Green eMotion Project

Key facts and analysis on driving and charge patterns

Dynamic data evaluation

Sara Gonzalez-Villafranca, IREC

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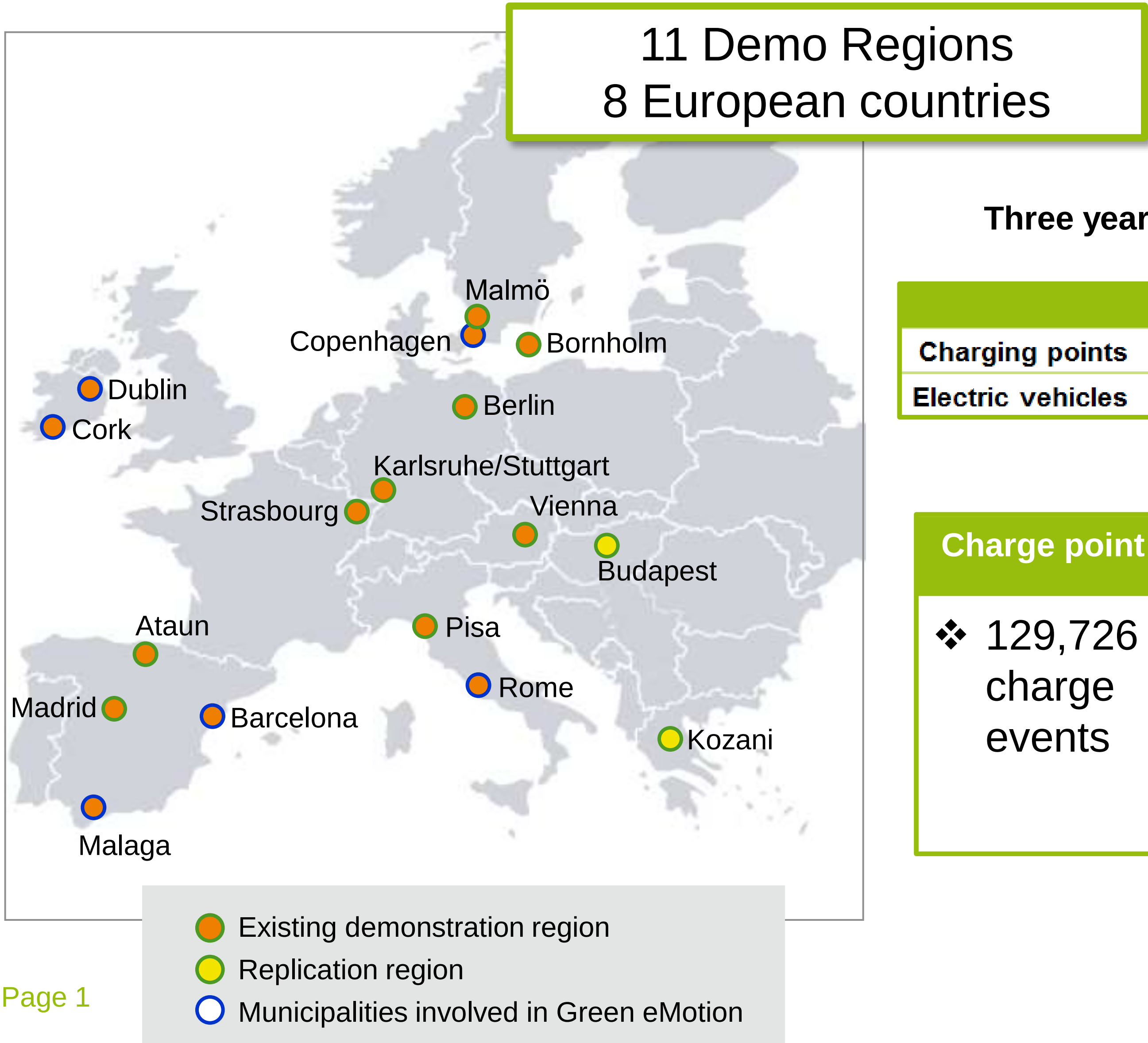
Introduction



Three years of monitoring period

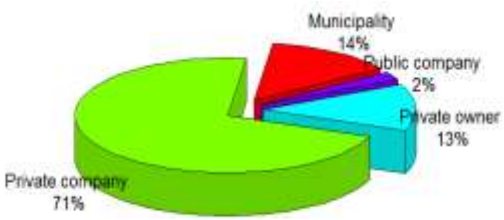
	Registered	Monitored	%
Charging points	2682	1659	62%
Electric vehicles	685	462	67%

Charge point	Electric vehicle
❖ 129,726 charge events	❖ 77,620 charge events ❖ 94,488 trips

