D4.4 Report Scenario Modeling

eBRIDGE: Empowering e-fleets for business and private purposes in cities

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1. Executive Summary

This report presents the key finding arising from the participating sites Berlin (Germany), Bregenz (Austria), Carmarthen (Wales), Lisbon (Portugal), Milan (Italy), Valencia (Spain) and Vigo (Spain) using car sharing schemes for business and private urban travel. The extensive volume of EVs trial data collected in the project was used to comprehensively characterize the operational urban fleet performances. This analysis is important in the European context, as there is limited (although rapidly growing) recording data of actual EVs usage and charging patterns. The data collected is covering a period of more than two years, therefore provides a relevant input into understanding the following factors:

1. Total number of Trips per Hour of Day
2. Total number of Trips per Day of Week
3. Total number of Trips per Month
4. Total travelled Distance (km) per Month
5. Total number of Trips per Trip Duration
6. Total number of Trips per Trip Distance
7. Total number of Trips per Trip Av. Speed

The evidence collected on actual usage patterns were used to calculate the weekly EV usage probability and this stresses the importance of the quantitative data gathered in the eBRIDGE trials.

The characteristics of the EV demand are very relevant to understand the charging behavior and the charging stations usage. This can be used by the Distribution System Operators (DSOs) to estimate the additional electricity demand for the EV charging and assist network planning operators to accommodate the EVs additional load. The analysis of the eBRIDGE trial data covers:

1. Total number of Ch. Events per Hour of Day
2. Total number of Ch. Events per Day of Week
3. Total number of Ch. Events per Month
4. Total consumed Energy (kWh) per Month
5. Total number of Ch. Events per Ch. Event Duration
6. Total number of Ch. Events per Ch. Event Energy
7. Av. Energy Consumption vs Av. Speed

Analyzing the data the probability of EVs charging station occupancy was calculated for the car sharing EV fleet in Lisbon, the trial that provided the most comprehensive set of data.

When considering the well-to-tank emissions of EVs for year 2020 the predicted electricity generation mix is highly important, as EVs do not cause local emissions but could shift emissions to power generation facilities. The CO_2 reduction analysis for year 2020 was based on the following factors:

1. Projected number of ICE vehicles
2. Carbon intensity of ICE vehicles
3. Projected number of EVs
4. Energy consumption efficiency of EV
5. Carbon intensity of electricity generation
6. Annual travelled distance of ICE vehicles and EVs

2. Introduction

Electric vehicles (EVs) are potentially an important component of a clean and sustainable transport future. Across the world, governments have started to implement CO_2 emissions cuts based on vehicle tax systems, targeting either acquisition taxes or annual road taxations [1]. The ‘50 by 50’ Global Fuel Economy Initiative [2] sets the goal to increase the global car fleet efficiency by 50% by 2050, for which a higher portion of cars are expected to be EV. To reach this ambitious goal a higher portion of private transportation has to be covered by EV as conventional cars are getting closer to the limits of the theoretical efficiency of combustion engines and are unlikely to improve much further [1]. According to Citigroup Global Markets, CO_2 emission standards are a strong driver to introduce ‘zero’ or ‘near-zero’ emission cars [3]. The innovation captured by electric vehicles is the reduction of CO_2 emissions and the resulting revolution in road transport particularly in highly urbanized areas. Electricity is likely to become the preferred energy vector for a new generation of road vehicles. But the overall reduction potential of electric vehicles is highly dependent on the assumed mixture of electricity supply and the related carbon-intensity. Electric vehicles do not cause local emissions but could move emissions to power generation facilities. Environmental benefits arising from electro-mobility concept needs to be designed in a way that emission reduction in the transport sector is not offset by increases of emission in other sectors.

eBRIDGE is a co-funded EU project to promote electric fleets for urban travel in European cities. The project aims to bring innovation and new technologies to make today’s mobility cleaner, more efficient and sustainable. During eBRIDGE, alternatives to current mobility patterns will be explored in order to analyze whether electric mobility is a feasible option to make cities cleaner and more sustainable. The project aims to demonstrate how the introduction of electric vehicles in fleets for business and private urban travel can efficiently contribute to the improvement of market conditions for the electric mobility sector.

3. Background and purpose of the deliverable

A detailed analysis of the data collected from the participating sites Berlin (Germany), Bregenz (Austria), Carmarthen (Wales), Lisbon (Portugal), Milan (Italy), Valencia (Spain) and Vigo (Spain) was conducted in order to analyze the usage patterns and travel behavior of the car-sharing EV fleets. The data collected in each trial covered three board areas: (i) characteristics of the EVs fleet (e.g. EVs type, number of cars, brand, vehicle range) (ii) the distance and duration of each EV trip and (iii) the battery state of charge and the energy consumption. Based on the data collected an analysis of EVs trips and EV energy consumption was performed to evaluate the predicted EVs usage based on historical data collected. The content of this analysis came from the authors’ expertise and knowledge in analysis data from similar trials in UK [4] [5] [6].

This report is the deliverable of Task 4.4 of Work Package 4—*Evaluation and Scenarios*—of the pilot schemes. In order to address the carbon reduction (IEE common performance indicator), the CO_2 emissions analysis was performed based on the projected carbon intensity of the grid for each country and the predicted EVs uptake.

The participating sites car sharing fleets characteristics are:

1. **Berlin** - The case study is based on the e-Flinkster fleet located on the EUREF Campus, a business and research cluster with more than 40 companies and around 2,000 employees. Flinkster is the car sharing offer of DB FuhrparkService, operating a fleet of 240 vehicles in Berlin, of which 40 are electric (as of 2013).
2. **Austria** - Caruso peer-to-peer car sharing for both business and private purposes.
3. **Vigo** - "The Galician Automotive Cluster (CEAGA) gathers 105 entities, 41 big companies and 64 SMEs. During eBRIDGE, a group of selected companies belonging to the Cluster will be provided with four full electric cars: 3 Citröen C-Zero and 1 Peugeot iOn, equipped with a monitoring system. From June 3rd 2013 to September 4th 2014, 372 people from 20 companies have used an electric car for their business trips.
4. **Valencia Palma** - E:Sharing started in 2011 as the first electric car sharing in Spain. operated by MOVUS in the metropolitan area of Valencia. Presently, the E:Sharing fleet consists of 9 electric cars of different models and stations in Valencia, Sagunto, Paterna and Alcoy.
5. **Milan** - GuidaMi car sharing fleet are located in the city center. GuidaMi offered ten E-vehicles (four full electric and six hybrids) to be used in a car sharing system by the citizens. The full electric vehicles are Citroen C-Zero and the hybrids are Toyota Prius.
6. **Lisbon -** Municipal de Lisboa and Occam electric vehicles in municipal fleet. By 2011 the municipality had already 5 light passenger EVs for generic transport activities and by the end of 2013 reached a total of 57 electric vehicles.
7. **Carmarthen** - the first local authority in Wales to introduce electric vehicles into its fleet. The Carmarthenshire County Council mixed car pool joined the eBRIDGE project with a fleet of six diesel and two electric cars in the beginning of 2011 (and the option to order an additional four EVs).

The **BASE fleet vehicles** presented in table below are used only for business and corporate trips during the day and returned to the pool at the end of working hours. The users are employees driving for business purposes.

BASE electric fleets	Goal
Galician Automotive Cluster (CEAGA - Cluster de Empresas de Automoción de Galicia) CEAGA Business e-car Sharing (Vigo, Spain)	To test the suitability of EVs for business travel of the CEAGA companies
City of Lisbon Fleet (CML - Câmara Municipal de Lisboa) (Lisbon, Portugal)	To optimize the fleet configuration of a municipal carpool of conventional cars and EVs To test the suitability of the new electric models and match them with concrete municipal tasks/ activities
Carmarthenshire County Council Fleet (Carmarthen, UK)	To reduce economic (mileage costs) and environmental (CO_2 emissions) impacts of staff travel

The **SHARE fleet vehicles** presented in table below can be booked for business and private trips. The e-car sharing users are employees and individuals. Companies and organizations can include e-car sharing in their business mobility portfolio and individuals can benefit from mobility on demand and avoid car ownership inconveniences.

SHARE electric fleets	**Goal**
e-Flinkster Carsharing (Berlin, Germany)	To analyze potential of e-car sharing to complement business mobility
Caruso Carsharing (Austria)	To address the lack of working concepts and business models for P2P e-CS fleets
E:Sharing (Valencia, Spain)	Optimization of the E:Sharing model
Regional Government of the Balearic Islands (CAIB - Govern de les Illes Balears) (Palma de Mallorca, Spain)	To create a proper policy framework for the promotion of electric mobility in the Balearic Islands
GuidaMi (Milan, Italy)	To promote e-car sharing and EVs among the GuidaMi customers

4. Analysis on EV trips

4.1 Data description

Data related to the trips of the car-sharing fleets were provided from each project partner. The data are classified into three categories: per trip (PT), per booking (PB) and aggregated (A). The PT category includes information about each trip of each EV in the corresponding car-sharing fleet. The PB category refers to the cases where the information was not available in a per trip granularity, but was recorded in the start/end of each vehicle booking. In such cases one booking may include more than one trip. Nevertheless, useful knowledge about the usage patterns can be extracted. In some cases the provided data included only aggregated information for the whole car-sharing fleet (A category).

The data included information about the travelled distance, the date, the start times and duration, the average speed and the number of trips from each car-sharing EV fleet. Table 1 shows the EV trips data availability and granularity from each car-sharing EV fleet.

Table 1: EV trips Data

Pilot	Spain		Italy	Portugal	UK	Germany	Austria
Data -per trip **PT** -per booking **PB** -aggregated **A**	Vigo	Valencia	Milan	Lisbon	Carmarthen	Berlin	Bregenz
Distance	PT	A	A	PT	PB	PB	PT
Date	PT	-	-	PT	PB	PB	PT
Average speed	PT	-	-	PT	-	-	-
Start Time	PT	-	-	PT	PB	PB	PT
Duration	PT	-	-	PT	PB	PB	PT
Number of trip	A	A	A	A	A	A	A

4.2 Analysis & Results

In order to analyze the usage patterns and travel behavior of the car-sharing EV fleets, eight characteristics were studied.

1. **Total number of Trips per Hour of Day**

This characteristic studies the hourly distribution in a day of the start times of all trips per fleet. By studying this characteristic, we extract information regarding the usage patterns of the EVs in each car-sharing fleet. Looking at the customer's perspective, this characteristic helps in drawing conclusions regarding the purpose of using a car-sharing fleet: (i) fleets for work trips only Vigo, Lisbon, Carmarthen and (ii) commercial car sharing fleets, i.e. for all trip purposes: Berlin, Valencia, Austria, Milan. The necessary data for studying this characteristic is the start hour of each trip.

The results are presented in Fig. 1-6:

Vigo – The fleet is used for private trips

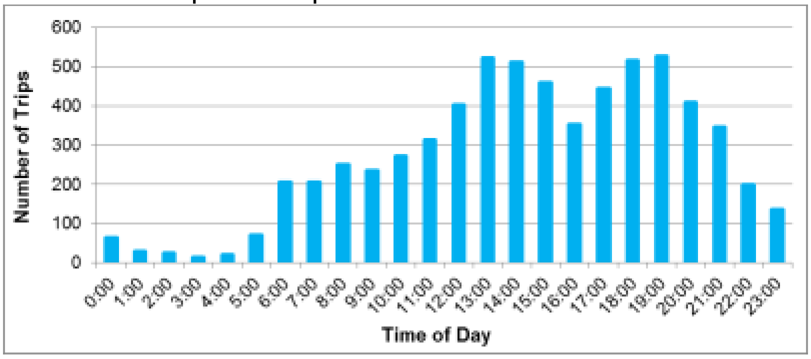

Fig. 1

Carmarthen – The fleet is used by employers for work trips only

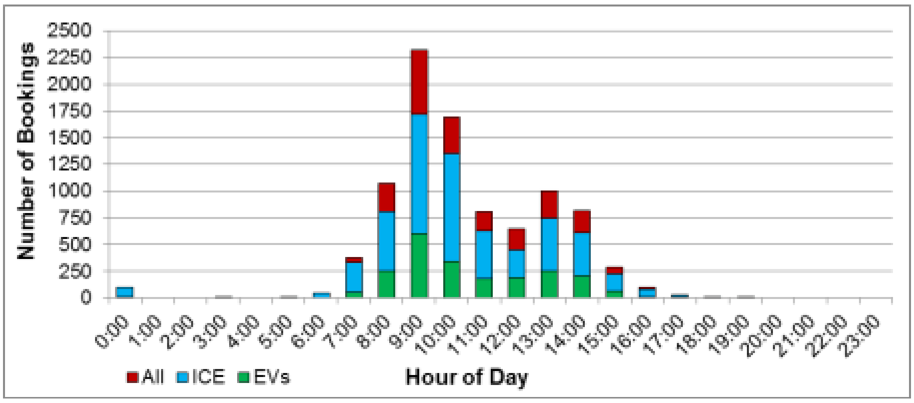

Fig. 2

Lisbon - The fleet is used for private trips

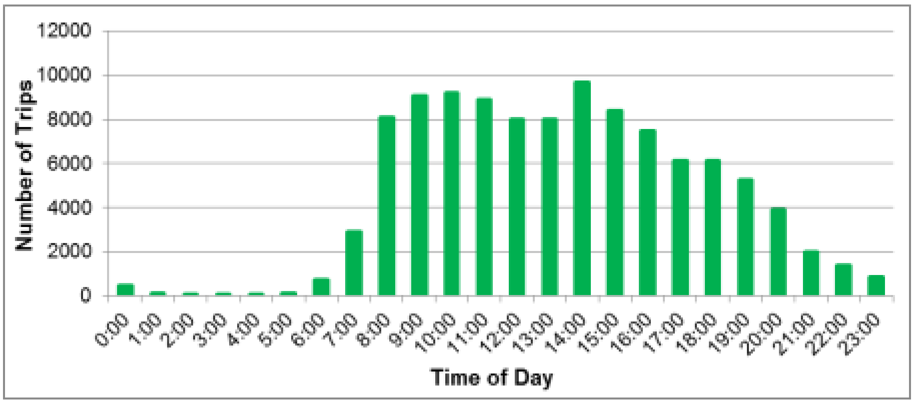

Fig. 3

Berlin - commercial car sharing fleets, i.e. for all trip purposes:

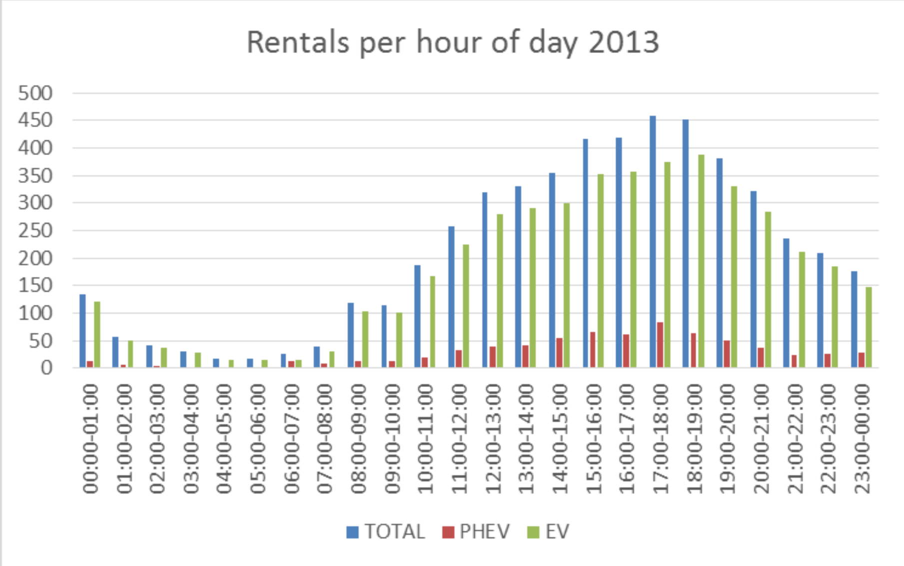

Fig. 4

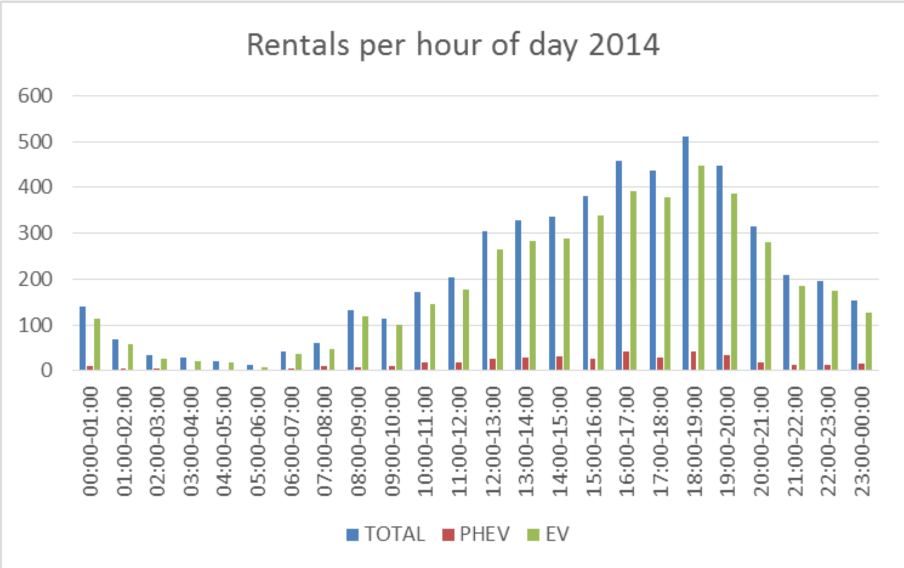

Fig. 5

Bregenz - Peer-to-peer car sharing, all trip purposes

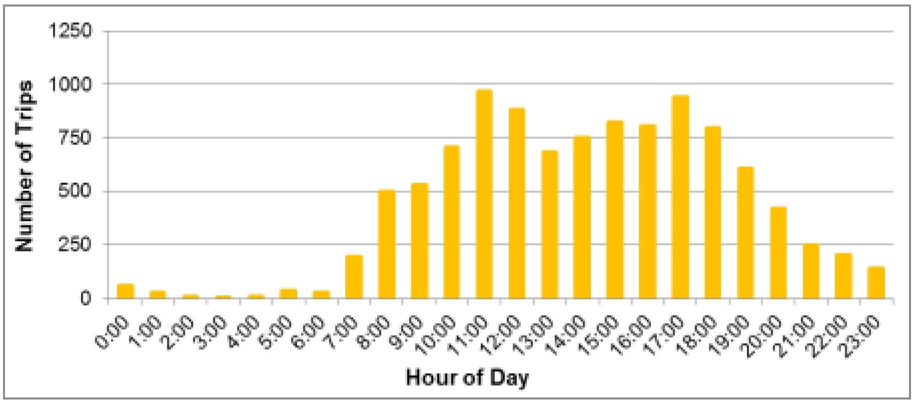

Fig. 6

As seen from above figures, the start time for the majority of the trips was during daytime. In Vigo, Lisbon, Berlin and Bregenz the start trip time's distribution is similar and have few trips during night hours. However, in Carmarthen there were no trips during night hours. This is because the Carmarthen fleet is used only for work related trips during the working hours.

