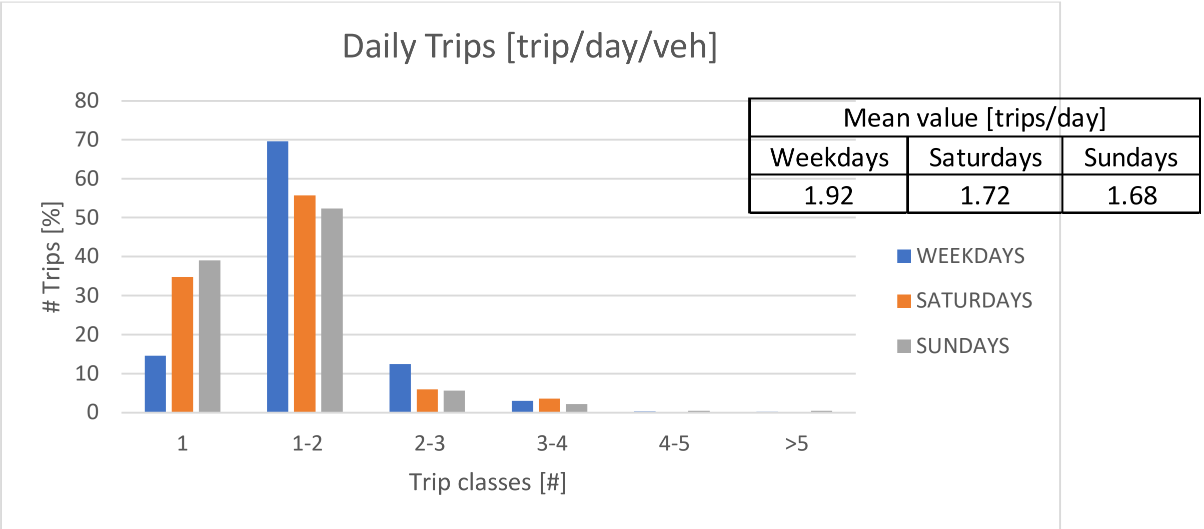
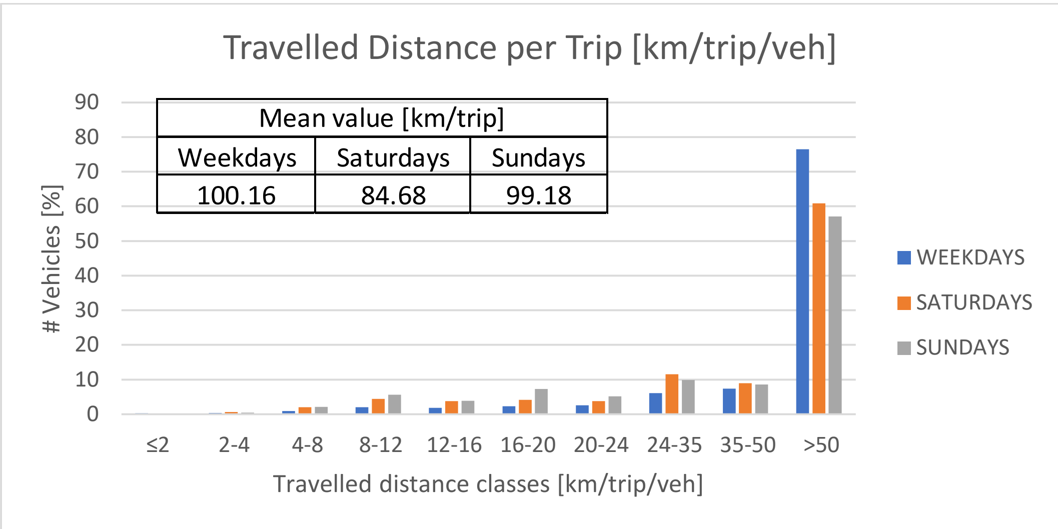