Electric vehicle (EV) and charging point (CP) characterization

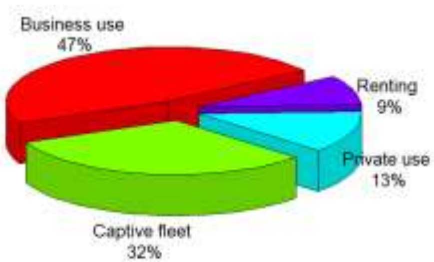
Electric vehicle fleet distribution

❖ EV Owner



Owner	N
Municipality	59
Private company	310
Private owner	58
Public company	10

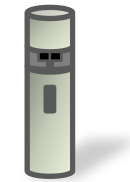
❖ EV Use



Use	N
Business use	187
Captive fleet	126
Private use	50
Renting	35

The fleet includes different EV types: bus, car, motorcycle and transporters. Only car's data is here analysed (corresponds to 81% of the fleet)

Charging point location



Location	N
Household	134
Office parking	323
Public access parking	88
Street	1443

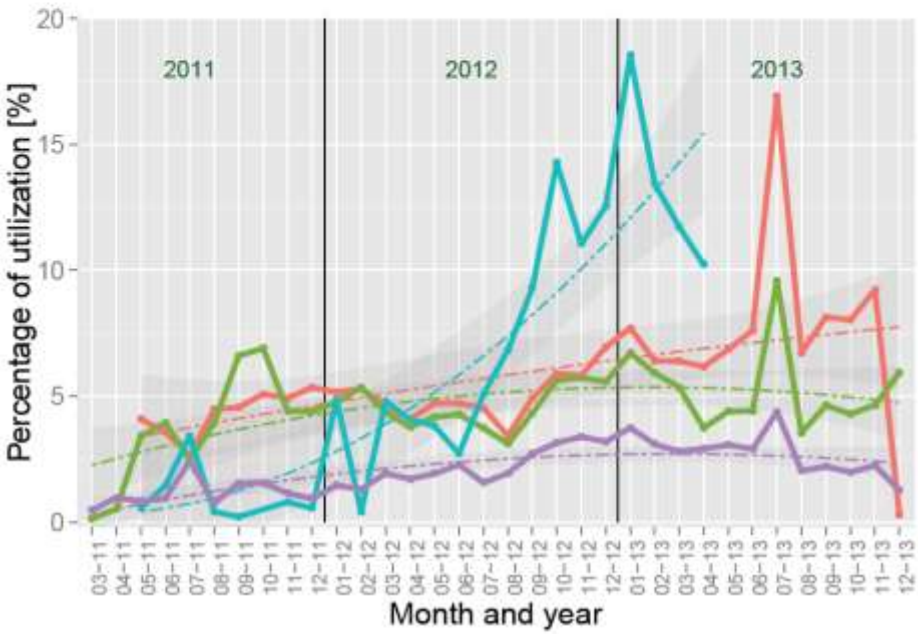
75% of the CPs operate Mode 3

Charging point capacity utilization

- Street CPs show the most under-utilized infrastructure: used an average of 2% of the time (30min every day)

- Public access parking CPs were busy on average 6% of the time

Location[1]	N Installed	% Installed	N Uses	% Uses
Household	134	7%	24840	29%
Office parking	323	16%	32537	37%
Public parking	88	4%	4368	5%
Street	1443	73%	25225	29%



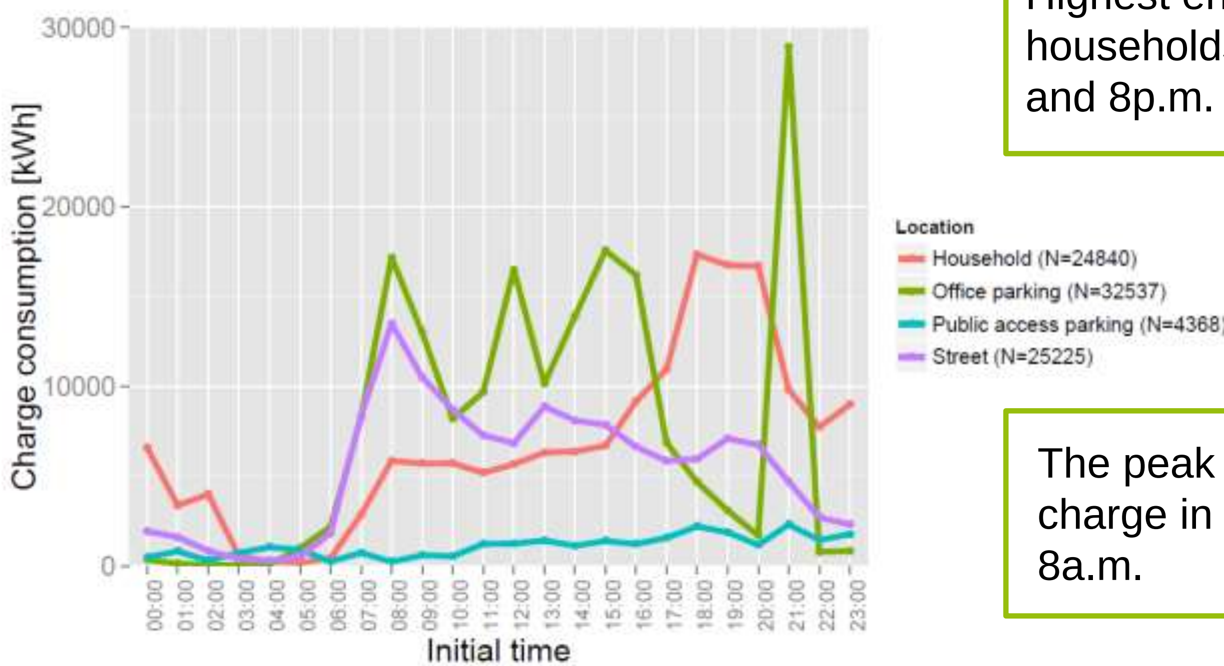
(N=86,839)