2. Total number of Trips per Day of Week

This characteristic studies the daily distribution in a week of all trips per fleet. Information regarding the daily usage patterns is extracted. By looking at the most preferable days on which the car-sharing fleets are used, information regarding the type of customers/users of e-CS commercial systems, but also users of the non-commercial fleets and their trip purpose is obtained. For example if the car-sharing EV fleet is used only in the weekdays and not on the weekends, there is an indication that the fleet may belong to a company and is only available for work related matters. The necessary data for studying this characteristic is the date of each trip.

The results are presented in Fig. 7-12:

Vigo

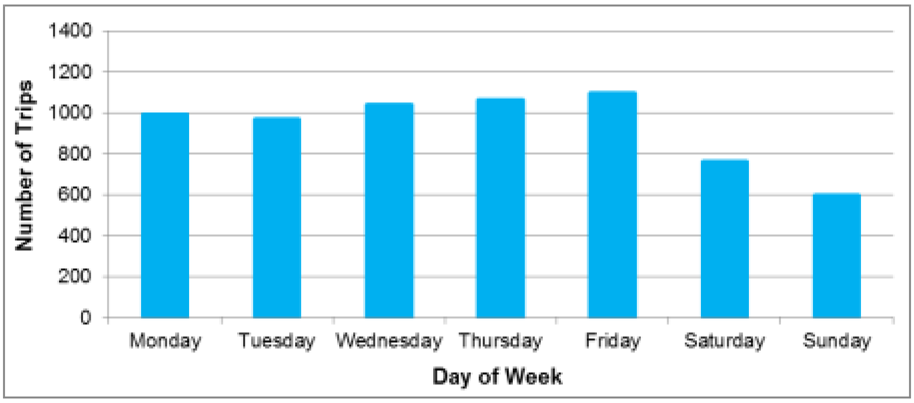

Fig. 7

Carmarthen

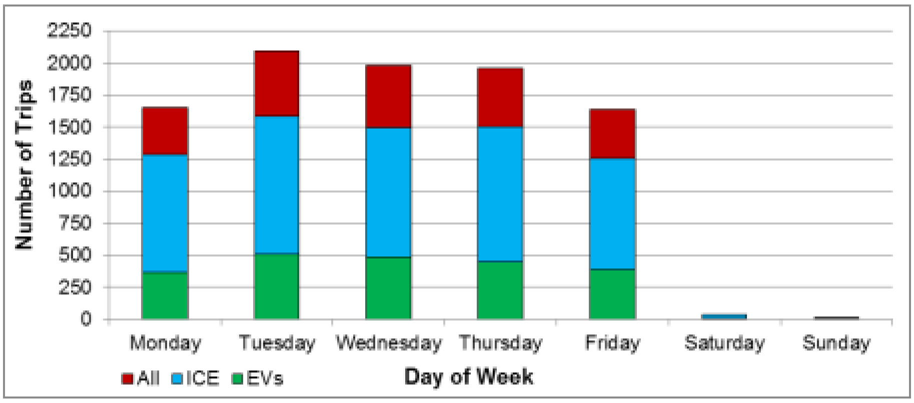

Fig. 8

Lisbon

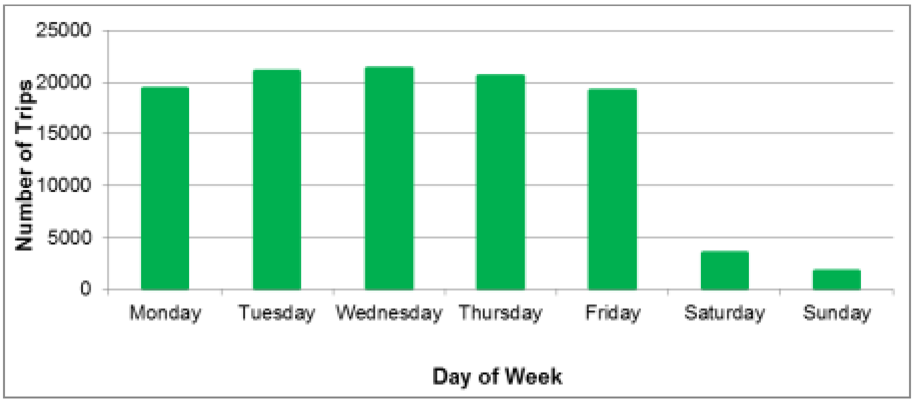

Fig. 9

Berlin

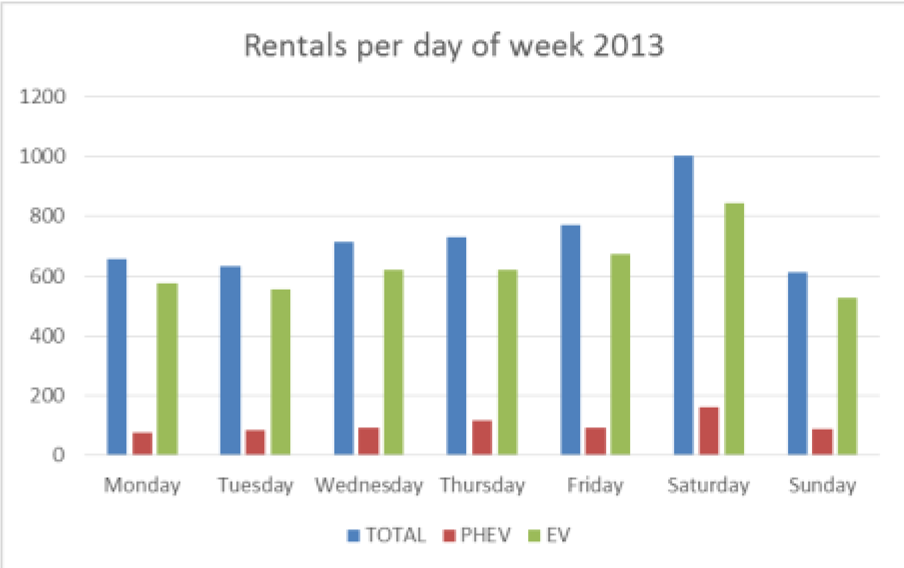

Fig. 10

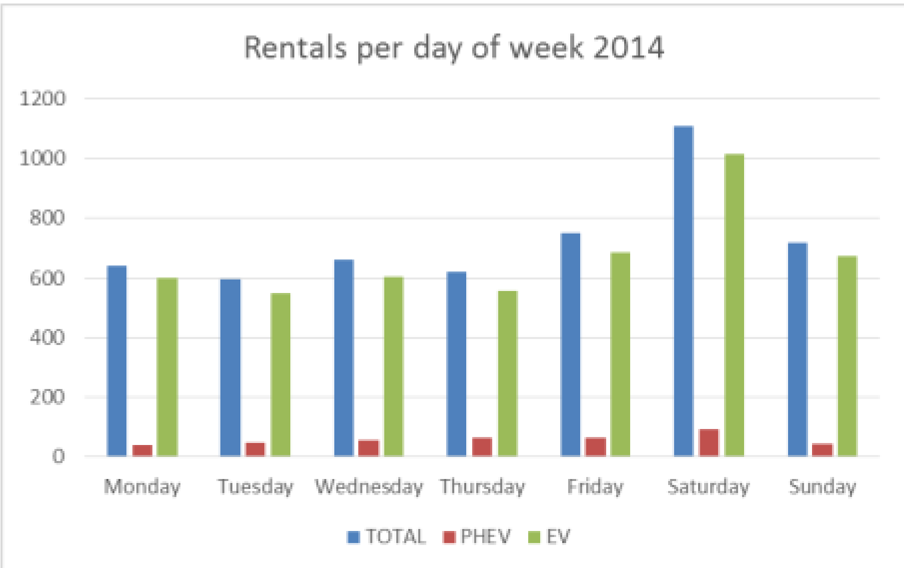

Fig. 11

Bregenz

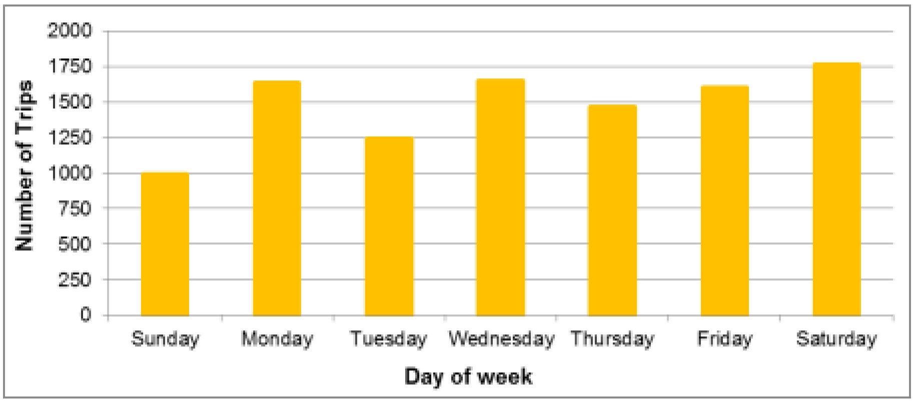

Fig. 12

In most cases except in Carmarthen, the car-sharing fleet was used for traveling in both weekdays and weekends. Fig. 10-12 shows that the most trips in Berlin and Bregenz occurred on Saturday. In the other cases, the majority of the trips occurred during weekdays.

3. Total number of Trips per Month

This characteristic shows the monthly distribution of all trips per fleet. By looking at the monthly change of EV usage, information regarding the popularity of each car-sharing EV fleet is extracted.

An increasing number of trips over time indicate success of the car-sharing scheme whereas a decreasing number of trips indicate the need of a change in the marketing policy for the commercial fleets. Low booking numbers for the other fleets indicate the need of greater employees' engagement with EVs, applying promotional measures, etc.

Furthermore using the monthly development, regression analysis can be also applied to calculate the trend and forecast the future usage of each car-sharing EV fleet. The necessary data for studying this characteristic is the date of each trip. Aggregated data can also be used.

The results are presented in Fig. 13-20:

Vigo

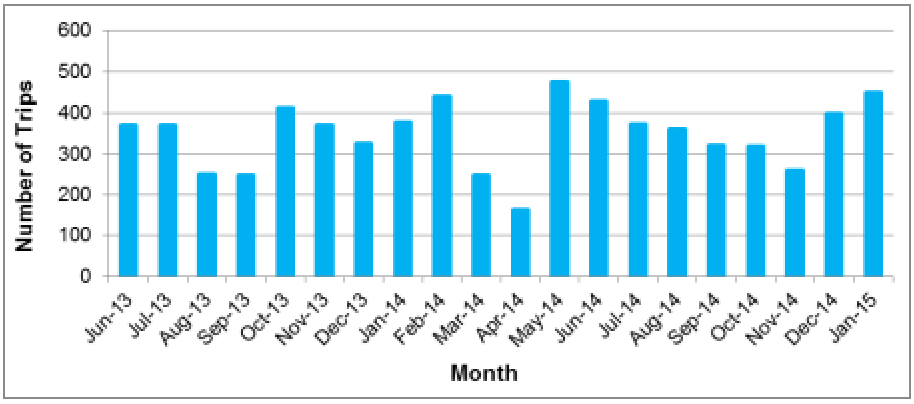

Fig. 13

Valencia

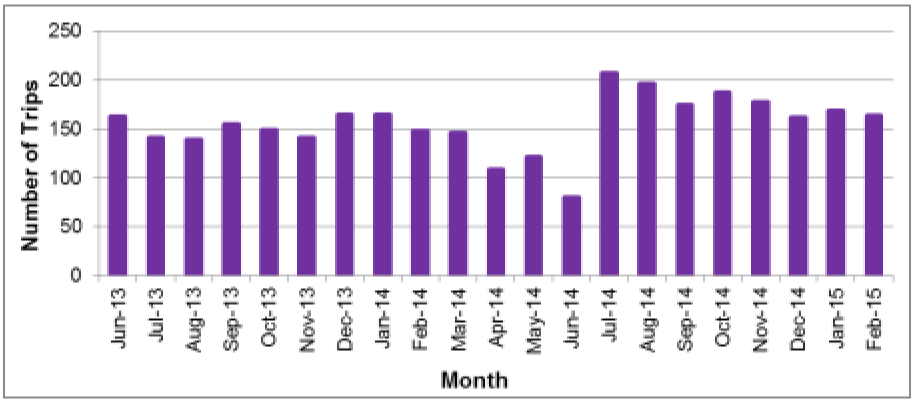

Fig. 14

Carmarthen

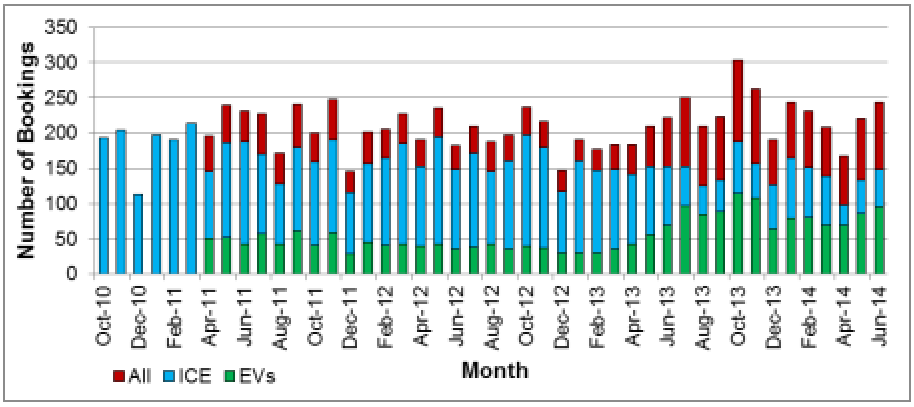

Fig. 15

Lisbon

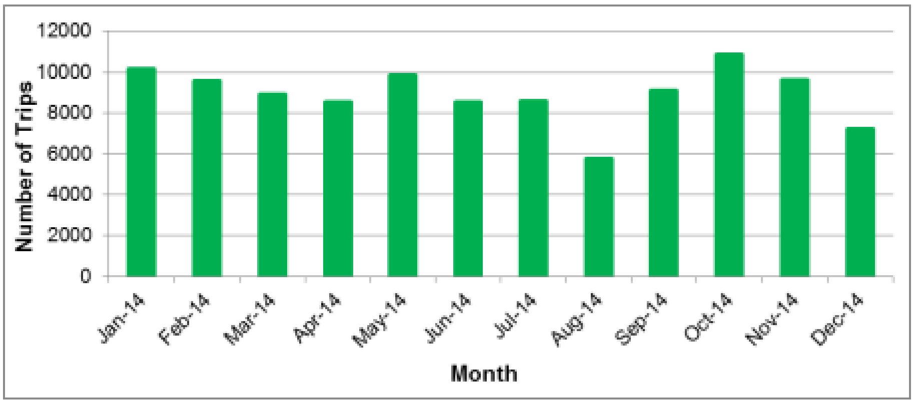

Fig. 16

Berlin

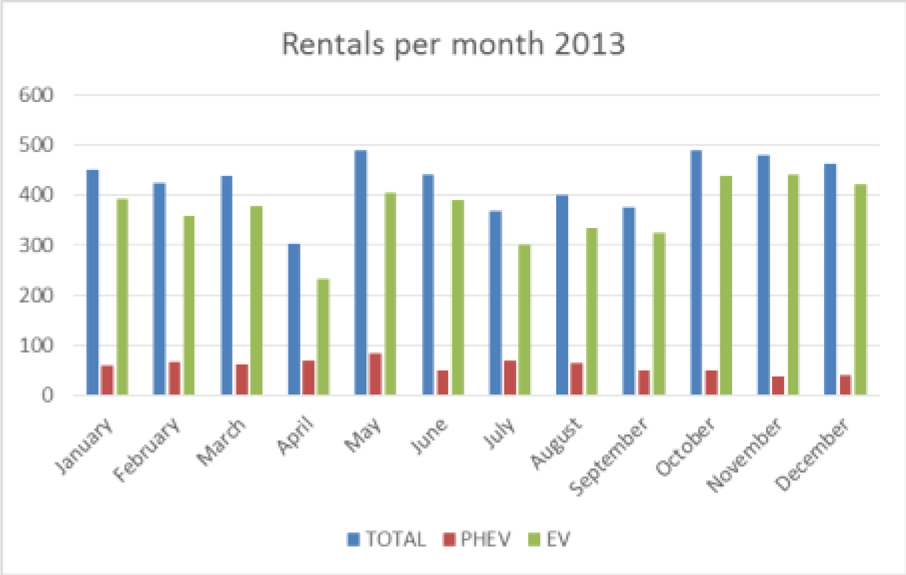

Fig. 17

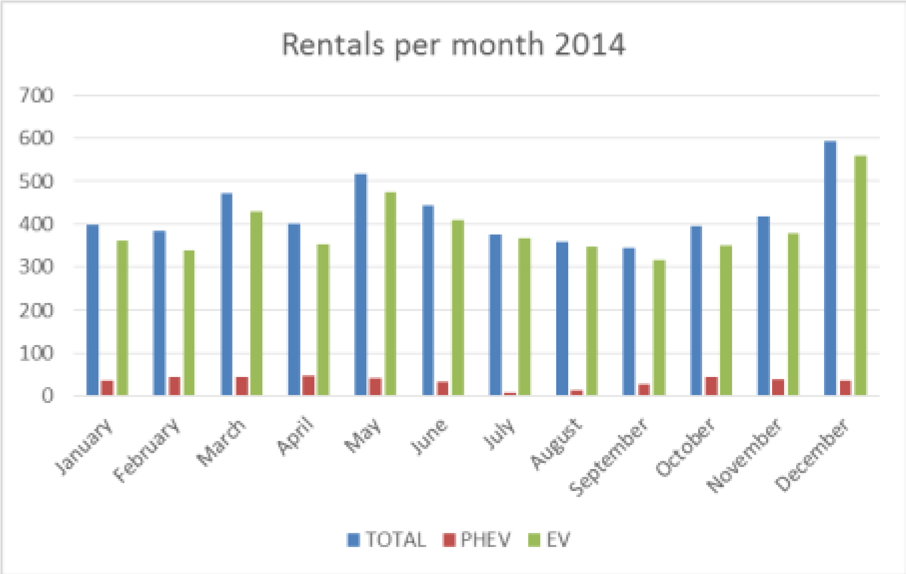

Fig. 18

Bregenz: The data collected for this trial are covering a period of more than 4 years. The eBRIDGE project started in April 2013 but we considered that it is valuable to present the whole set of data to highlight the positive trend in the number of trips.

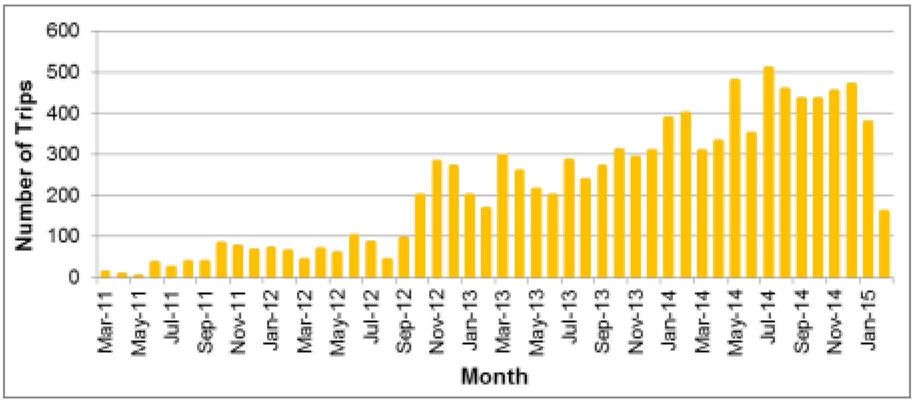

Fig. 19

Milan

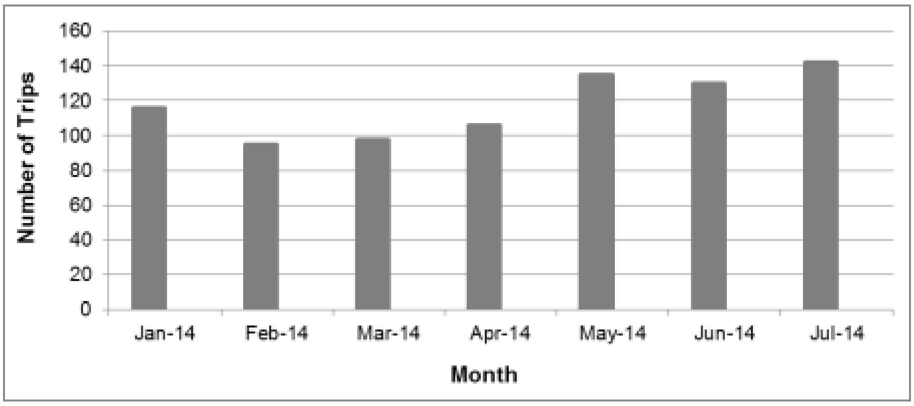

Fig. 20

Fig 17-20 showed an increasing trend of the Total number of Trips per Month in Carmarthen, Berlin, Bregenz and Milan. In the other pilots, the Total number of Trips per Month was more constant.

4. Total travelled Distance (km) per Month

This characteristic shows the monthly distribution of the aggregated travelled distance per fleet. The monthly travelled distance is also associated with the EV usage, indicating the energy requirements of the trips. Based on these energy requirements, the CO_2 emissions can also be calculated. Future projections are also possible, contributing to the scenario modelling. The necessary data for studying this characteristic is the date and distance of each trip. Aggregated data can also be used if available.

The results are presented in Fig. 21-28:

Vigo

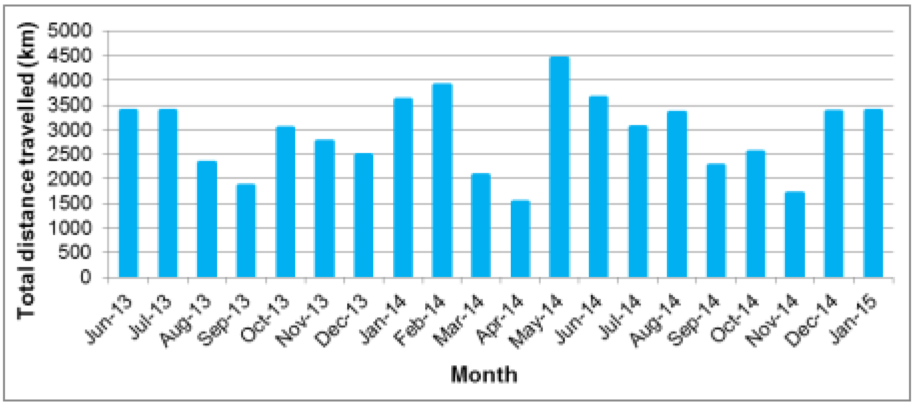

Fig. 21

Valencia

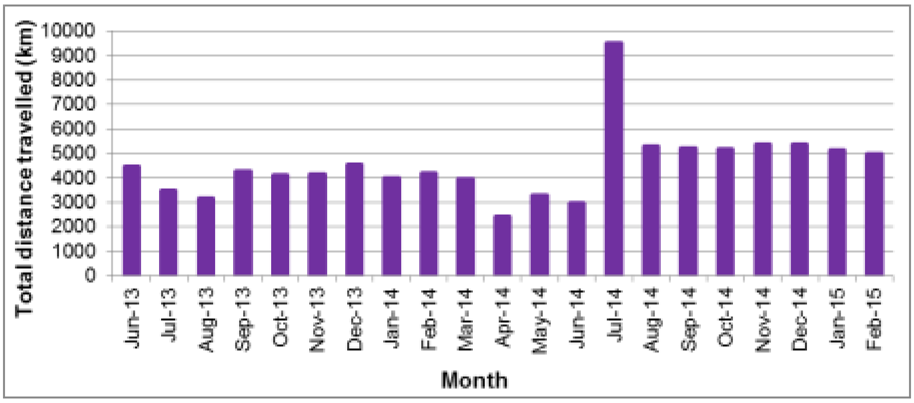

Fig. 22

Carmarthen The data collected for his trail are covering a period of more than 4 years. The eBRIDGE project started in April 2013 but we considered that is valuable to present the whole set of data to highlight the total distance travelled. A fluctuation in the number of available cars is quite typical for commercial car sharing fleet and private fleets.

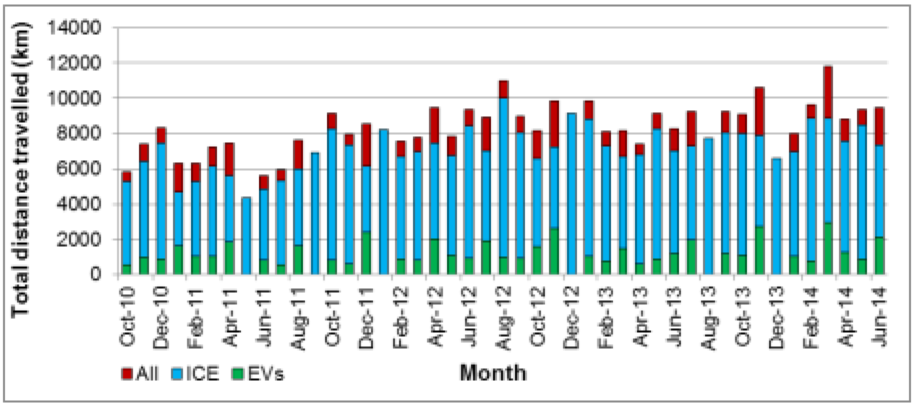

Fig. 23

Lisbon

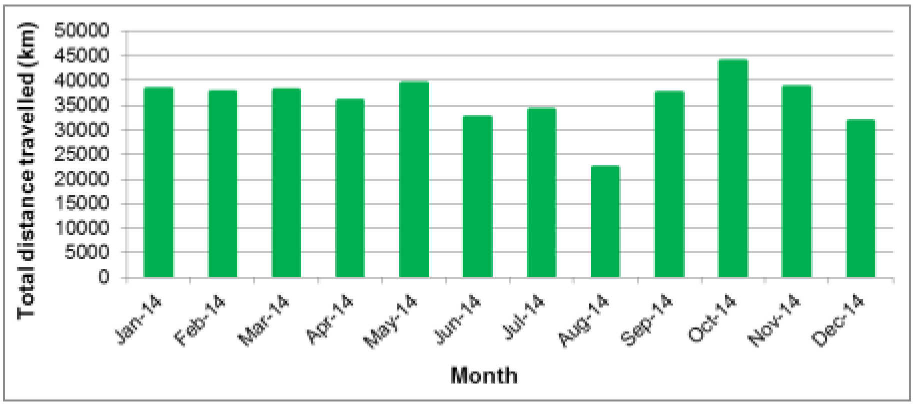

Fig. 24

Berlin

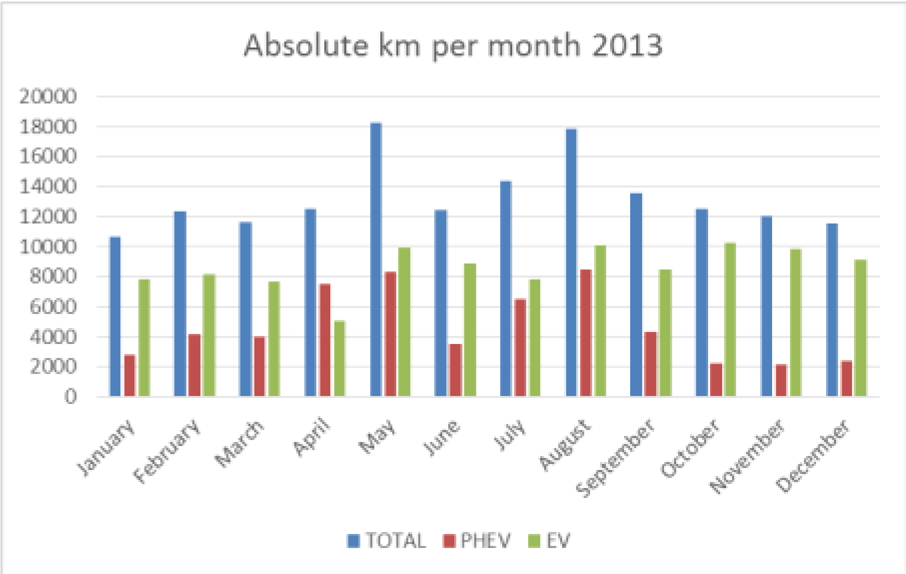

Fig. 25

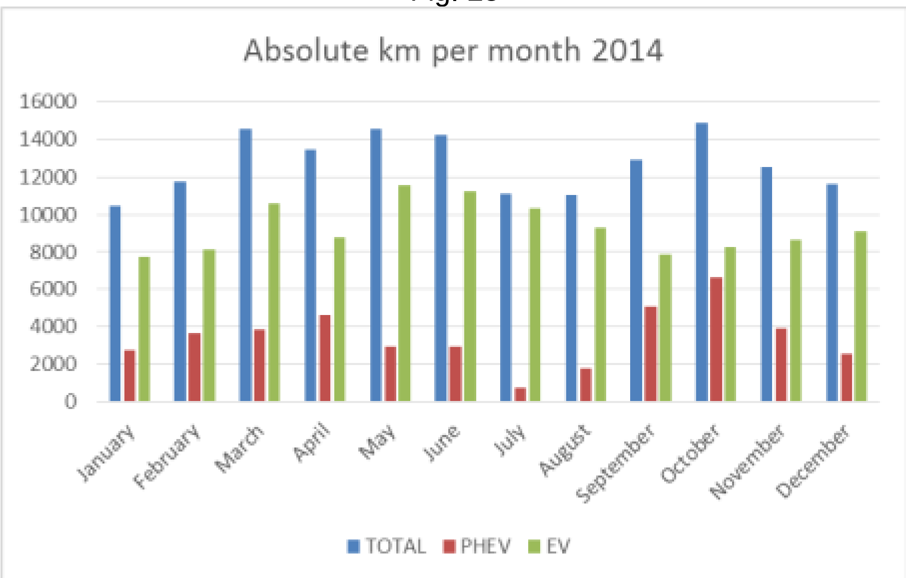

Fig. 26

Bregenz

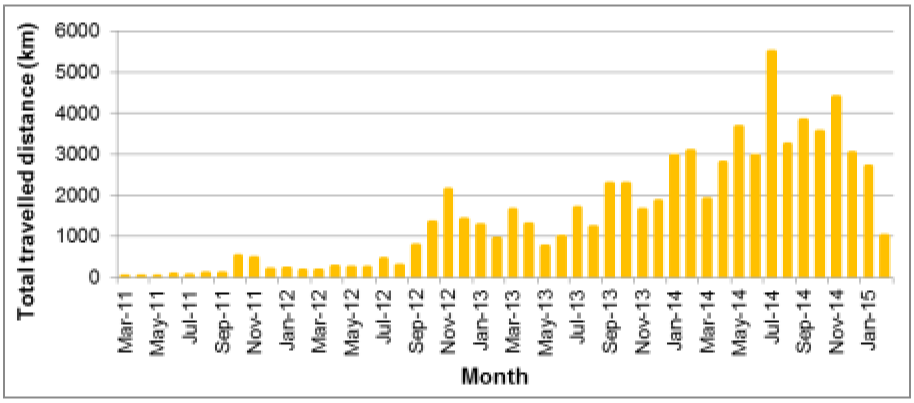

Fig. 27

Milan

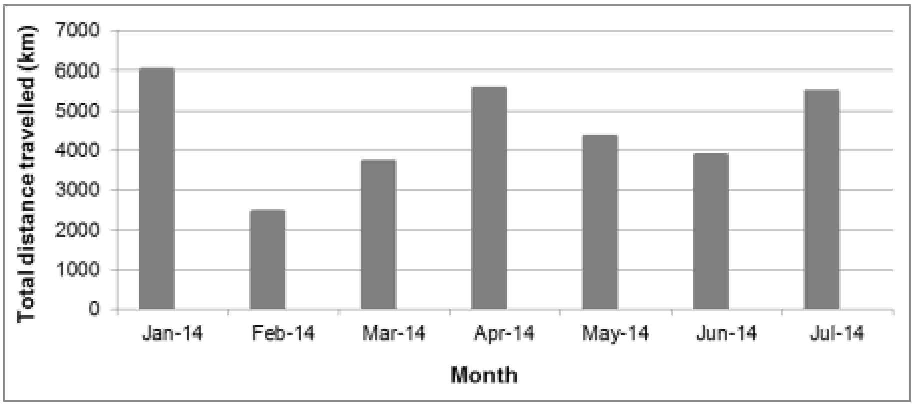

Fig. 28

Slight increasing trend of the total travelled distance is shown for all car-sharing fleets. Particularly in Bregenz, there is a significant increase in the total travelled distance. This proves the success of the car-sharing EV fleet. In other cases, incentives or a different marketing strategy could boost the popularity of the EV car-sharing fleet.

