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Multimodal choice model for e-mobility scenarios

Marina Ferrara[a], Carlo Liberto[b,a], Marialisa Nigro[a]*, Martina Trojani[a], Gaetano Valenti[b]

[a]*Department of Engineering, Roma Tre University, Via Vito Volterra 62, Rome 00146, Italy*

[b]*Laboratory of Systems & Technologies for Sustainable Mobility & Electric Energy Storage, ENEA, Via Anguillarese, 301 S.P. 116, Rome 00123, Italy*

Abstract

The paper focuses on the definition, calibration and testing of a simulation model that is able to represent multimodal choice behaviours for electric vehicles. Taking into account the interchange between public transport and electric private mobility, the model estimates the parking demand at the Park & Ride sites equipped with charging stations. The model is based on a data-driven approach, in which mainly Floating Car Data and open data of public transport have derived the explanatory variables. Specifically, a machine learning method (Random Forest) has been used to calibrate and test the model in the real case of the metropolitan area of Rome (Italy). We first perform a stability analysis, letting the parameters of the model vary. We then carry out a sensitivity analysis on the variables that can affect the user propensity to adopt the Park & Ride. Finally, we profile and test an incentive policy to boost the choice of Park & Ride. Results suggest that the model succeeds in simulating Park & Ride by electric vehicles and, therefore, it can be extremely valuable for planning financial support to the multimodal travel choice and forecasting vehicle-to-grid scenarios.

Keywords: Multimodal transport; Parking model; Machine Learning; Random Forest; electric vehicles.

* Corresponding author Tel.: +39-06-57333632 ; fax: +39-06-57333441
E-mail address: marialisa.nigro@uniroma3.it

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1. Introduction

Recent studies (Katona, M., Radnai, 2017; Liberto et al., 2017; Woo et al., 2017) have shown that e-mobility is one of the most promising solutions for reducing pollutant and greenhouse emissions, especially in large urban areas. Electrification of both private and public transport may also produce several improvements from an energy saving viewpoint. Nevertheless, the problem of traffic congestion is not going to be solved by the introduction of electric vehicles, because the number of circulating vehicles remains the same. The problem, instead, can be addressed by introducing appropriate restrictions on traffic entering the city center and/or by supporting multi-modal transportation choices. The adoption of a multimodal system that envisages the interchange between private electric mobility and public transport would require vehicles to stop in suburban areas, thus reducing the congestion of the central areas. This would also promote an efficient charging management through a vehicle-to-grid approach in which the electric vehicles assume the function of "demand peak stabilizers".

In this work, we develop a model able to represent multimodal choice behaviors that we use to assess the share of the private electric vehicle demand that can be moved onto public transport. In doing so, we assume that the Park & Ride (P&R) sites are equipped with charging stations that facilitate the transition from private to public mode. We also introduce a function to simulate an incentive policy that provides economic benefits for P&R users.

Unlike usual practice in transport engineering, we adopt a data driven approach to calibrate the P&R demand. We use real and open data obtained from different sources, i.e. geo-referenced traffic data from probe vehicles (Floating Car Data - FCD) and open data related to the planned service and the network structure of the public transport. The FCD adopted in the study include about 150’000 cars tracked during the whole month of May 2013 in the metropolitan area of Rome. The use of FCD to extract mobility patterns and travel behaviors in urban areas is widespread in the scientific literature (Liberto et al., 2010; Mastroianni et al., 2016; Fusco et al., 2016; Liberto et al., 2017; Nigro et al., 2017). The characterization of the P&R sites, instead, is based on the open data delivered by Rome public transport agencies, while information on the level of the public transport service (such as travel times and number of vehicles adopted for every origin-destination trip) is computed with CSA routing algorithms, as reported in Biazzo et al. (2017).

The outline of the remainder is as follows. In Section 2 we present the proposed methodology to build the P&R simulation model, providing details on its explanatory variables and the Random Forest algorithm that has been used to calibrate them. Section 3 summarizes the results for the Rome case study, including a sensitivity analysis. Finally, Section 4 proposes an economic benefits policy to increase P&R demand by electric vehicles and discuss avenues for future works.