CP **utilization has increased** in every location during the monitoring period

Energy consumption

- Total energy charged in GeM CPs: 794 MWh
- Average energy charged per event: 6.12 kWh

Total hourly energy consumption



Highest energy requirements in households start between 6p.m. and 8p.m.

The peak on energy demand to charge in the street starts around 8a.m.

Battery usage analysis

	CHARGE			TRIP		
OWNER	N total	Average INITIAL SOC	INITIAL SOC<20%	N total	Average FINAL SOC	FINAL SOC<20%
Municipality	7885	**63.8%**		39620	**74.5%**	
Private company	10350	**61.5%**		5187	**75.2%**	
USE						
Business use	7138	**62.7%**		5187	**75.2%**	
Captive fleet	5870	**64.2%**		34622	**75.5%**	
Private use	3212	**58.6%**				
Renting	2015	**62.5%**		4998	**67.2%**	

The average state of charge when starting a charge event is 60.5%

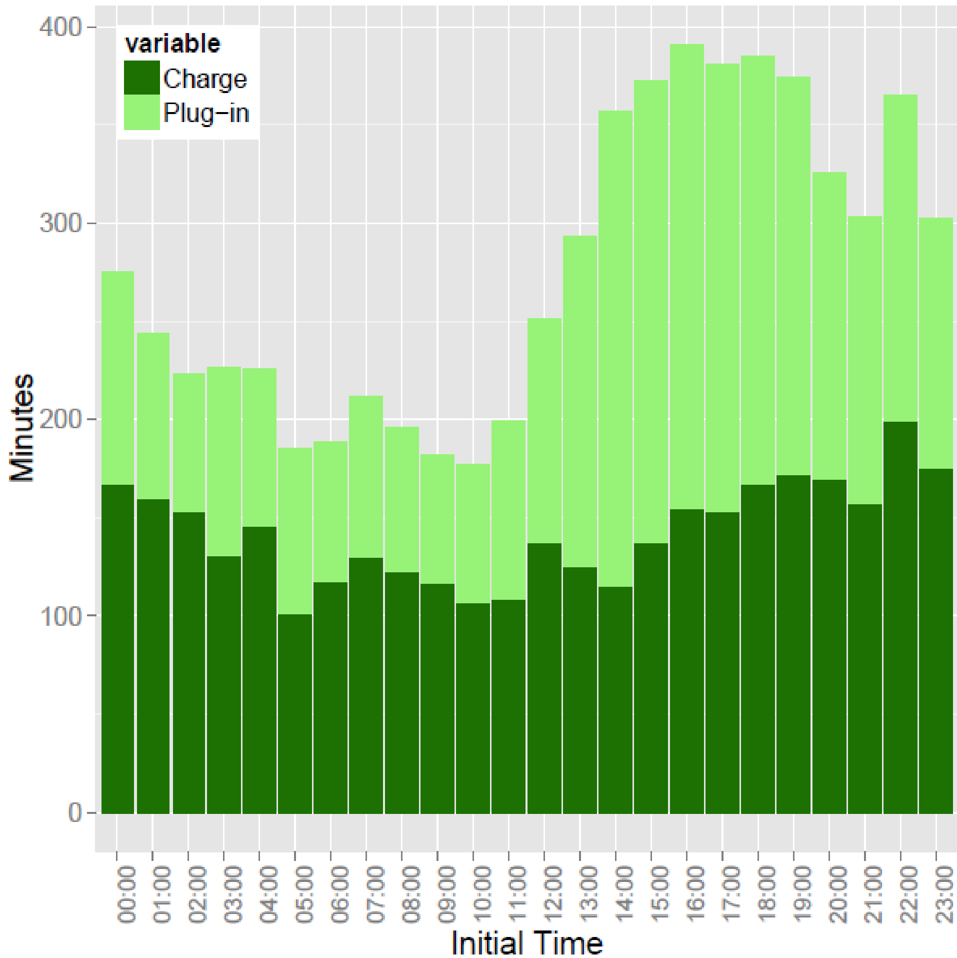
Battery usage analysis

	CHARGE			TRIP		
OWNER	N total	Average INITIAL SOC	INITIAL SOC<20%	N total	Average FINAL SOC	FINAL SOC<20%
Municipality	7885	63.8%	**3.50%**	39620	74.5%	**0.90%**
Private company	10350	61.5%	**4.10%**	5187	75.2%	**1.10%**
USE						
Business use	7138	62.7%	**3.90%**	5187	75.2%	**1.10%**
Captive fleet	5870	64.2%	**2.30%**	34622	75.5%	**0.50%**
Private use	3212	58.6%	**4.80%**			
Renting	2015	62.5%	**7.10%**	4998	67.2%	**3.40%**

The average state of charge when starting a charge event is 60.5%

Less than 2% of the trips end with a battery state of charge lower than 20%.

Charging time vs. Parking time



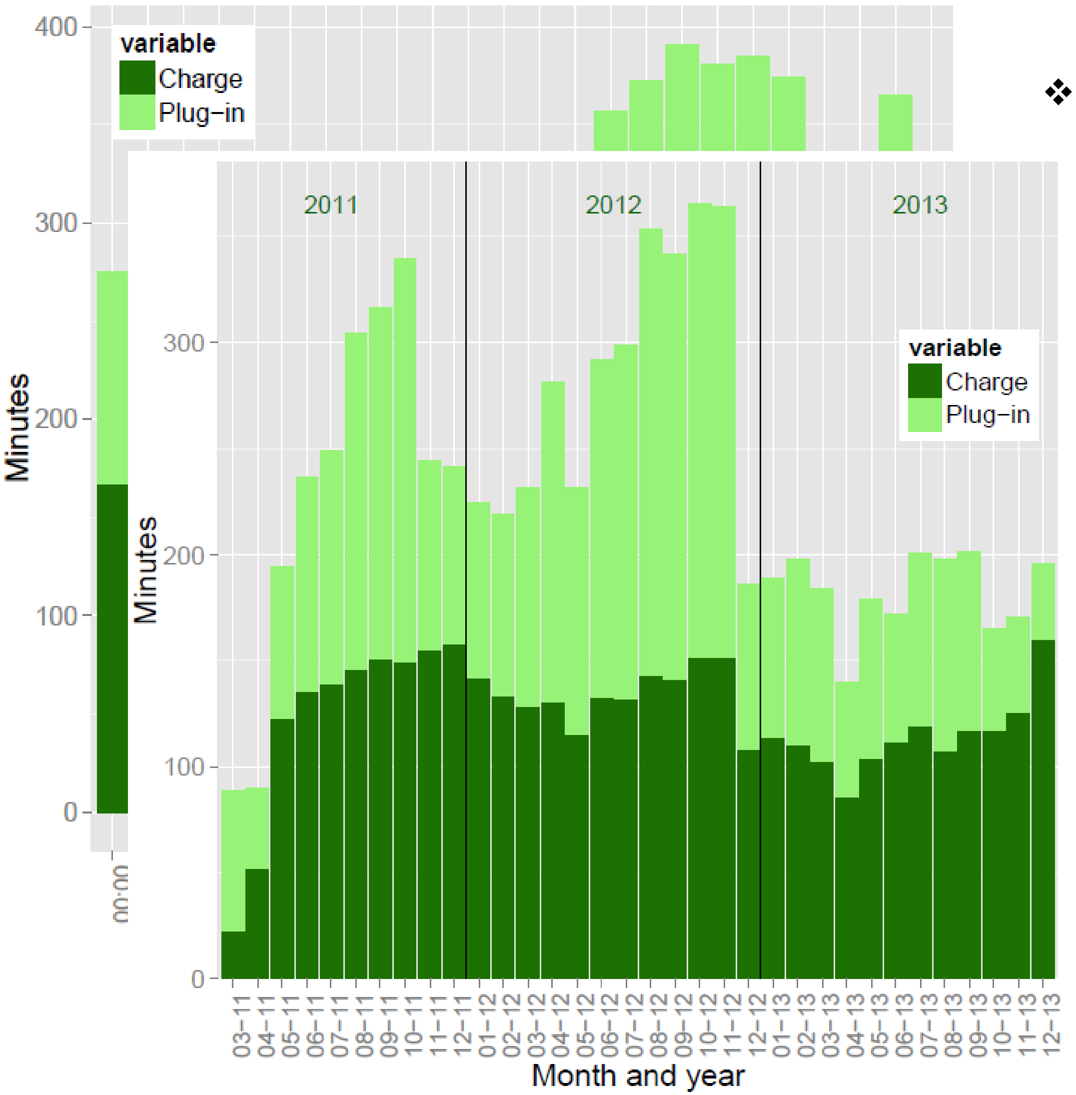
- Daily plug-in time is approximately 4h and 30min*, from which the EV is actually being charged an average of 2h 23 min*