5. Total number of Trips per Trip Duration

This characteristic classifies the trips according to their duration. Different fixed duration classes were used, adjusted to the characteristics of each individual fleet. In case the EVs were used for very short trips, a duration period of 5min was used to illustrate the distribution of the trips. On the other hand when the data were related to the vehicle bookings rather than trips, a longer duration period was used to separate the classes (30min or 1h). The pricing policy of the car-sharing company is affected by this characteristic and should optimize the trade-off between revenues and customer satisfaction. The necessary data for studying this characteristic is the duration of each trip.

The results are presented in Fig. 29-34:

Vigo

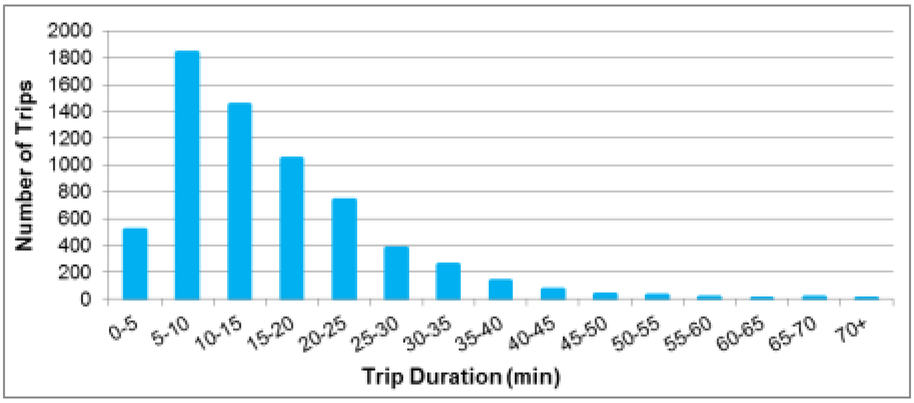

Fig. 29

Carmarthen

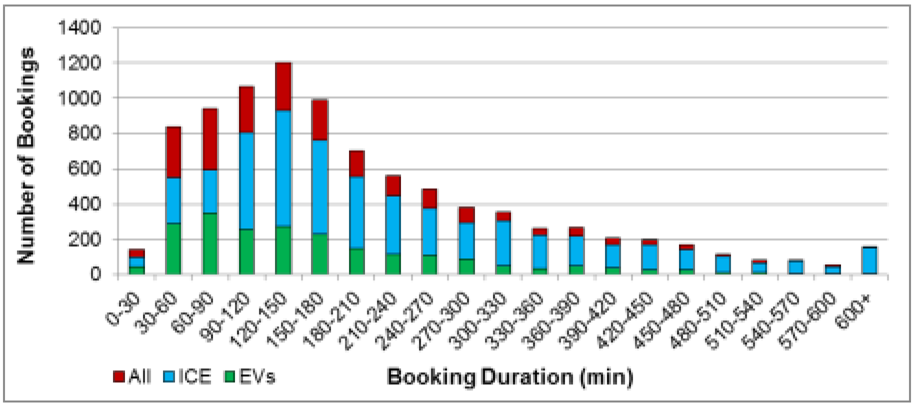

Fig. 30

Lisbon

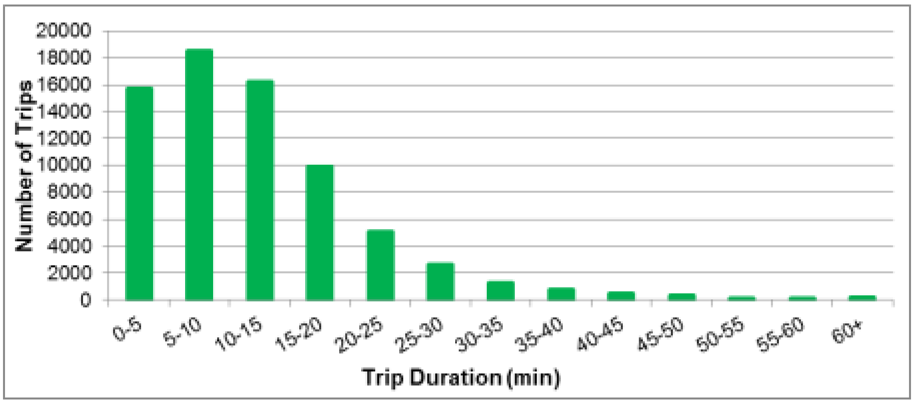

Fig. 31

Berlin

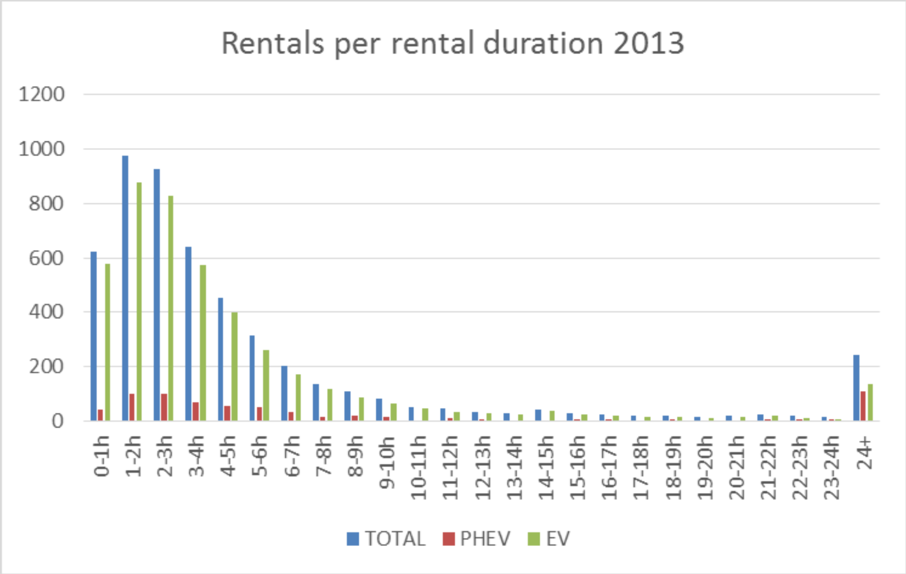

Fig. 32

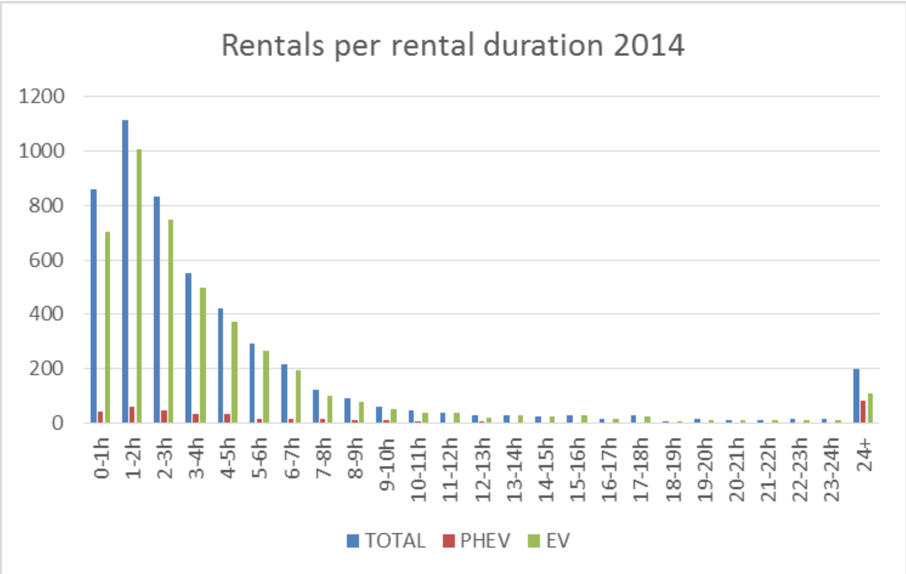

Fig. 33

Bregenz

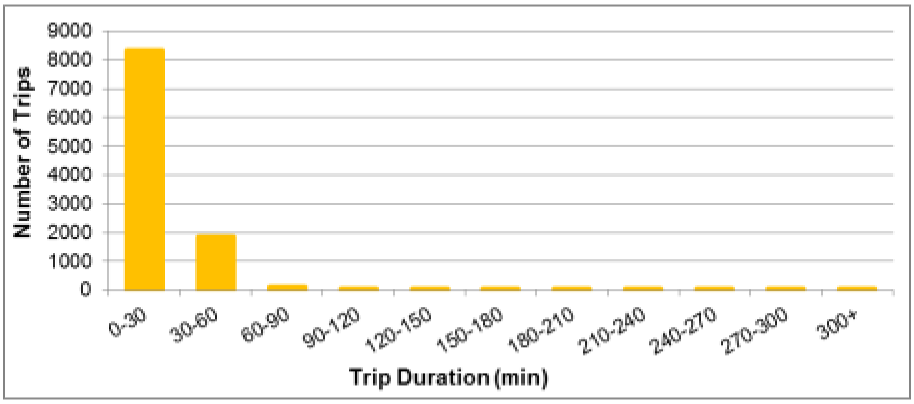

Fig. 34

Fig. 30 and Figs. 32-33 presents Total number of Bookings per Booking Duration due to the format of the provided data. This explains the longest durations shown on those figures. In Vigo, Lisbon and Bregenz, where the data represented actual trip information, the majority of the trips had duration of less than one hour.

6. Total number of Trips per Trip Distance

This characteristic classifies the trips according to their distance. Fixed distance classes of 5km (5miles for UK) were used. Similarly to the previous characteristic, such information can be used to study the driving behavior and the “range anxiety” of the EV drivers. This information could be used by the car-sharing companies to improve the fleet composition, by adjusting it to the customers’ driving needs. In case the trip distances of a car-sharing fleet are relatively short, small battery EVs are suitable. On the other hand, in case the trip distances are long, perhaps the extended driving range of plug-in hybrid vehicles could satisfy the customer driving needs. The necessary data for studying this characteristic is the duration of each trip.

The results are presented in Fig. 35-40:

Vigo The results reflect the usual travel distances that employees cover.

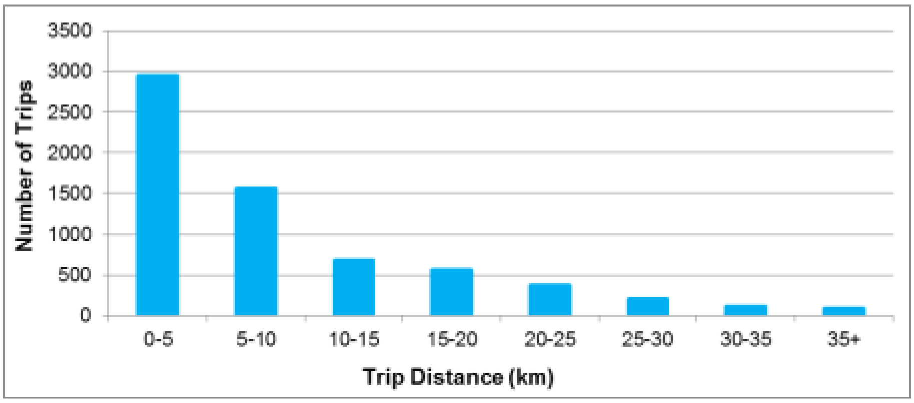

Fig. 35

Carmarthen

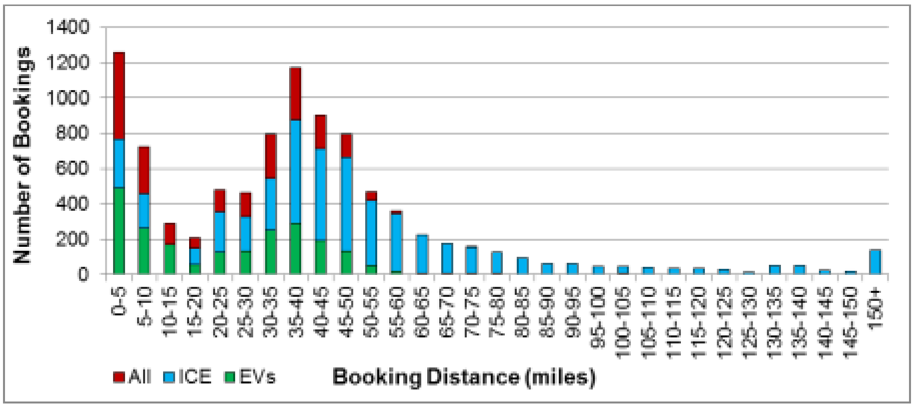

Fig. 36

Lisbon The results reflect the usual travel distances that employees cover.

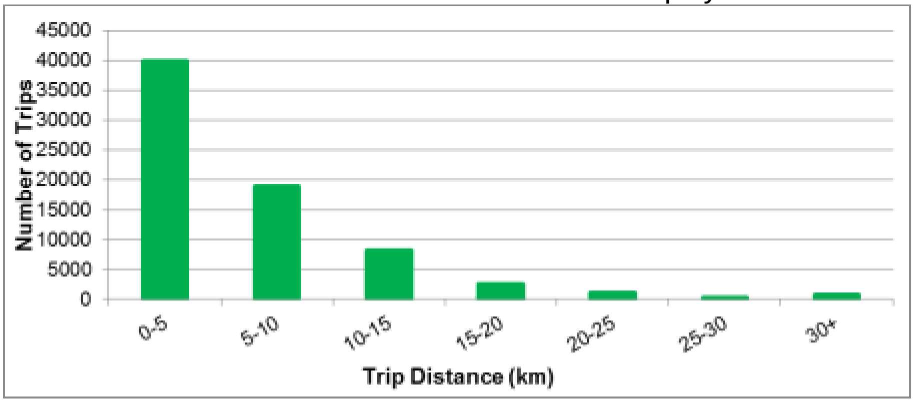

Fig. 37

Berlin

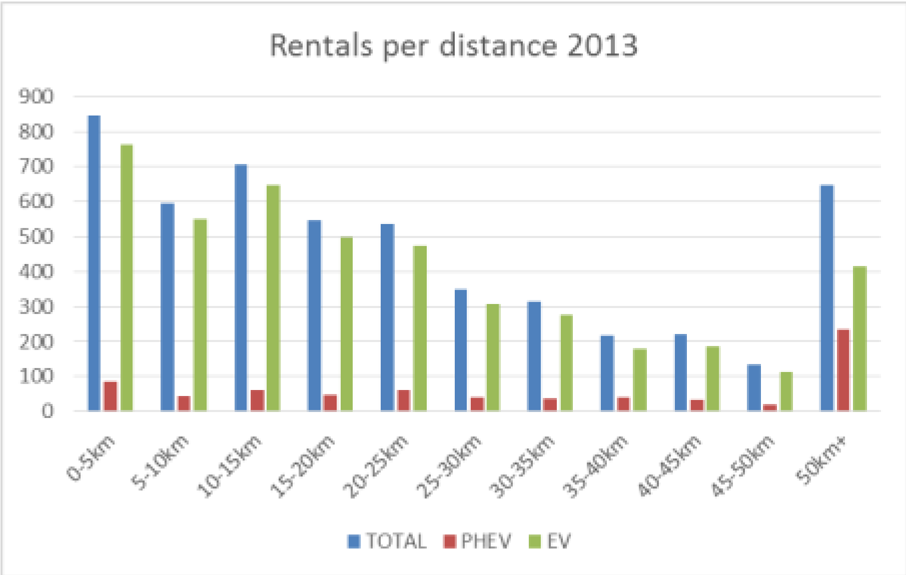

Fig. 38

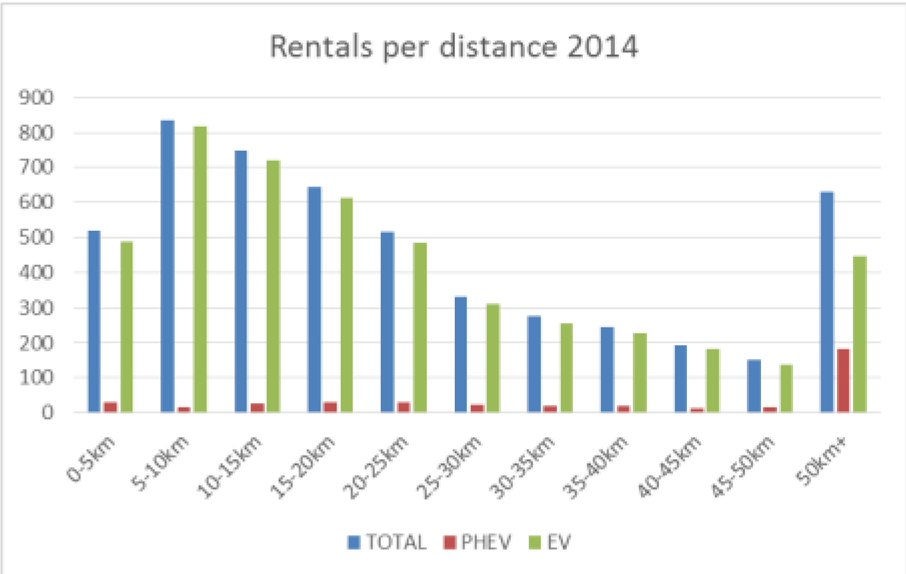

Fig. 39

Bregenz

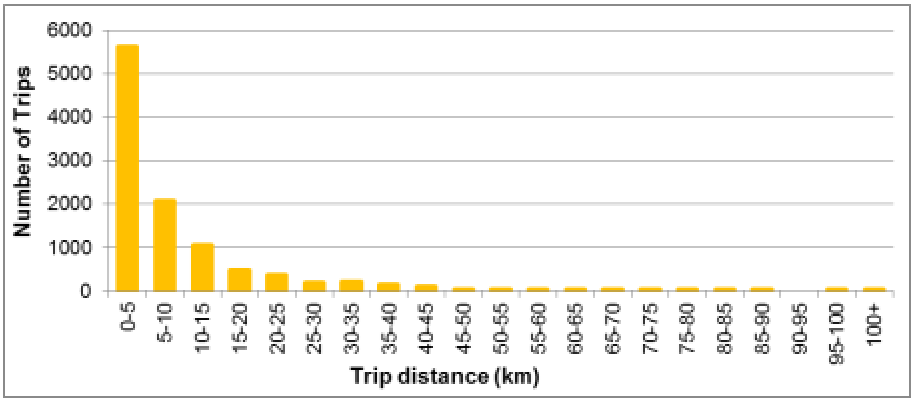

Fig. 40

The trip distances for the majority of the trips in all cases was less than 50km. In the cases where trip distance is shown, it is clear that the distance of the most EV trips was below 15 km. This factor proves that the range anxiety feeling due to low driving range of EVs is not justified.