2. Methodology

This section describes the methodology adopted for calibrating and validating the P&R model. The model is configured as a model of aggregated nature: the output is the P&R demand share generated by each traffic zone of the study area for each time interval during the average working day. However, differently from the common approach in literature, which founds the mode choice on random utility models, in this study we adopt a data driven approach. Thus, the demand model is calibrated based on real and open data from different sources, i.e. geo-referenced traffic data from probe vehicles (FCD), open data about the planned service and the network structure of the public transport, several statistical information. The general relation to be calibrated is the following:

$$(\mathrm{G_O^{Park}} /\ \mathrm{G_O})|\mathrm{Dt} \ = \ f(\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_n) \tag{1}$$

where $\mathrm{G_O^{Park}} /\ \mathrm{G_O}$ is the share of generated trips from the traffic zone O that would make P&R in the time interval Dt. For the calibration phase, this value can be obtained from probe vehicles, once computed the number of FCD data generated by zone O and reaching the P&R sites ($G_O^{FCD|Park}$), divided for the total number of FCD generated by zone O (G_O^{FCD}). The explanatory variables x_1, x_2, ... , x_n are mainly related to 1) the accessibility of the Park & Ride sites, 2) impedances due to the travel times on the public transport, 3) location and occupancy of the P&R sites; 4) characteristics related to the activity system in the starting point of the trip.

A machine learning technique, i.e. Random Forest (RF) method, is adopted for the calibration of the model, with reference to an application case of high dimensions and high complexity (the city of Rome, Italy).

In the following, details of RF and of the explanatory variables are reported.

2.1. Random Forest (RF)

The method used for the calibration and validation of the model belongs to the Machine Learning (ML) techniques.

Since the functional form of the model is unknown, nor it is known which of the explanatory variables can mostly affect the increase/decrease of the P&R share, we decided to adopt a ML technique for the identification of the function *f* in (1). ML are non-parametric techniques (Hastie et al., 2008), i.e. not constrained by a functional form and free from any kind of a priori assumption of statistical distribution. The idea behind ML is to replicate the learning process of the analysed phenomenon, making decisions and predictions based on the available data.

The specific ML adopted is called Random Forest (RF). Breiman (2001) proposed RF as a new classification and regression technique in supervised learning. RF creates an ensemble of decision tree and randomly selects a subset of features to grow each tree. This method provides the class mode (in the case of classification) or the average prediction (in the case of regression) of individual trees. The final model (Figure 1) is obtained by combining several parallel decision trees and averaging the probability obtained by each tree. Each tree is trained on a subset of the data and it is validated on the remaining ones (so-called training and test phases).

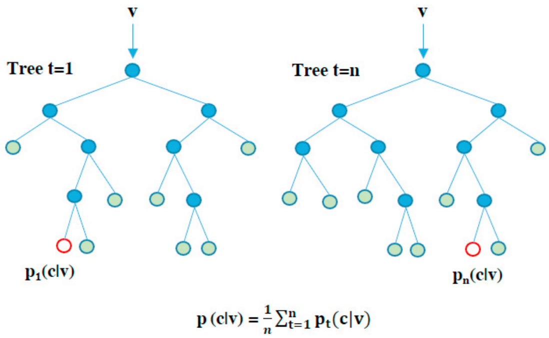

Fig. 1. Random Forest and Decision Tree.

In transport engineering, advanced ML techniques such as decision trees or RF have been recently exploited due to the increase in the availability of traffic data and the consequent diffusion of data-driven approaches.

Usually, in transport literature, similar techniques are used for travel time prediction. Zhang and Haghani (2015) tested a Gradient Boosting Regression Tree (GBM) for the forecast of travel times in a freeway. Kažic et al. (2015) applied RF to predict the vehicle flow by using car traffic counts from loop detectors. Zarei et al. (2013) adopted RF for a short-term traffic prediction, using traffic data from the peak and off-peak hours of the day and training different models for each period.

If we consider the use of RF for demand forecasting, there are few and very recent contributions in literature. Ghasri et al. (2017) used decision tree and RF for reproducing individual mobility patterns without reflecting individual behaviours. Ashqar et al. (2017) used RF to predict the number of bikes available at bike sharing stations. Liu et al. (2017) compared RF with two regression methods (autoregressive integrated moving average, ARIMA, and support vector regression, SVR) to estimate the demand for four different on-demand shared transport services.