On average, EVs charge 52% of the time they are parked

Longest parking times are given from midday until the end of the day.

*Only slow charge processes

Charging time vs. Parking time



- Daily plug-in time is approximately 4h and 30min*, from which the EV is actually being charged an average of 2h 23 min*

On average, EVs charge 52% of the time they are parked

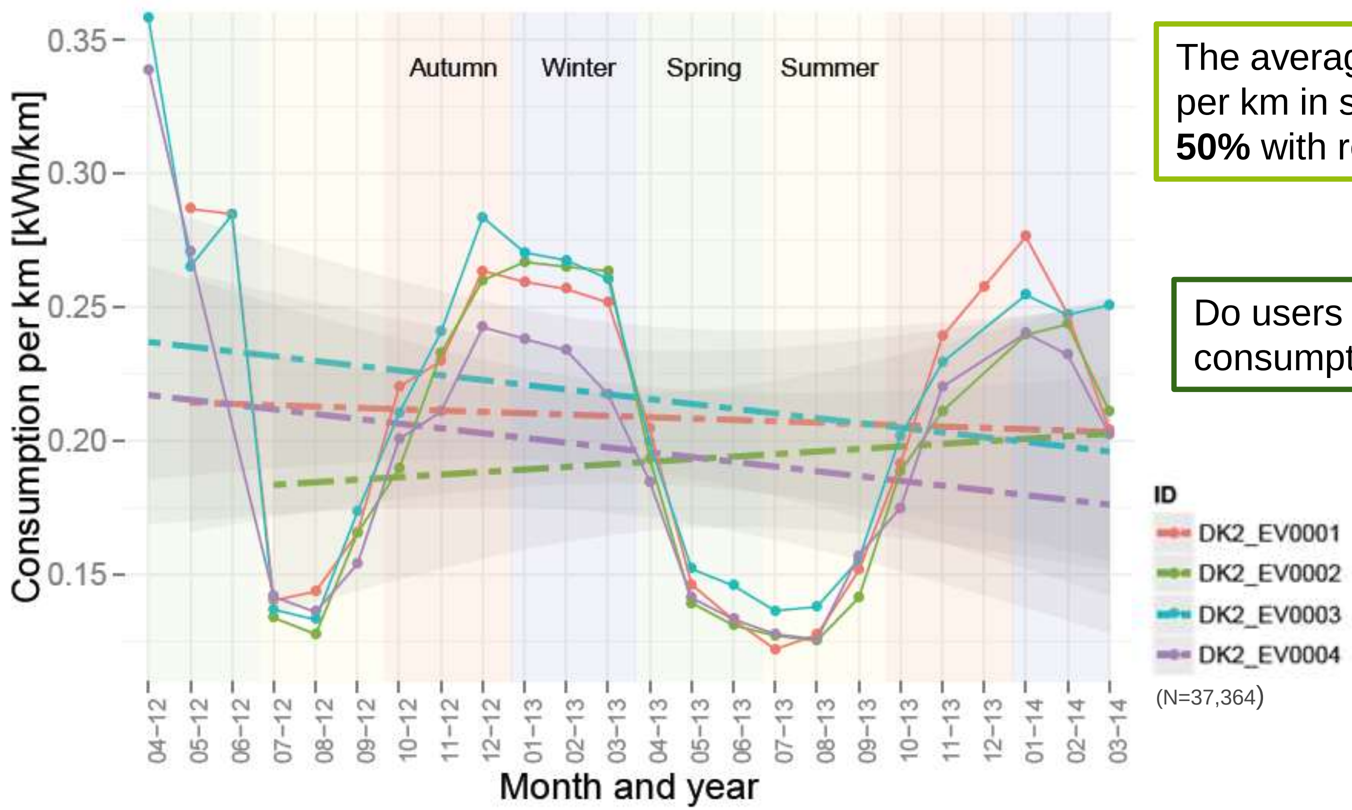
Longest parking times are given from midday until the end of the day.