7. Total number of Trips per Trip Av. Speed

This characteristic classifies the trips according to their average speed. Fixed speed classes of 10km/h were used to reflect the driving behavior of the EV drivers. Different driving speed results in different energy consumption of the EV battery. According to [7], there is a point (optimal speed) at which the energy consumption (kWh/km) is minimum, and thus the driving range is maximum. By studying this characteristic, we investigate whether the fleet vehicles are travelling at the minimum consumption or not. This characteristic can be used by the car-sharing companies to either incentivize their customers to drive in an optimal way, or modify the composition of their fleet and choose vehicles that meet the customers' driving habits. The necessary data for studying this characteristic is the average speed of each trip.

The results are presented in Fig. 41-42:

Vigo

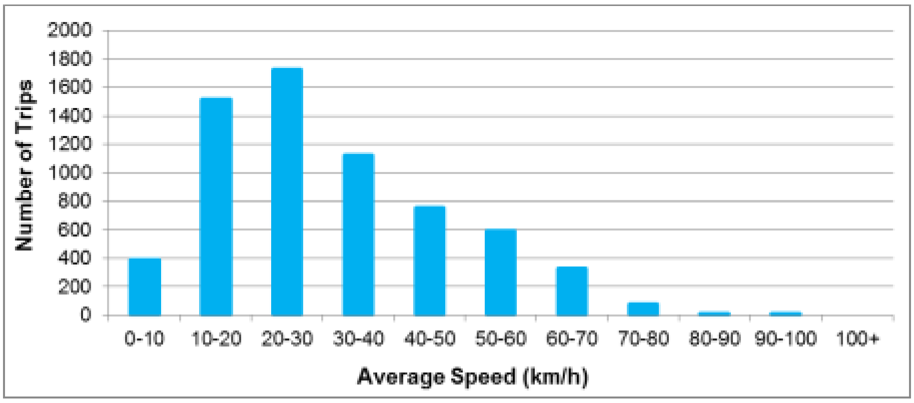

Fig. 41

Lisbon

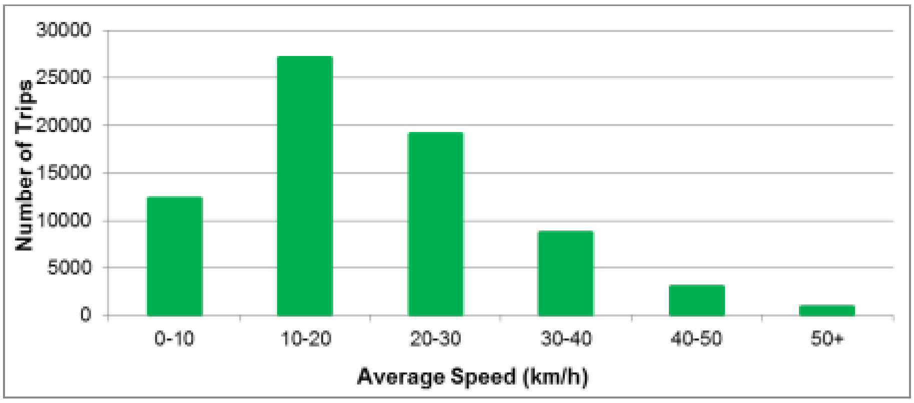

Fig. 42

Results related to average speed per trip were available only for Lisbon and Vigo. As seen from the above figures, the average speed was relatively low in both cases. This characteristic reflects the fact that EVs were used for driving inside the city.

8. EV usage Probability (weekly)

This characteristic shows the probability of having at least one vehicle of the car-sharing fleet occupied during one week. By looking at this characteristic, a car-sharing company can understand the usage patterns of its fleet and organize its operations accordingly (maintenance, charging, cleaning etc). The usage probability is calculated using the procedure presented in Fig. 43.

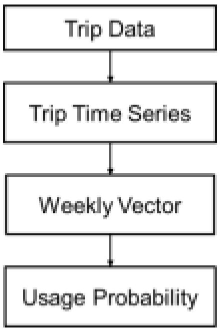

Fig. 43

Trip Data: Data regarding the date, the start time and the duration of each trip are used to calculate the usage probability.

Trip Time series: An hourly time series is created for the whole period of the dataset, containing the number of trips for every hour of the dataset, as presented in Fig. 44.

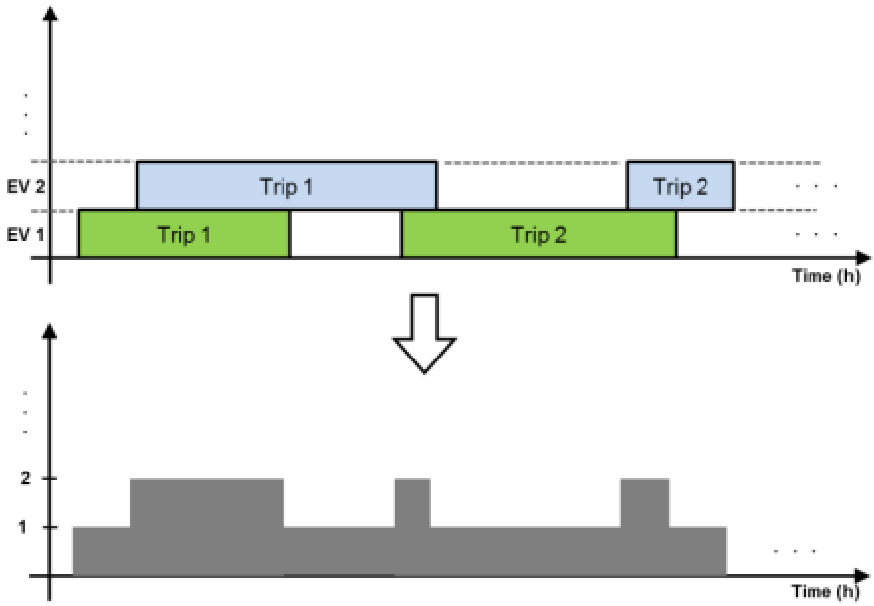

Fig. 44

Weekly Vector: A vector is created containing 168 values with the total number of trips on each hour. Eq. 1 is used. N represents the total number of weeks in the dataset.

$$f(i) = \sum_{n=0}^{N-1} (168 \cdot n + i), \; i = 1...168 \qquad \text{Eq. 1}$$

Usage Probability: The weekly vector is normalized so that all of its values sum to 1. The total number of trips is calculated and every value of the vector is divided with it. The remaining vector is the usage probability of the car-sharing fleet.

The results are presented in Fig. 45-47:

Vigo

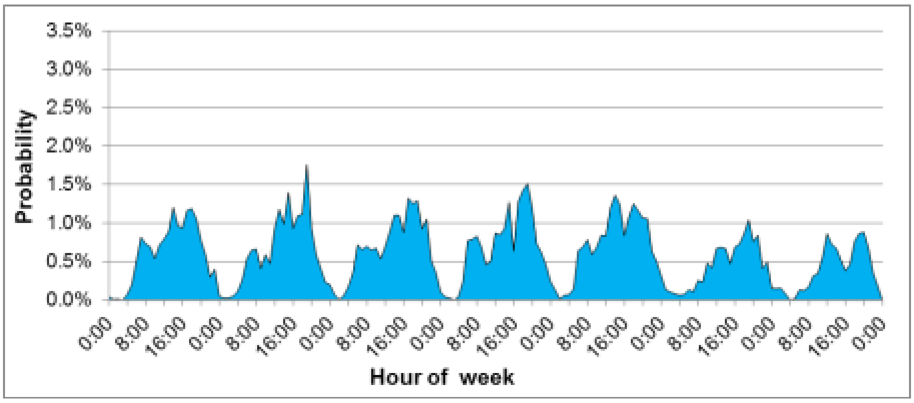

Fig. 45

Carmarthen

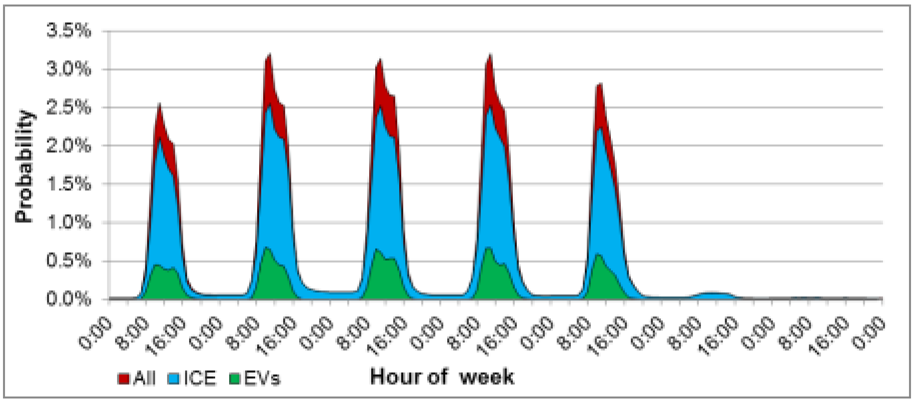

Fig. 46

Bregenz

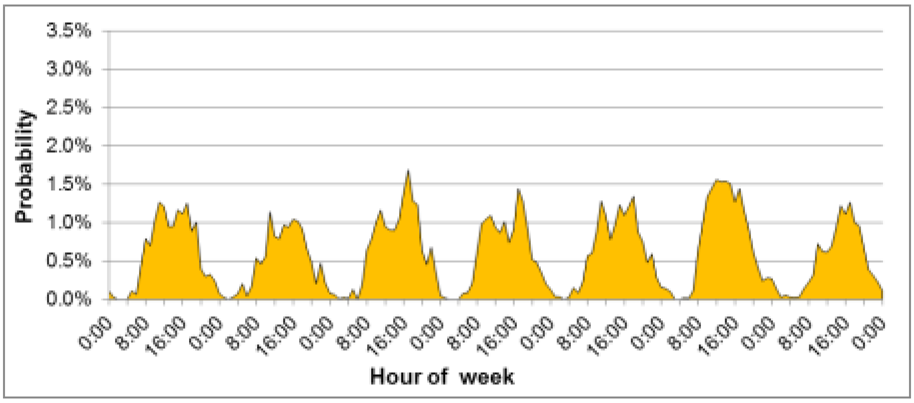

Fig. 47

The above figures show the hourly probability of an EV to be travelling during a week. In Bregenz and Vigo the EV usage probability is periodically repeated every day including weekend while in Carmarthen the EV usage probability is almost zero. This indicates the minimum usage of EVs during weekends for the car-sharing EV fleet in Carmarthen.

4.3 Conclusions

The variation in the results depends by the type of the car sharing fleet: BASE fleet vehicles or SHARE fleet vehicles as well as by the type and frequency of the data collected during trials.

5. Analysis on EV electricity consumption

5.1 Data description

Limited data related to the electricity consumption of the car-sharing fleets were provided from some project partners. The data are classified into two categories: per charging event (PE) and aggregated (A). The PE category includes information about each charging event of each EV in the corresponding car-sharing fleet. This requires a data recording capability from the EV charging stations used by the car-sharing EV fleets. So far, this kind of data is available only for the EV fleet in Lisbon. Aggregated data regarding the overall electricity consumption was available for the fleets in Vigo (Spain) and Bregenz (Austria).

The data included information about the booking date, the start times and duration, the energy consumption and the number of charging events from the car-sharing EV fleets. Table 2 shows the EV electricity demand data availability and granularity from each car-sharing EV fleet.

Table 2: EV electricity demand Data

Pilot / Data -per charging event **PE** -aggregated **A**	Spain		Italy	Portugal	UK	Germany	Austria
	Vigo	Valencia	Milan	Lisbon	Carmarthen	Berlin	Bregenz
Start Time	-	-	-	PE	-	-	-
Date	-	-	-	PE	-	-	-
Energy Consumption	A	-	-	PE	-	-	A
Duration	-	-	-	PE	-	-	-
Number of charging event	-	-	-	A	-	-	-

5.2 Analysis & Results

In order to analyze the charging patterns and electricity consumption of the car-sharing EV fleets, the following eight characteristics were studied.

1. **Total number of Ch. Events per Hour of Day**

This characteristic studies the hourly distribution in a day of the start times of all charging events of the EVs in each fleet. Information is extracted regarding the charging patterns of the EVs in each car-sharing fleet. This characteristic identifies the hours at which the charging demand is high (peak hours). Third party companies that manage the EV charging

stations could use this information to design a proper charging strategy, according to their targets (cost minimization, etc.). The necessary data for studying this characteristic is the start hour of each charging event.

The results are presented in Fig. 48:

Lisbon

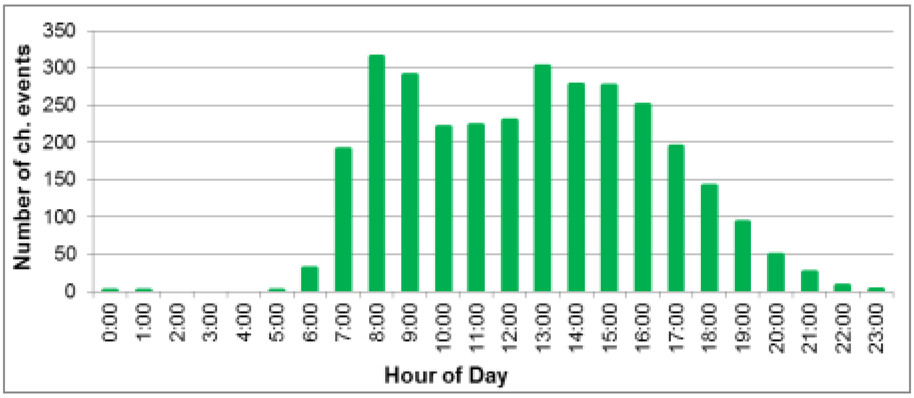

Fig. 48

Fig. 48 shows the distribution regarding the start times of charging events in Lisbon. As seen from figure the majority of these charging events started during daytime. This will result in an increase of the electricity demand during the grid's peak hours (18.30-21.00 for Portugal). Installation of smart EV chargers could manage the charging events postponing them up to the off peak times (night hours) in a day, minimizing the overloading of the existing electricity infrastructure in the distribution networks.

2. Total number of Ch. Events per Day of Week

This characteristic studies the daily distribution in a week of all charging events per fleet. Information regarding the occurrence of charging events during a week is extracted. The days on which the car-sharing fleets are recharging indicate days with high electricity consumption and consequently increased mileage. The necessary data for studying this characteristic is the date of each charging event.

The results are presented in Fig. 49:

Lisbon:

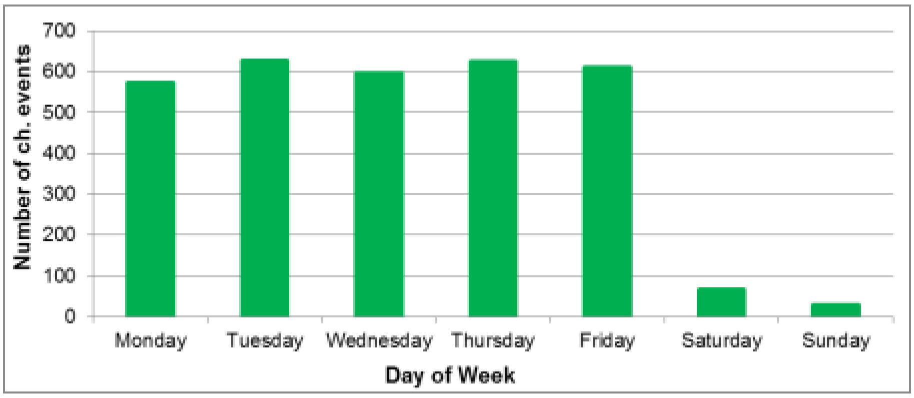

Fig. 49

The majority of the charging events occurred following a uniform distribution during weekdays.