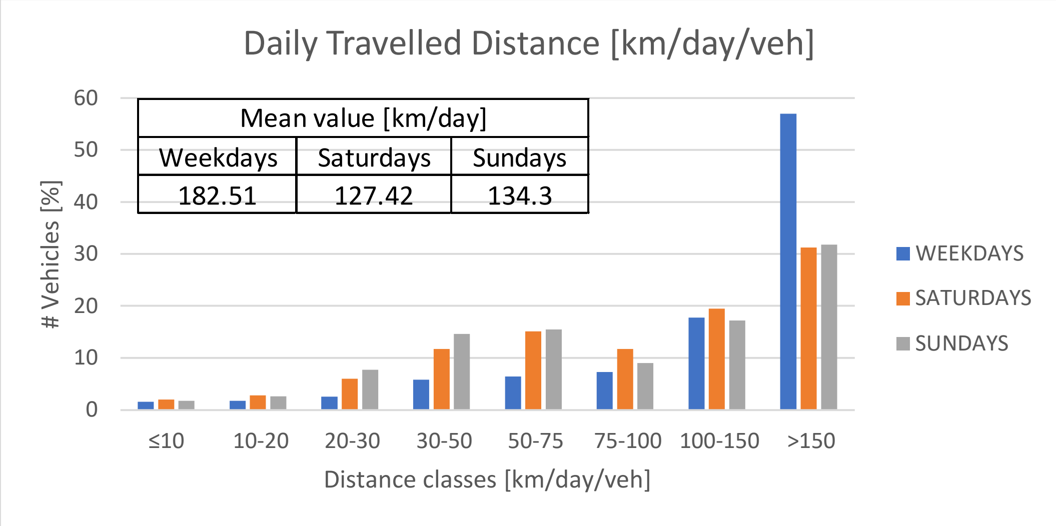
Figure 44. Bar graphs for internal trips (LCVs).

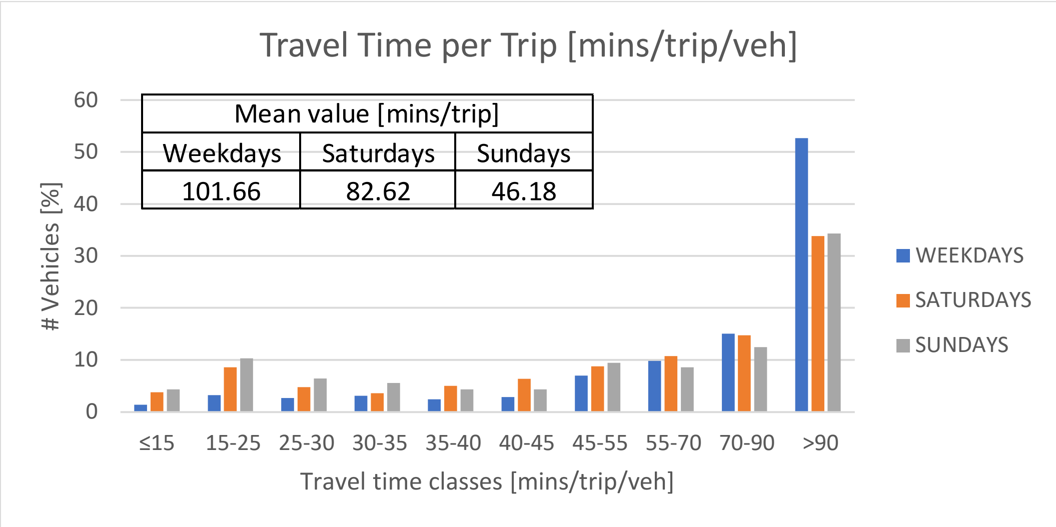
– <u>external trips</u>:

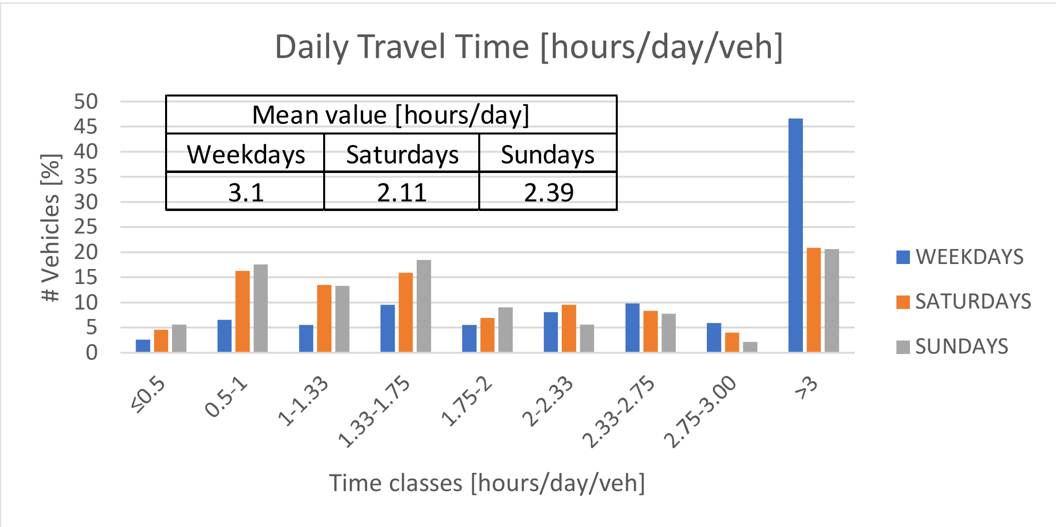
Mean number of total trips		
WEEKDAYS	SATURDAYS	SUNDAYS
1049	296	153

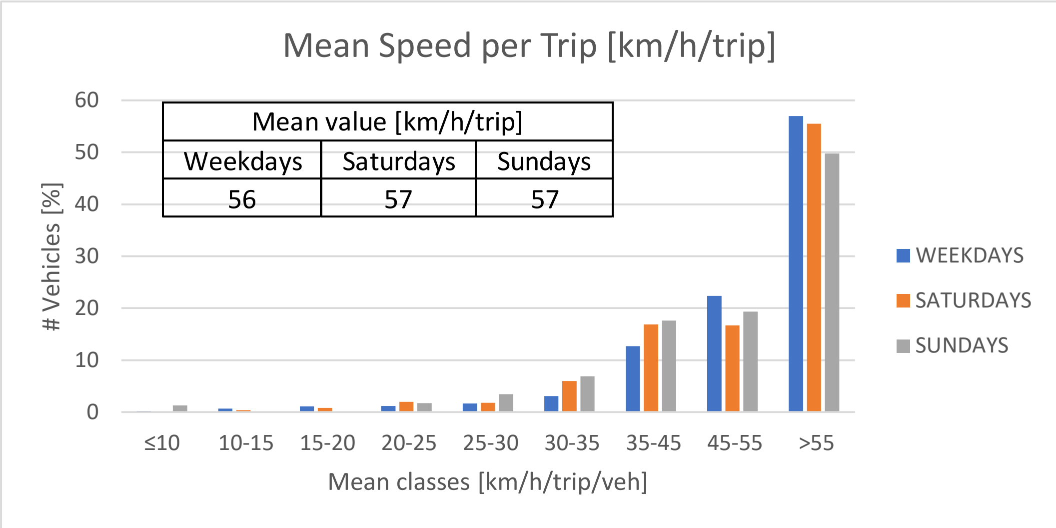





Daily Travelled Distance [km/day/veh]
Mean value [km/day]
Weekdays
Saturdays
Sundays
182.51
127.42
134.3
Vehicles [%]
0
10
20
30
40
50
60
≤10
10-20
20-30
30-50
50-75
75-100
100-150
>150
Distance classes [km/day/veh]
WEEKDAYS
SATURDAYS
SUNDAYS


Travel Time per Trip [mins/trip/veh]
Mean value [mins/trip]
Weekdays
Saturdays
Sundays
101.66
82.62
46.18
Vehicles [%]
0
10
20
30
40
50
60
≤15
15-25
25-30
30-35
35-40
40-45
45-55
55-70
70-90
>90
Travel time classes [mins/trip/veh]
WEEKDAYS
SATURDAYS
SUNDAYS