Higher infrastructure availability at the end of the period

*Only slow charge processes

Seasonality on energy consumption

- Different energy consumption pattern detected depending on season
- Geographical location / user behaviour influences EV range



(N=37,364)

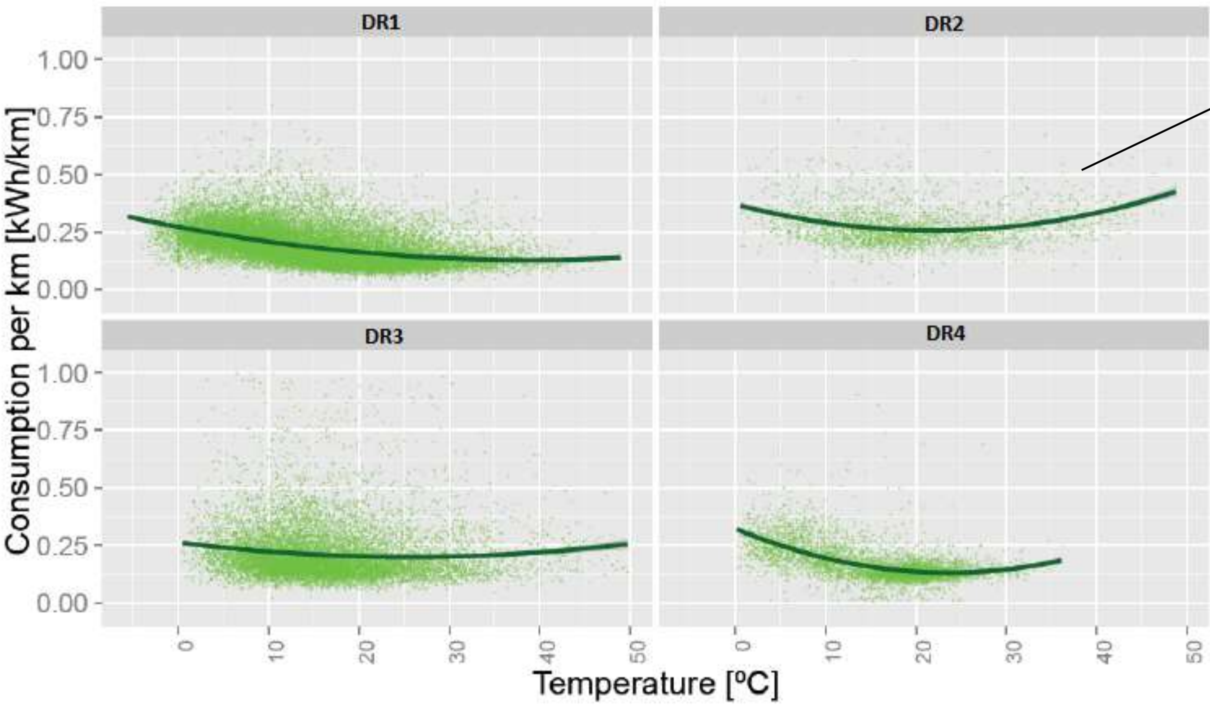
The average energy **consumption** per km in summer **decreases up to 50%** with respect to colder months

Do users learn to reduce their trip consumption?

Temperature effect on trip consumption

How does temperature influence trip consumption?

- Trip consumption increases with high and low temperatures



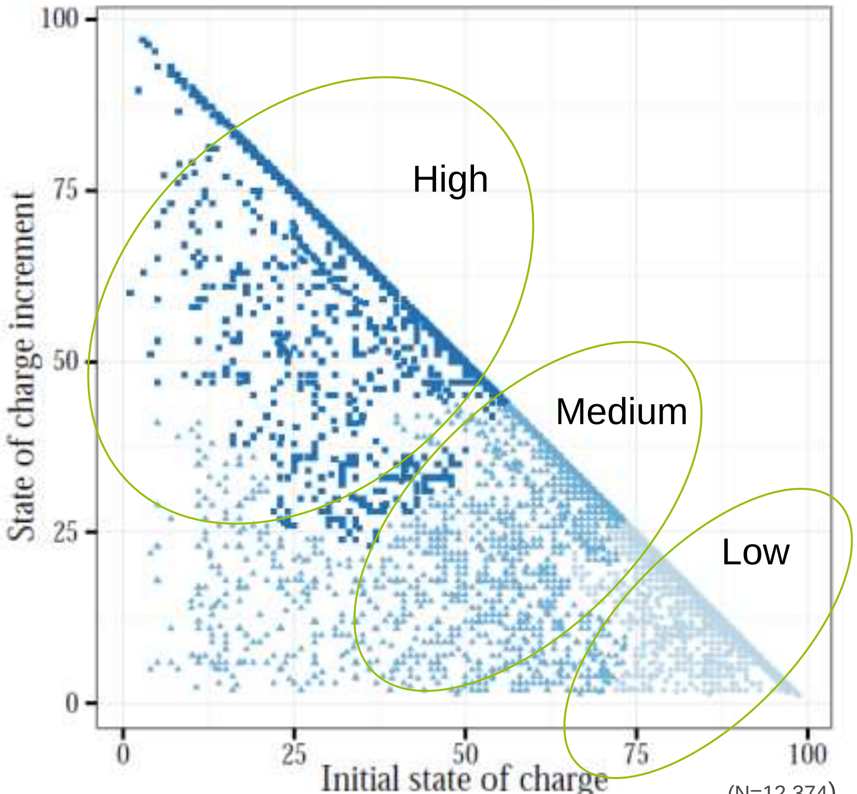
A second order polynomial fits the regression