3. Total number of Ch. Events per Month

This characteristic shows the monthly distribution of all charging events per fleet. By looking at the change of the number of charging events over time, information regarding the utilization trend of the fleet's charging stations is extracted. An increasing number of charging events over time indicates the success of the car-sharing scheme and its popularity among the customers. The necessary data for studying this characteristic is the date of each charging event.

The results are presented in Fig. 50:

Lisbon

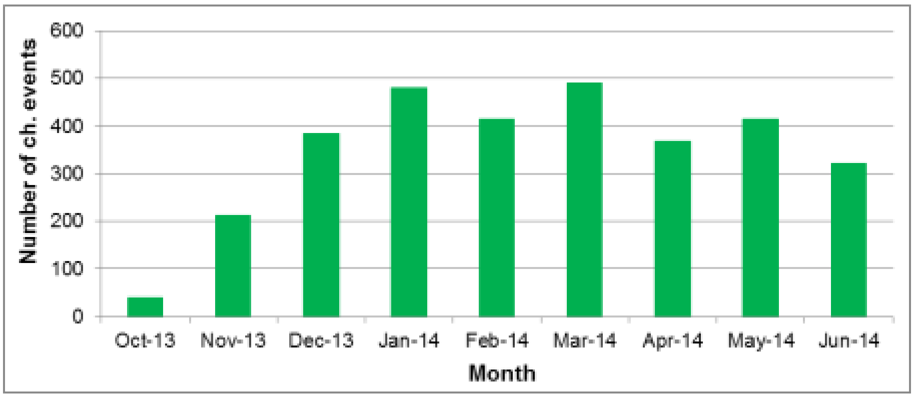

Fig. 50

Fig. 50 shows the Total number of Ch. Events per Month in the car-sharing fleet in Lisbon. As seen from Fig, an increasing trend is shown, indicating the increasing energy requirements of the EV fleet.

4. Total consumed Energy (kWh) per Month

This characteristic shows the monthly distribution of the aggregated electricity that was consumed for charging each car-sharing EV fleet. The monthly energy requirements are highly correlated with the total mileage of each car-sharing EV fleet, indicating the aggregated travelled distance in a month. Based on these energy requirements, the CO_2 emissions can also be calculated. Future projections are also possible using regression analysis, contributing to the scenario modelling. The necessary data for studying this characteristic is the date and energy of each charging event. However, due to unavailability of data from all the car-sharing fleets, in some cases the Total travelled distance per month was used to calculate the total consumed energy per month. A typical energy consumption of 0.16kWh/km was applied to calculate this characteristic [8].

The results are presented in Fig. 51-58:

Vigo

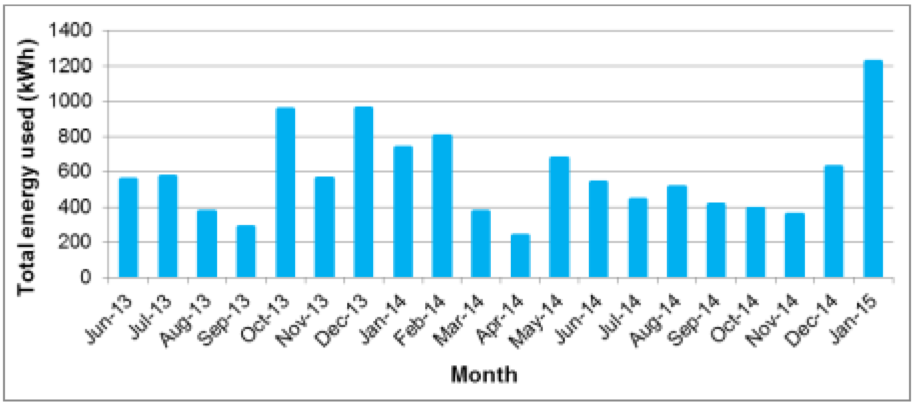

Fig. 51

Valencia

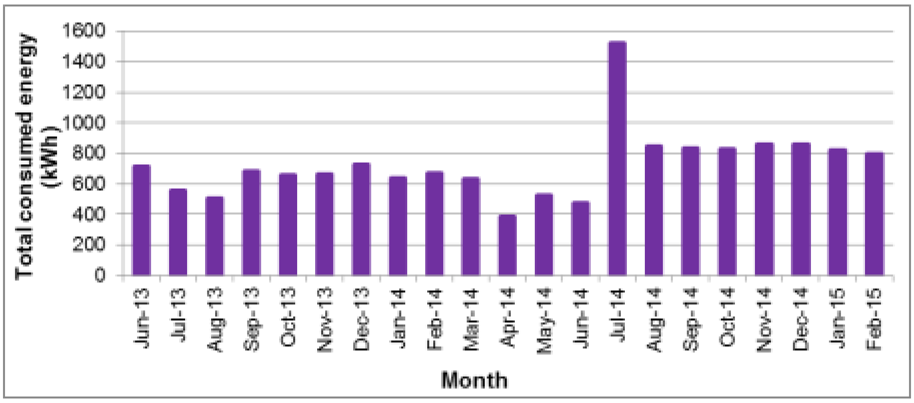

Fig. 52

Carmarthen

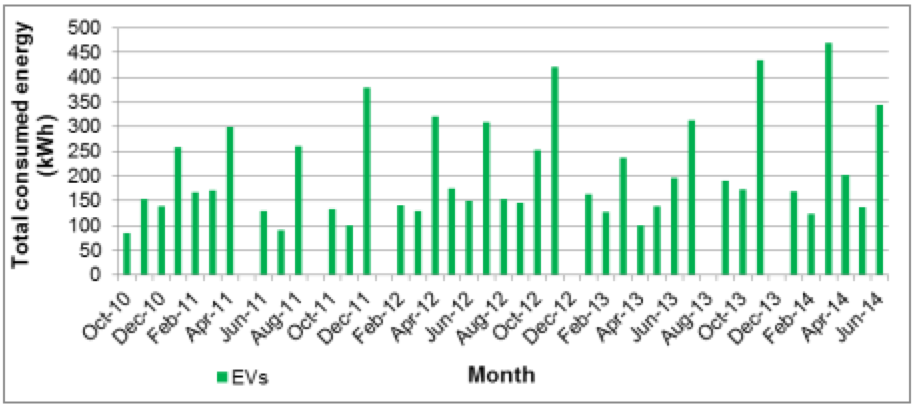

Fig. 53

Lisbon

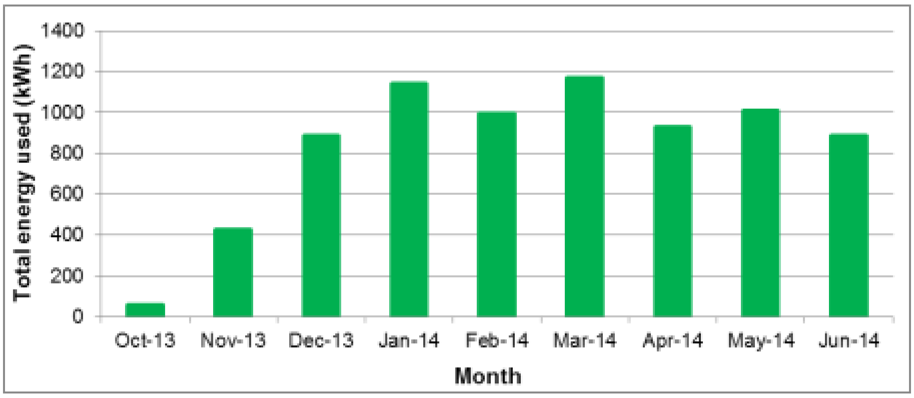

Fig. 54

Berlin

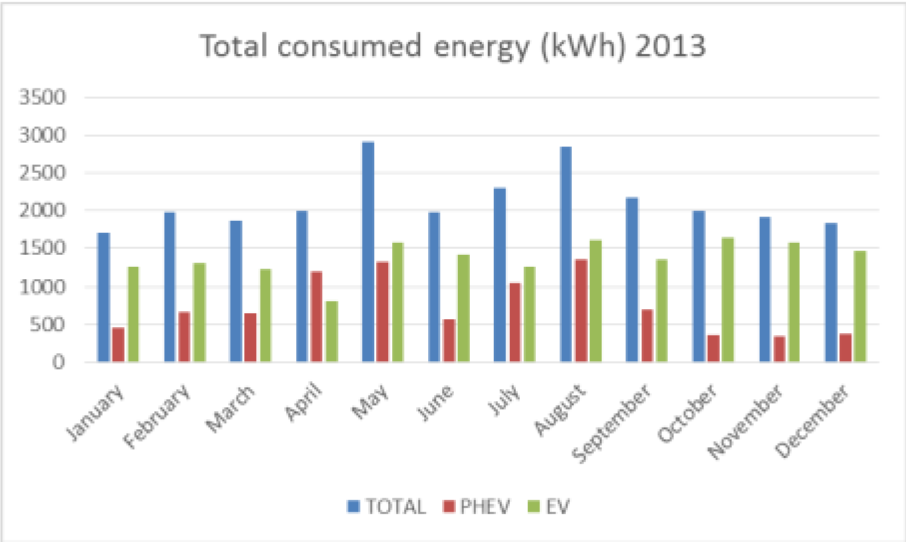

Fig. 55

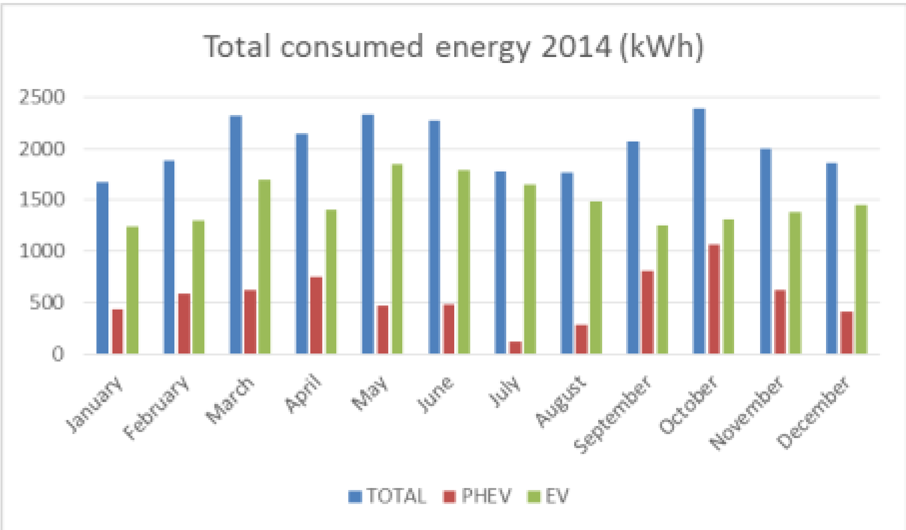

Fig. 56

Bregenz

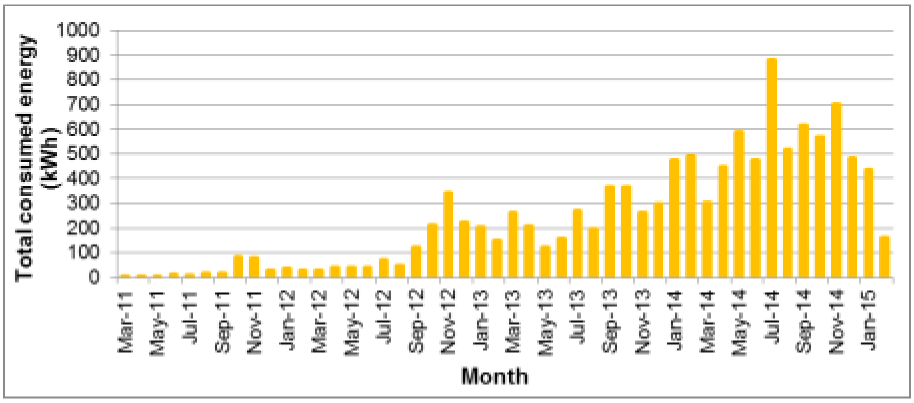

Fig. 57

Milan

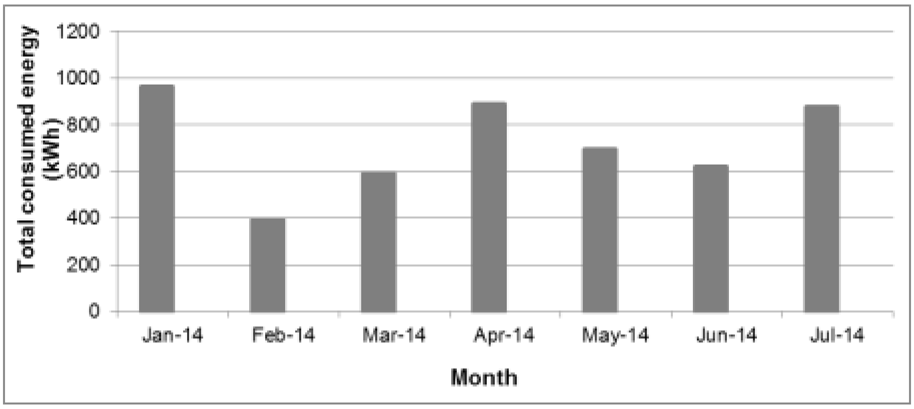

Fig. 58

The above figures show the Total consumed Energy (kWh) per Month for all car-sharing EV fleets. The above figures are highly associated with the total travelled distance per month for all corresponding car-sharing EV fleets.

5. Total number of Ch. Events per Ch. Event Duration

This characteristic classifies the charging events according to their duration. Fixed duration classes were defined using a 30min interval. The duration of the charging events indicates the utilization of the charging station as well as the trip's length. Short charging events indicate that the EVs of the car-sharing fleet are being used for relatively short distances. Such information can also be used to study the "range anxiety" of the EV drivers due to its correlation with the charging frequency. The necessary data for studying this characteristic is the duration of each charging event.

The results are presented in Fig. 59:

Lisbon

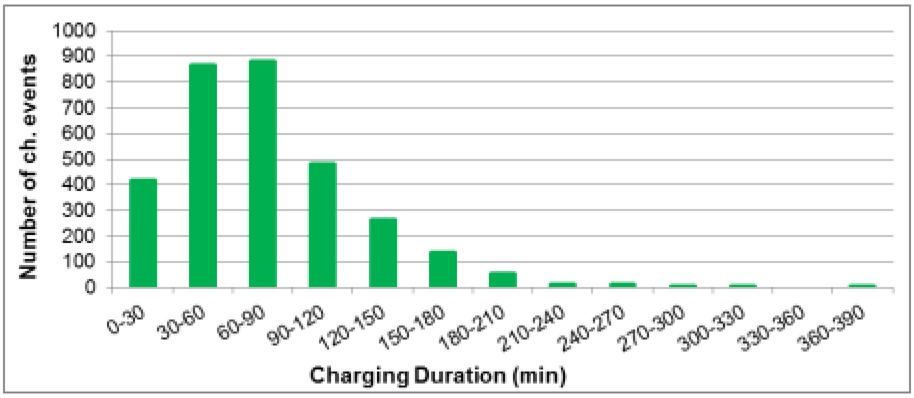

Fig. 59

Fig. 59 shows the distribution of the charging duration of all charging events occurred in the car sharing EV Fleet in Lisbon. The majority of the charging events lasted between 30 and 90 minutes. This indicates that EVs were frequently charged so that their batteries didn't reach low battery state of charge (SOC) levels. Specifically for Lisbon pilot it was found that the drivers used to charge the batteries at the beginning of the trip without consideration of the battery SOC. This behavior was improved in time as they were coming familiar with the battery range in real conditions.

6. Total number of Ch. Events per Ch. Event Energy

This characteristic classifies the charging events according to their energy. Fixed distance classes of 1kWh were used. Similarly to the previous characteristic, such information can be used to study the utilization of each charging station. Conclusions can be also drawn regarding the necessary technical characteristics of the charging stations in a car-sharing company. In case the energy requirements are low, a slow charger could be sufficient to deliver the necessary energy. On the other hand, if the energy requirements are high, a fast charger with high power rate is needed. In this case the investment cost is increased affecting the pricing policy of the car-sharing company. This information could be used by the car-sharing companies to improve the charging infrastructure, and install the suitable charging equipment. The necessary data for studying this characteristic is the energy of each charging event.