Daily Travel Time [hours/day/veh]
Mean value [hours/day]
Weekdays
Saturdays
Sundays
3.1
2.11
2.39
Vehicles [%]
0
5
10
15
20
25
30
35
40
45
50
≤0.5
0.5-1
1-1.33
1.33-1.75
1.75-2
2-2.33
2.33-2.75
2.75-3.00
>3
Time classes [hours/day/veh]
WEEKDAYS
SATURDAYS
SUNDAYS



Mean value [km/h/trip]		
Weekdays	Saturdays	Sundays
56	57	57

Mean value [mins/trip]		
Weekdays	Saturdays	Sundays
195.03	162.03	201.16
Mean value [hours/trip]		
Weekdays	Saturdays	Sundays
3.25	2.70	3.35

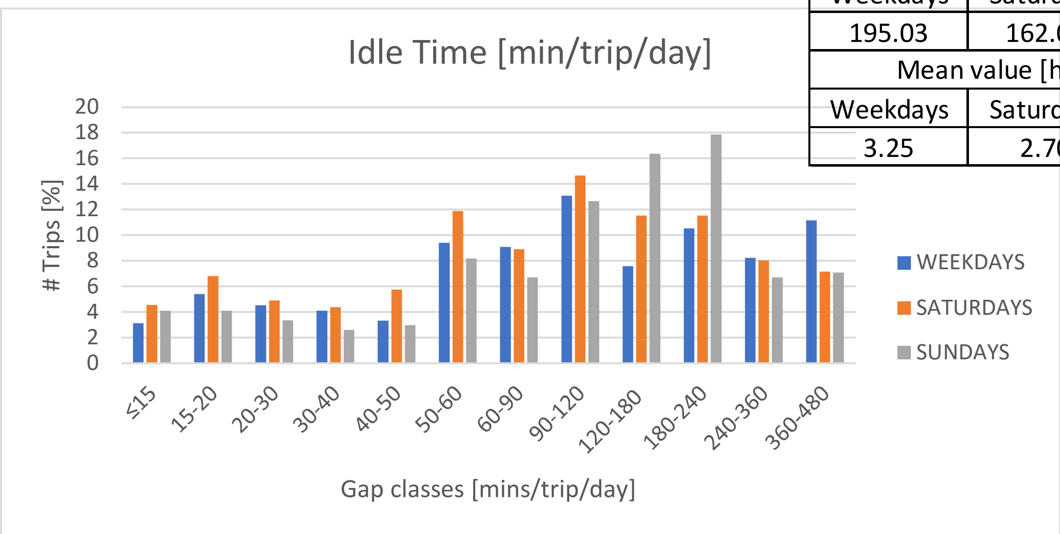


Figure 45. Bar graphs for external trips (LCVs).

References

ACI, Automobile Club d'Italia website. *Data about circulating vehicles in Italy and Turin.*

Ancitel Energia & Ambiente S.p.a. *Linee guida per la mobilità elettrica. 2016.*

Bass, Frank M. 1969. *A new product growth for model consumer durables. 1969.*

Bass, Frank M. Management Science. *Comments on "a new product growth for model consumer durables. 2004.*

Coordinamento FREE. *Il piano nazionale energia e clima*. 2018.

Daimler. *Case – intuitive Mobility: Connected, Autonomous, Shared, Electric.*

Damascène Mazimpaka J. & Timpf S. *trajectory data mining: A review of methods and applications. 2016.*

Dalla Chiara Bruno. *An introduction to ITS:definition, architectures, components and applications. 2019.*

Enel. *Electrify 2030 – electrification, industrial value chains and opportunities for sustainable future in Europe and Italy.*

EV Database. *Battery capacities and energy consumptions*. 2020.

GreenStart website, mobilità sostenibile. *Hybrid-Electric cars purchases.*

Jensen et al. *Predicting the potential market for electric vehicles. 2015.*

Juan de Dios Ortùzar. *Modelling transport*.