Optimal consumption is reached with mild temperatures approaching **20 ºC**

Charging patterns - Classification

- The aim is to identify patterns taking into account car life trajectories
- A clustering analysis suggests the classification of trip and charge events into three groups

	N	Initial SoC	SoC increment
Low	4267	83%	15%
Medium	4795	55%	26%
High	3309	35%	51%

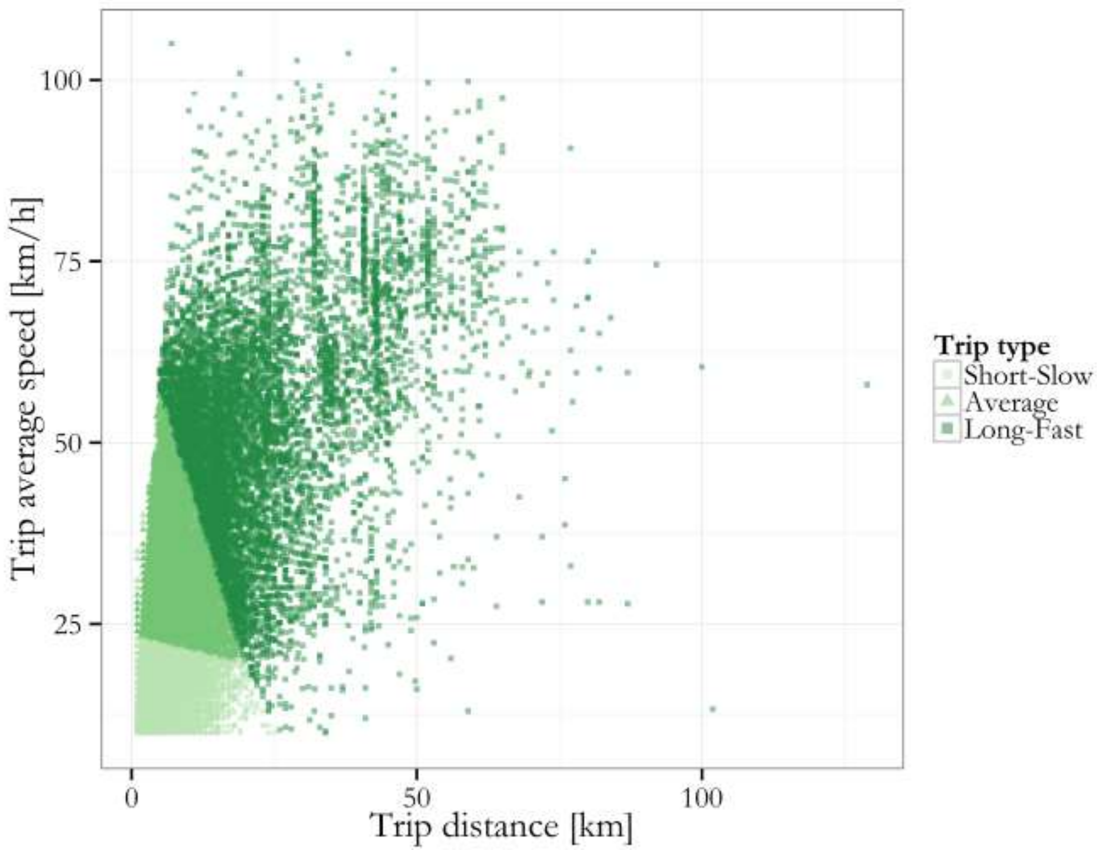


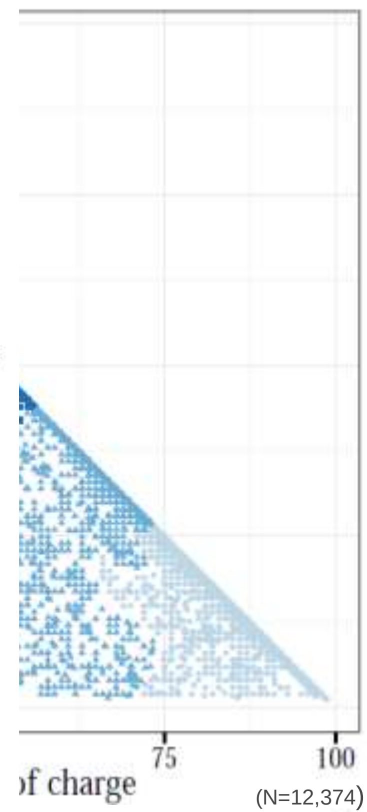
(N=12,374)