The results are presented in Fig. 60:

Lisbon

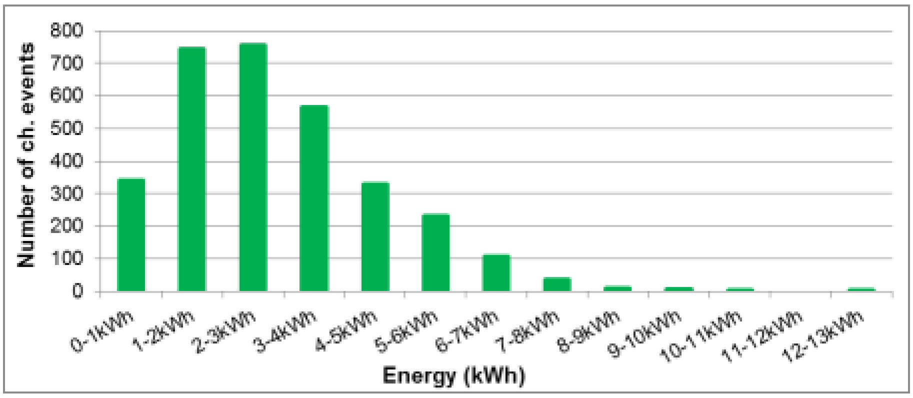

Fig. 60

7. Av. Energy Consumption vs Av. Speed

This characteristic presents the correlation between the average speed (km/h) and the energy consumption (kWh/km) for all trips of a car-sharing fleet. As mentioned before, different driving speed results in different energy consumption of the EV battery. This is illustrated with this characteristic by presenting the different energy consumption rate (kWh.km) for every driving speed. This characteristic can be used by the car-sharing companies to understand the performance of the EVs in their fleet and their customers' driving habits. The necessary data for studying this characteristic is the average speed and consumed energy of each trip.

The results are presented in Fig. 61-62:

Vigo

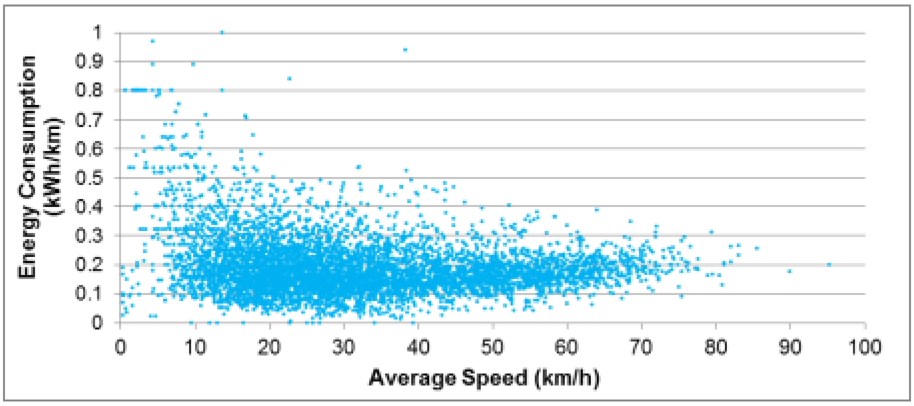

Fig. 61

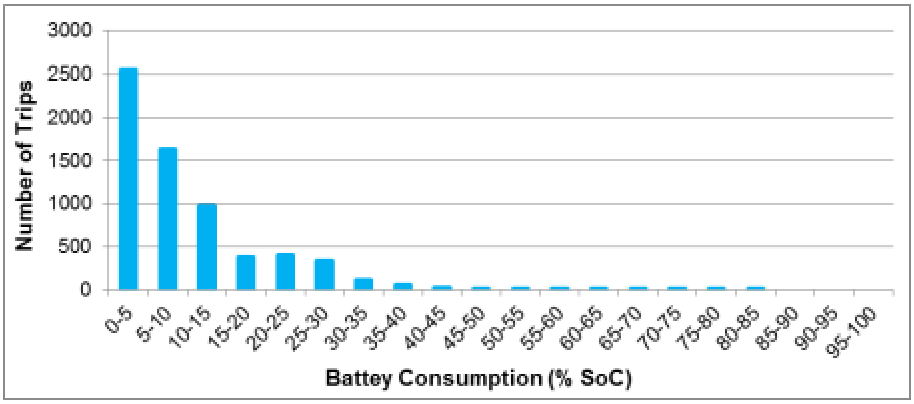

Fig. 62

Fig. 61 shows a scatter plot between average speed and average consumption considering the provided trip data of Lisbon. Fig. 62 shows a histogram about the average battery consumption per trip. The above information could help car sharing company take decisions about the composition of the EV fleet and the pricing policy as well.

8. EV Ch. Station Occupancy Probability (weekly)

This characteristic shows the probability of having at least one charging station of the car-sharing fleet occupied during one week. By looking at this characteristic, a car-sharing company can understand the recharging patterns of its fleet. If incentivized, the car-sharing company could offer ancillary services to the electricity distribution network operators from its charging stations [9, 10, 11, 12]. The occupancy probability is calculated using the procedure presented in Fig. 63.

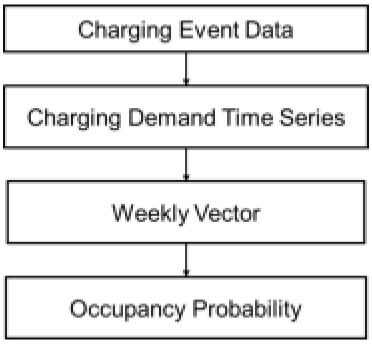

Fig. 63

Charging Event Data: Data regarding the date, the start time and the duration of each charging event is used to calculate the occupancy probability.

Charging Demand Time series: An hourly time series is created for the whole period of the dataset, containing the number of charging stations occupied on every hour of the dataset as presented in Fig. 64.

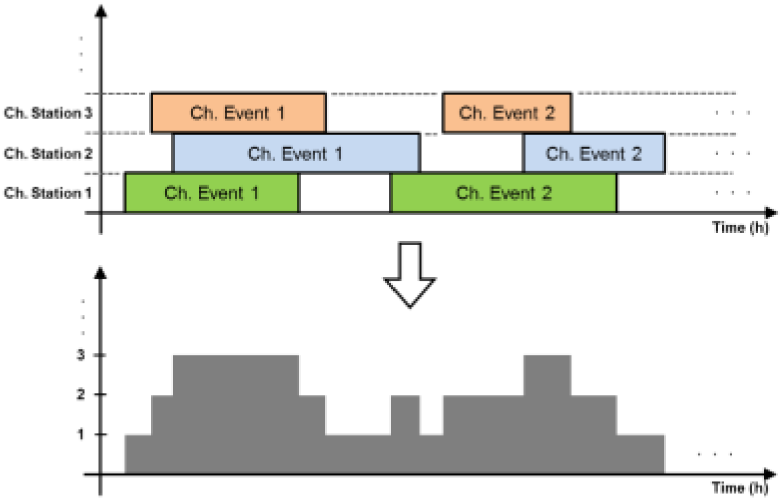

Fig. 64

Weekly Vector: A vector is created containing 168 values with the total number of occupied stations on each hour, using Eq. 1.

Occupancy Probability: The weekly vector is normalized so that all of its values sum to 1. The total number of charging events is calculated and every value of the vector is divided with it. The remaining vector is the occupancy probability of the charging stations of the car-sharing company.

The results are presented in Fig. 65:

Lisbon

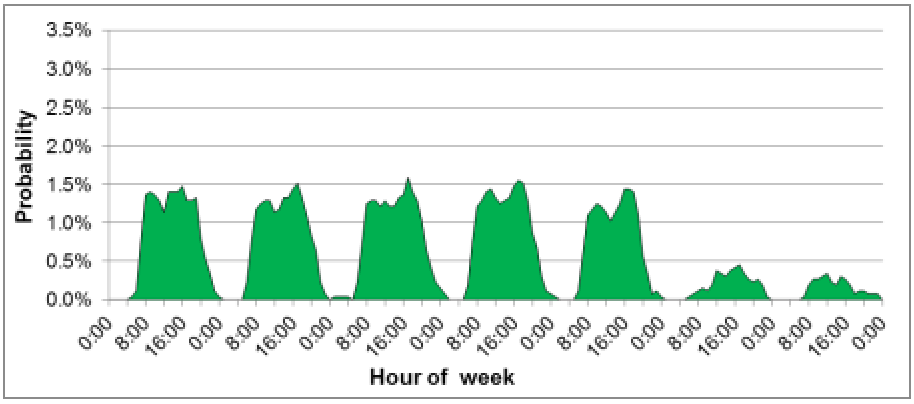

Fig. 65

The above figure shows the hourly probability of a charging station to be occupied (due to charging) during a week for the car sharing EV fleet in Lisbon. The occupancy probability of the charging stations reflects the fact that the majority of the charging events occur during weekdays.

5.3 Conclusions

A diversity effect is observed for the charging demand between pilots due to the type of car sharing fleets. Trial data analysis has shown that the shape of the EV charging demand depend on several factors, such as the number of vehicles involved, user type and day of the week. The energy used per charging event is dependent on a number of factors: battery capacity, the length of the charge, the type of charging and not least the driver behavior.

It is an expectation that the customer behavior will improve in time as they were coming familiar with the battery range in real conditions with a beneficial effect in the reduction of barriers to wide-spread of EVs adoption. Understanding the charging profile of vehicle drivers and the impact of charging to local grid reliability is a key concern for utility providers. Additionally, evaluating charging characteristics and behaviors can provide valuable insight into the optimal charging levels required for home, workplace and public charging.

6. Analysis on CO_2 emissions

6.1 Data description

Data related to the carbon emissions of each country were provided from the project partners. The data are classified in two categories: Transport Statistics (TS) and Energy Mix (EM). The TS category includes information about the road transport fleet composition and the average daily travelled distance. The EM category includes information regarding the energy generation mix. Table 3 shows the provided data from each project partner.

Table 3: Data related to carbon emission calculations

Pilot / Data	Spain	Italy	Portugal	UK	Germany	Austria
Transport Statistics (TS)						
Number of ICE vehicles	✓	✓	✓	✓	✓	✓
Number of private-hire vehicles	×	✓	✓	✓	✓	✓
Number of EVs	✓	×	✓	✓	✓	✓
Average Daily Travelled Distance	✓	×	✓	✓	✓	✓
Energy Mix (EM)						
Energy Generation Mix	✓	×	✓	✓	✓	✓

6.2 Data analysis methodology

In order to analyze the CO_2 emissions and produce future scenarios, the following factors were considered:

1. Projected number of ICE vehicles (N_{ICE})

Historical data were used to create future projections for 2020 and 2030. A time series was created, presenting the total number of ICE cars for a country over time. Linear regression analysis was applied on the time series, in order to calculate the mathematical formula describing the relationship between the number of ICE cars (Y) and time (X in years). The formula is described with Eq. 2:

$$Y = \beta_0 + \beta_1 X + \varepsilon \qquad \text{Eq. 2}$$

, where β_0 and β_1 are the constant regression coefficients and ε is the random disturbance (error). The slope β1 expresses the annual change of the number of ICE cars (in cars/year). Using the Least Squares Method described in [13],the constant regression coefficients were calculated. The number of ICE passenger vehicles for each country is presented in Table 4.

Table 4: Number of ICE passenger vehicles

Year \ Country	Spain	Italy	Portugal	UK	Germany	Austria
2015	25776400	39654600	5790600	30734800	44271300	4779252
2020 (projected)	28576300	42058200	6584200	32859300	46371800	5124847
2030 (projected)	34176100	46865400	8171400	37108300	50572800	5816037

2. Carbon intensity of ICE vehicles (CI_{ICE})

The carbon intensity is measured in gCO_2/km and describes the CO_2 emissions per travelled km. According to [7], the current average carbon intensity of an ICE car is 172.2 gCO_2/km. The average carbon intensity of an ICE car is expected to reduce in future and reach 117.42 gCO_2/km and 73.88 gCO_2/km in 2020 and 2030 respectively [14].

3. Projected number of EVs(N_{EV})

This factor describes the road transport electrification targets of each country in the project, and defines the corresponding scenarios. Four scenarios were defined, subject to the data availability. The Business as Usual (BAU) scenario assumes that the number of EVs will continue to increase with the current rate. No further actions will be taken to encourage electric cars and only existing incentives continue. Depending on the road transport electrification support level of each country, 3 additional scenarios were considered, namely Medium (M), High (H) and Extreme (E).

The projected number of EVs for each country is presented in Table 5.

Table 5: EV projections per country (thousands of EVs)

Scenario \ Country	Spain		Portugal		UK		Germany		Austria	
	2020	2030	2020	2030	2020	2030	2020	2030	2020	2030
BAU	-		26		270	3000	650	4500	-	
M	1200		53.4		800	4100	-	-	256	
H	2500		-		1550	11200	1000	8000	-	
E	-		-		3100	20600	-	-	-	

4. Energy consumption efficiency of EV (Ef_{EV})

The energy consumption efficiency of an EV is measured in kWh/km and describes the average required energy in kWh for travelling 1 km. According to [8], the current average energy efficiency for a medium size EV is 0.16 kWh/km. This number is expected to decrease due to future development on the EV technology (battery, motor, etc.). According to

the same source, the energy efficiency of an EV in 2020 and 2030 will be 0.13 kWh/km and 0.11 kWh/km respectively.

5. Carbon intensity of electricity generation (CI_{grid})

The carbon intensity of electricity generation represents the CO_2 emissions related to the electricity generation of each country. According to the EU directives [15], targets of 20% and 40% CO_2 emissions reduction compared to the 1990 levels are set for 2020 and 2030 respectively. The total CO_2 emissions for each country are presented in Table 6.

Table 6: CO_2 emissions (in Mt)

Country / Year	Spain	Italy	Portugal	UK	Germany	Austria
1990	77.66	137.21	16.33	237.74	426.95	13.84
2015	111.65	152.25	20.49	191.57	353.85	14.56
2020 (target)	62.12	109.77	13.06	190.19	341.56	11.07
2030 (target)	46.59	82.33	9.80	142.64	256.17	8.31

This factor is affected by the energy mix of each country, and its developments on electricity generation (future penetration of renewable energy sources, decarbonisation of grid etc.). Linear regression was applied on historical data, and the electricity generation was projected to 2020 and 2030. In order to calculate the carbon intensity of the electricity generation of each country, the CO_2 emissions targets were divided with the projected electricity generation of the corresponding year. The current and projected carbon intensity of the electricity grid of each country is presented in Table 7.

Table 7: Carbon intensity of electricity grid (in gCO_2/kWh)

Country / Year	Spain	Italy	Portugal	UK	Germany	Austria
2015	328.01	467.24	368.26	485.71	569.71	203.12
2020 (projected)	162.61	314.25	213.43	462.47	526.93	145.12
2030 (projected)	100.12	207.78	135.52	320.61	364.71	97.08

6. Annual travelled distance of ICE vehicles and EVs (D_{ICE} , D_{EV})

The average daily travelled distance as well as the total number of cars is used to calculate the annual travelled distance from ICE vehicles and EVs. The projected travelled distance of ICE passenger vehicles for each country is presented in Table 8 for each scenario.

Table 8: Travelled distance projections from ICE vehicles per country (billions of km)

Country / Scenario	Spain		Portugal		UK		Germany		Austria	
	2020	2030	2020	2030	2020	2030	2020	2030	2020	2030
No EVs	388.8		89.6		447.1	504.9	631.0	688.2	69.7	
BAU	-		89.2		443.4	464.1	622.1	626.9	-	
M	372.5	-	88.9	-	436.2	449.2	-	-	66.2	-
H	354.8		-		426.0	352.5	617.4	579.3	-	
E	-		-		404.9	224.6	-	-	-	

The projected travelled distance from EVs for each country is presented in Table 9 for each scenario.

Table 9: Travelled distance projections from EVs per country (billions of km)

Country / Scenario	Spain		Portugal		UK		Germany		Austria	
	2020	2030	2020	2030	2020	2030	2020	2030	2020	2030
BAU	-		0.4		3.7	40.8	8.8	61.2	-	
M	16.3	-	0.7	-	10.9	55.8	-	-	3.5	-
H	34.0		-		21.1	152.4	13.6	108.9	-	
E	-		-		42.2	280.3	-	-	-	

The procedure to calculate the carbon emissions (CE) is described in Fig. 66

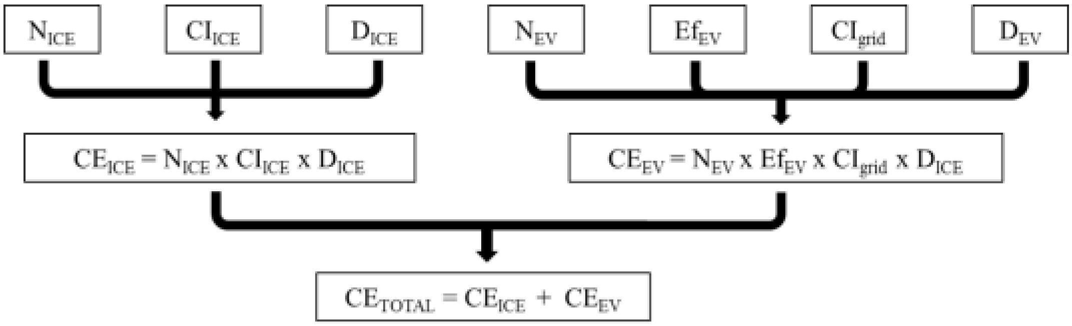

Fig. 66

Using Tables 4-9 and the methodology described in Fig. 66, the results for each country are presented in Fig. 67-76.