Malghieri Patrizia (TRT). *Scenari di impatto della mobilità elettrica nelle città. 2017.*

Massiani, Gohs. *The choice of Bass models coefficients to forecast diffusion for innovative products: An empirical investigation for new automotive technologies. 2015.*

Minstero dell'Ambiente, Ministero dello Sviluppo Economico, Ministero delle Infrastrutture e dei Trasporti. *Elementi per una Roadmap della Mobilità Sostenibile. 2017.*

Ministero dello Sviluppo Economico. *Integrated National and climate Plan.*

Nicoli Monica. *Wireless positioning: fundamentals and applications*. *2019.*

Open Charge Map. *Charging stations localization.*

Politecnico di Milano. *Smart Mobility Report. La sotenibilità nei trasporti: opportunità e sfide per la filiera e gli end user.* 2020.

Soumia A. & Maaroufi M. *Diffusion models for predicting electric vehicles market in Morocco. 2019.*

Unione Petrolifera. *La centralità del downstream petrolifero nella transizione verso una mobilità low-carbon.* 2018.

United Nations. *The Paris agreement. 2015.*

University of Tennessee. *Transition to Electric Vehicles in the California Automobile. 2017.*

UNRAE. *Auto 2009 – sintesi statistica*.

UNRAE. *Analisi del mercato autoveicoli in Italia*. 2019.

Wegner. *Stock of electric cars in Denmark 2010-2020*. 2020

Wikipedia. *Turin Metropolitan Area, municipalities and their population*.

Zap Map. *Charging at home*.

RINGRAZIAMENTI

Ringrazio anzitutto IL Professore Francesco Paolo Deflorio. Grazie Professore per la fiducia accordatami accettando il ruolo di Relatore per questo lavoro di tesi, ma soprattutto grazie per la professionalità e la passione che mette nell'insegnare. Se oggi so che la strada che voglio seguire è quella del mondo dei trasporti, il merito è soprattutto il suo.

Un sincero ringraziamento va alla mia correlatrice, la dottoressa Cristiana Botta. Grazie Cristiana per la tua disponibilità, le tue indicazioni e i tuoi consigli. Grazie per il tuo supporto puntuale, preciso ed esperto, senza il quale non sarei mai stato in grado di portare a termine un lavoro di cui sono così orgoglioso.

Un doveroso ringraziamento va all' Ing. Maurizio Arnone e a tutto il team di Links Foundation per avermi dato l'opportunità di affrontare e vivere l'ultimo "spostamento" del mio viaggio universitario con loro. Questa è stata la prima esperienza che mi ha realmente avvicinato a ciò che voglio fare nel mondo del lavoro. Non avrei mai potuto chiedere di meglio.

Grazie ai miei genitori. Grazie per avermi insegnato il valore delle cose. Grazie per avermi insegnato a non giudicare mai un libro dalla copertina, ma grazie per avermi fatto capire che lì fuori tutti fanno il contrario. Grazie per avermi insegnato a non essere come loro. Grazie mamma, grazie papà perché siete e resterete un punto di riferimento, un modello a cui ispirarsi per avere una vita piena, piena di tutto, di dolcezza, di felicità, di amore. Se sono fiero di me stesso è soprattutto per merito vostro, per come mi avete cresciuto e educato. Grazie per avermi trasmesso la passione per i viaggi, perché so che senza crociere avrei vissuto una vita completamente diversa! E io amo la vita che mi avete dato. Grazie genitori per esserci sempre.
Vi voglio bene.

Grazie a mia sorella. Il regalo più bello che potessi ricevere dalla vita. Sei sempre con me sorellina. Sei con me quando vedo un frenchie per strada, sei con me quando in tv trasmettono Harry Potter, sei con me quando dal nulla passano una canzone di Grease. Grazie per i tuoi sorrisi, perché sono in grado di rendermi felice ogni volta che ho la fortuna di condividerli. Continua a sorridere sorellina perché sei bellissima quando lo fai. Grazie sorella perché sei l'unica persona a cui non ho paura di dire "per sempre".
Ti voglio bene.

Grazie alla mia famiglia. Grazie perché siete la mia Casa. Questo traguardo lo dedico a voi.

"...no matters when or where, be humble be kind..."