Charging patterns - Classification

- The aim is to identify patterns taking into account car life trajectories
- A clustering analysis suggests the classification of trip and charge events into three groups

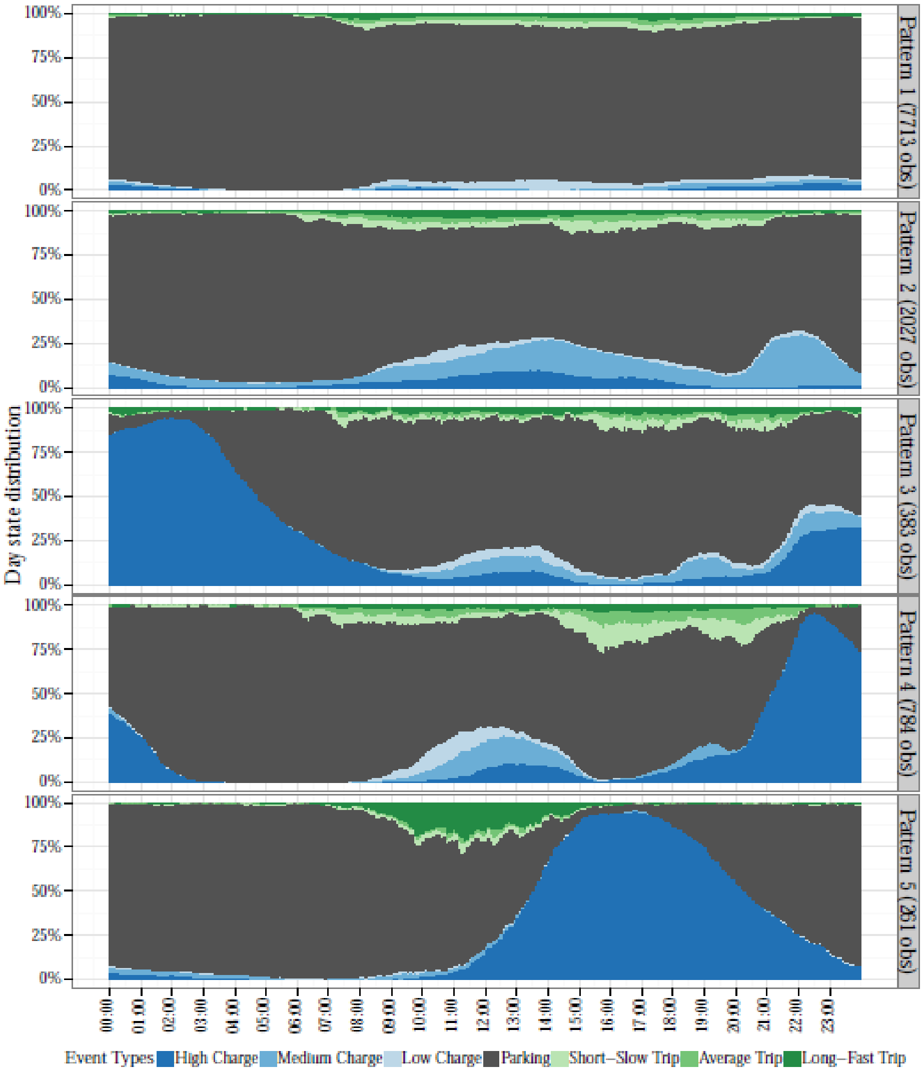
Low				
Medium				
High				





(N=12,374)

EV user profiles



Daily state distribution of the sequences for a five pattern classification

EV user behaviour can be classified into 5 groups

Each pattern has its own characteristics: for instance, pattern 5 is characterized by long trips in the morning followed by high charge events

Conclusions and applications

The knowledge extracted can be applied:

- To **simulate the user car behavior** required to optimize grid integration.
- To provide accurate **information about the charge cycles** in order to estimate the EV battery life span
- To identify **client segmentation** for car manufacturers, utilitites and e-mobility service providers
- To **help policy makers** to regulate and promote the use of EV with objective data.
- To **better understand the deployment of EV**: user's behaviour, charging/driving patterns, differentiation by type of use (fleet, private,etc)

Thank you

Sara Gonzalez–Villafranca IREC
sgonzalez@irec.cat