Spain

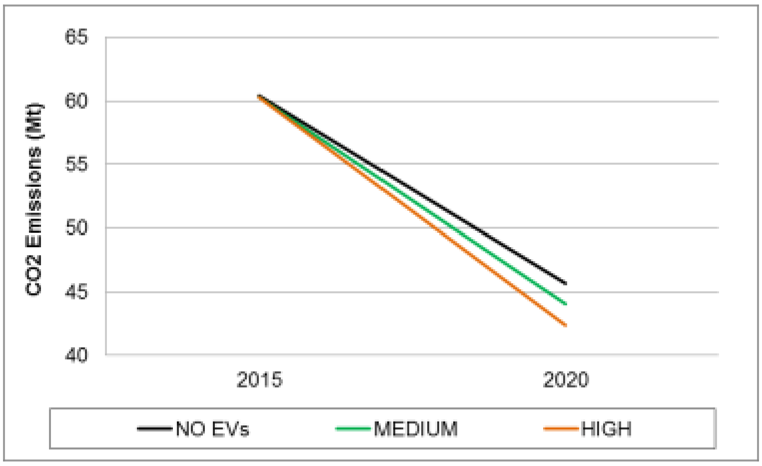

Fig. 67

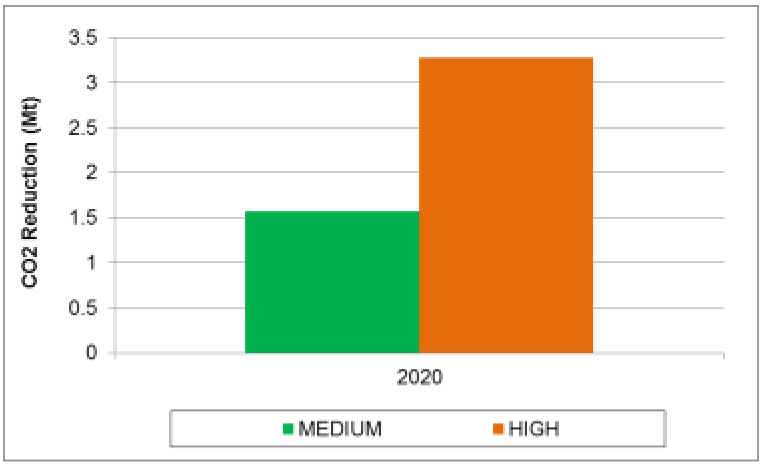

Fig. 68

Portugal

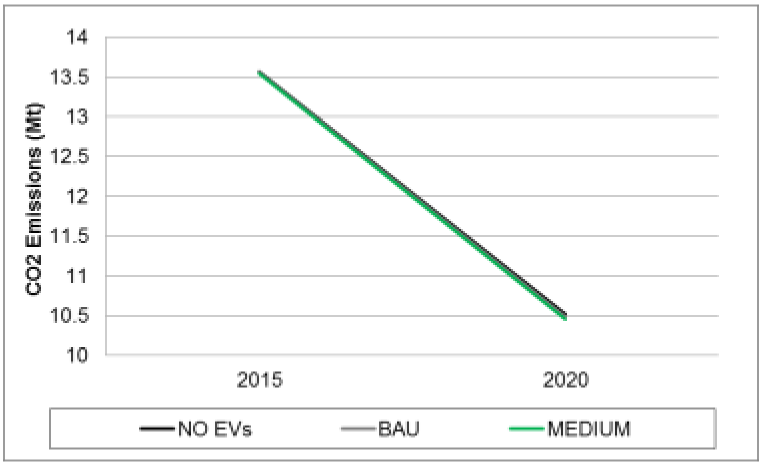

Fig. 69

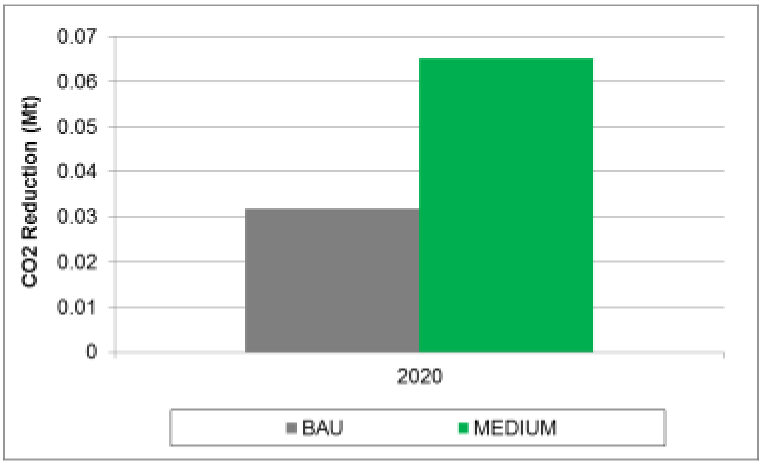

Fig. 70

UK

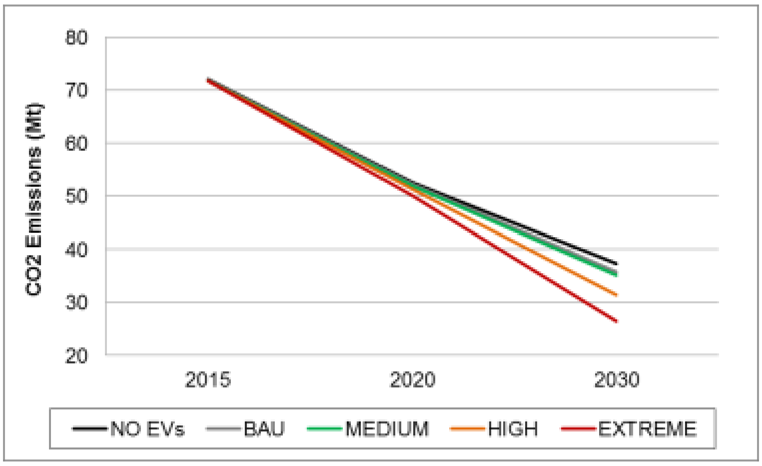

Fig. 71

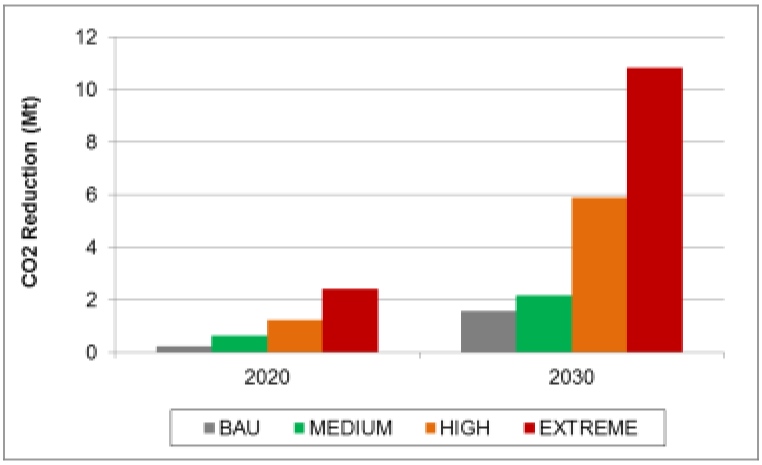

Fig. 72

Germany

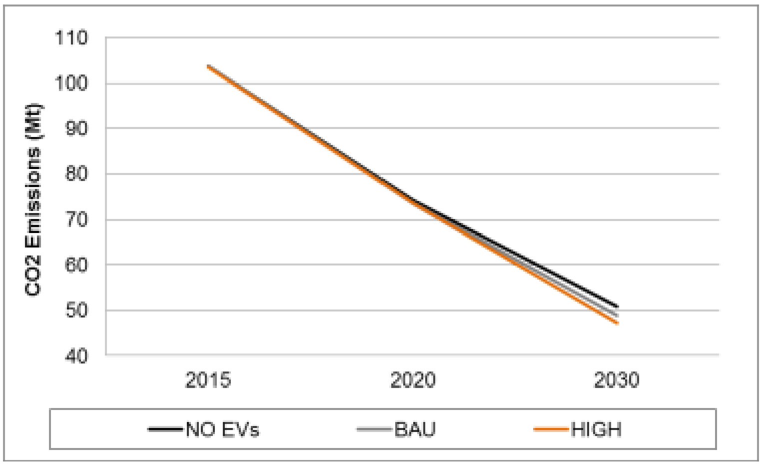

Fig. 73

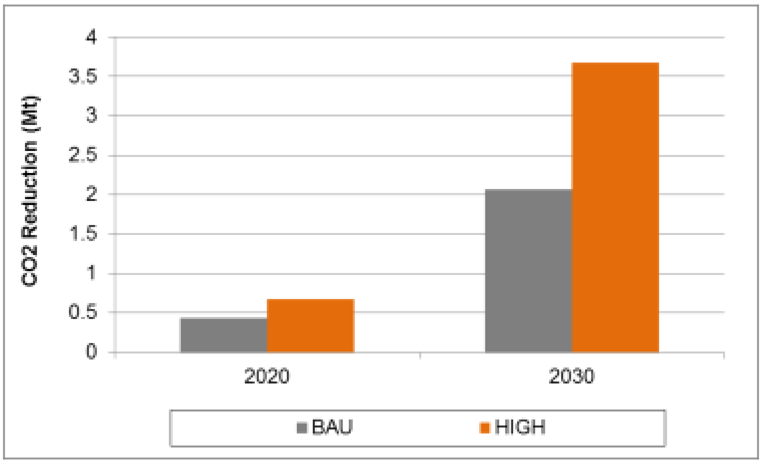

Fig. 74

Austria

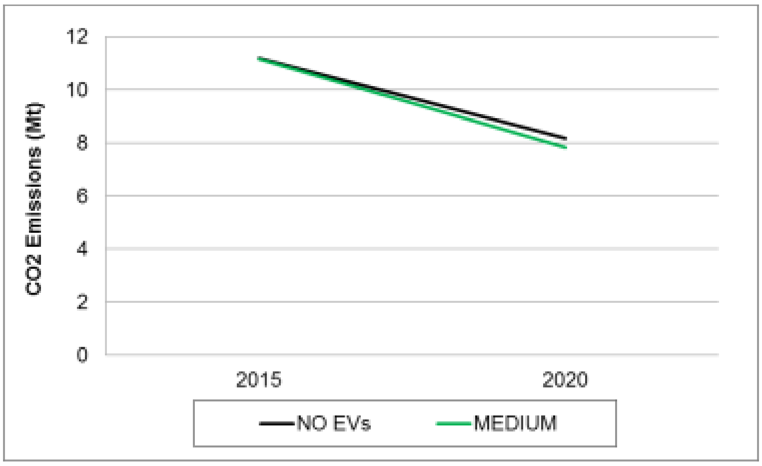

Fig. 75

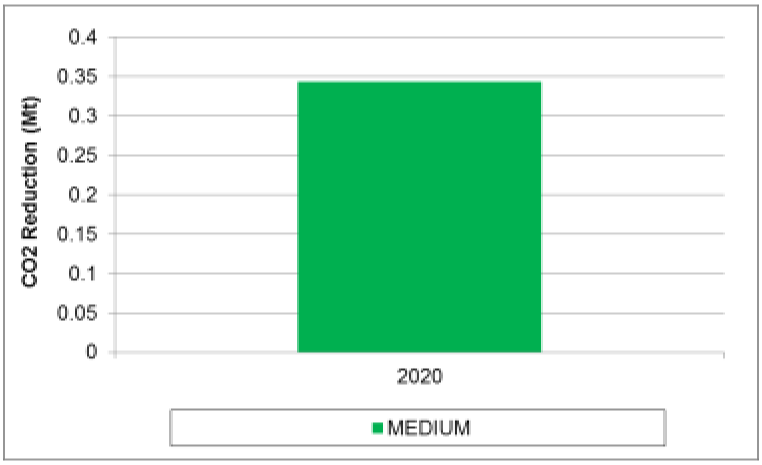

Fig. 76

The above results refer to the electrification of the total passenger car fleet of each country. Considering only the rental cars in the electrification scenarios, the CO_2 reduction figures are much lower. The projected CO_2 emission reduction due to the electrification of the total rental/car-sharing fleet per country is presented in Table 10 for each scenario.

Table 10: Projected CO_2 emission reduction due to the electrification of the rental fleet (tn)

Country / Scenario	Portugal		UK		Germany		Austria	
	2020	2030	2020	2030	2020	2030	2020	2030
BAU	494.9		1052.6	7881.3	2163.3	10336.5	-	
M	1016.5		3118.7	10771.1	-	-	1079.0	
H	-	-	6042.6	29423.5	3328.2	18376.1	-	-
E	-		12085.1	54118.3	-	-	-	

6.3 Conclusions

In order to analyze the CO_2 emissions reduction arising from electric vehicle fleet in different countries it was important to consider the predicted EVs uptake for year 2020 and 2030. This study considered four scenarios for Electric Vehicles uptake: Business as Usual, Medium, High and Extreme, and the choice of these scenarios was based on the data availability in each country.

One of the key factors in determination of the environmental benefit from EVs was found to be the energy mix used for charging the battery.

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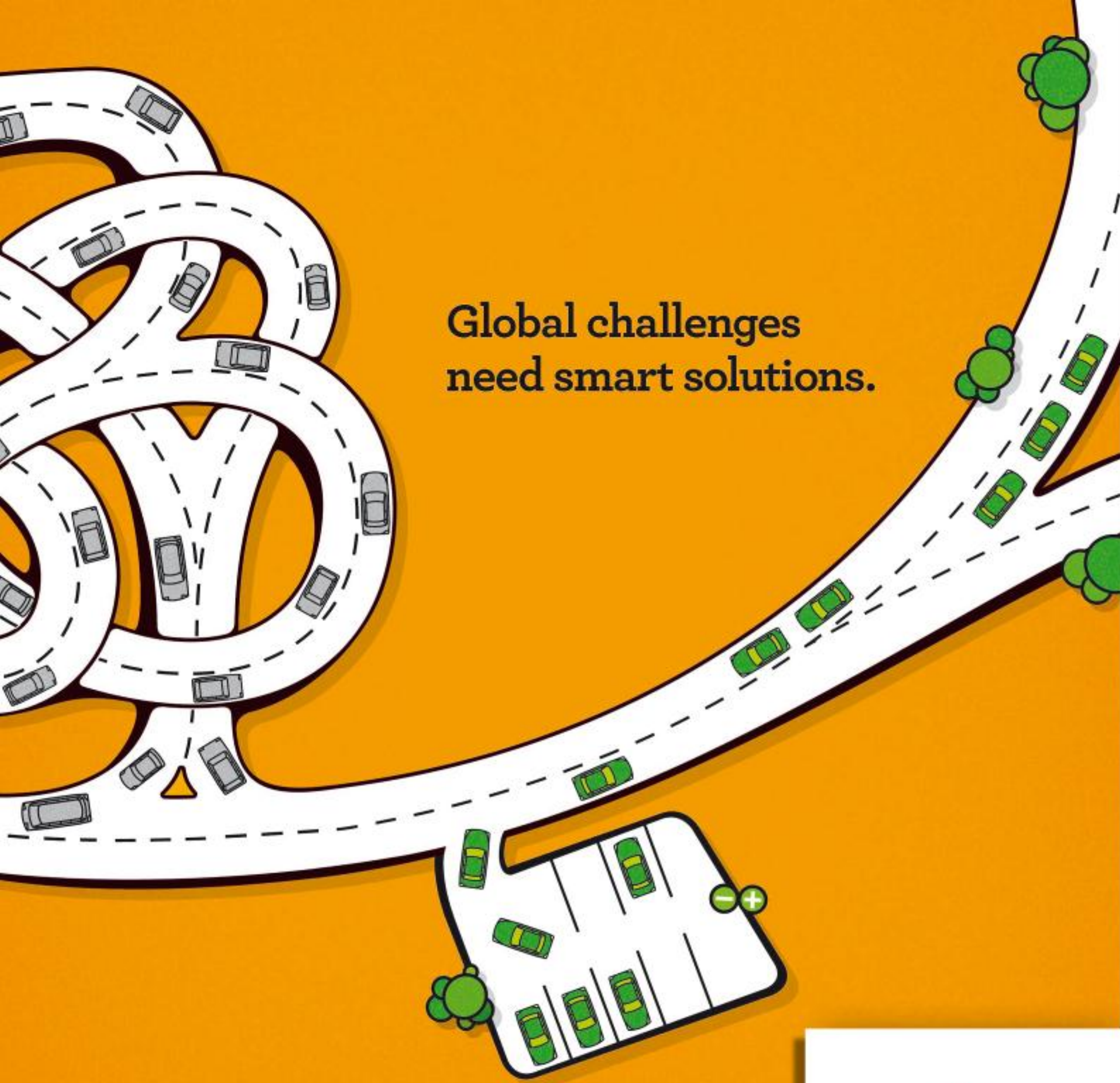
The Project

eBRIDGE is a co-funded EU project to promote electric fleets for urban travel in European cities. The project aims to bring innovation and new technologies to make today's mobility cleaner, more efficient and sustainable.

The project explores alternatives to the current mobility patterns and evaluate whether electric mobility is a feasible option to make cities cleaner and more sustainable.

The seven pilots, Berlin (Germany), Milan (Italy), Lisbon (Portugal), Vigo (Spain), Valencia (Spain), a selection of Austrian municipalities and Carmarthen (Wales) are developing actions to optimise operational fleet performance, test and launch solutions to increase the convenience and ease of use of car sharing offers and finally, raise awareness among the target groups through engaging marketing approaches on the suitability of electric mobility for urban transport and commuting.

The eBRIDGE team involves technical experts, academics, associations, public administrations, mobility providers and public transport and car sharing operators.



eBRIDGE
Power to urban fleets

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