2.2. Explanatory variables

The variables considered as an input for the training phase of RF can be classified as:

- Variables depending on the starting point of the trip (origin/starting traffic zone O) and the starting time interval (Dt) of the trip, specifically:
  - Impedance on private transport x_1 (2), i.e. the average access time from the traffic zone O to the P&R sites belonging to the catchment area of O, weighted for the O-P&R flows;
  - Impedances on public transport: x_2, x_2_bis, x3, x3_bis:
    x_2 (3) is an average travel time from the P&R sites belonging to the catchment area of O to all the destinations, weighted for the O-P&R flows; x_2_bis (4) is similar to x_2, but it considers the number of transfers by public transport instead of the travel time.
    In x_3 (5) the travel times on public transport are weighted for the origin-destination (OD) flow, while x_3_bis (6) is similar to x_3, but it considers the number of transfers by public transport instead of the travel time;
  - Travel time differences between P&R and car-only mode x_4 (7); x_4 represents the travel time advantage the user may have following the adoption of the P&R mode. The advantage is positive if the total travel time, sum of the parking access plus the travel time by public transport, is less than the time required to go from O to D by car;
  - The average occupancy of the P&R sites belonging to the catchment area of the origin/starting traffic zone O, x_5 (8).
- Variables depending only on the characteristics of the starting point of the trip (origin/starting traffic zone O) and not by the time interval, specifically:
  - The variable x_6 that represents the geographical extent of the origin/starting traffic zone O [km^2];
  - The variable x_7 that represents the population density of O (between 18 and 70 years old as possible users of the P&R service);
  - The variable x_8, i.e. a binary variable equal to 1 if O is within the Main Ring Road of Rome (where the metro lines are located), 0 otherwise;
  - The variable x_9 that represents the number of urban railway stations and metro stations in the starting zone O.
- Variables depending only on the time interval, specifically:
  - The dummy variable x_{10}, that is equal to 1 if the starting time interval of the trip is inside the morning peak (between 6:00am and 11:00am for home-work trips by public transport), 0 otherwise.

$$x_1 = (\sum_{P\in O} t_{OP} f_{OP})/(\sum_{P\in O} f_{OP}) = (\sum_{P\in O} t_{OP} f_{OP})/ G_O^{Park} \tag{2}$$

$$x_2 = (\sum_{P\in O} t_{P\to *}{}^{TP} f_{OP})/(\sum_{P\in O} f_{OP}) = (\sum_{P\in O} t_{P\to *}{}^{TP} f_{OP})/ G_O^{Park} \tag{3}$$

$$x_2\_bis = (\sum_{P\in O} m_{P\to *}{}^{TP} f_{OP})/(\sum_{P\in O} f_{OP}) = (\sum_{P\in O} t_{P\to *}{}^{TP} f_{OP})/ G_O^{Park} \tag{4}$$

$$x_3 = (\sum_D f_{OD}((\sum_{P\in O} t_{PD})/n_{P\in O}))/ G_O \tag{5}$$

$$x_3\_bis= (\sum_D f_{OD}((\sum_{P\in O} m_{PD})/n_{P\in O}))/ G_O \tag{6}$$

$$x_4 = \sum_D (t_{OD} - (\sum_{P\in O}(t_{OP} + t_{PD})/n_{P\in O})) \tag{7}$$

$$x_5 = (\sum_{P\in O} r_P)/n_{P\in O} \tag{8}$$

where:

t_{OP} = travel time by car from the origin/starting traffic zone O to the P&R site P;
f_{OP} = vehicle flow from the origin/starting traffic zone O to the P&R site P;
G_O^{Park} = generated trips from the origin/starting traffic zone O making P&R;
$t_{P\to *}{}^{TP}$ = average travel time on public transport to reach all the destinations of the city from the P&R site P;
$m_{P\to *}{}^{TP}$ = average number of transfers by public transport to reach all the destinations of the city from the P&R site P;
m_{PD} = number of transfers by public transport from the P&R site P to the destination D;
f_{OD} = vehicle flow from the origin/starting traffic zone O to the final destination D;
t_{PD} = travel time by public transport from the P&R site P to the final destination D;
$n_{P\in O}$ = number of P&R sites belonging to the catchment area of the origin/starting traffic zone O;

G_O = generated trips from the origin/starting traffic zone O
t_{OD} = travel time by private transport from the origin/starting traffic zone O to the final destination D;
r_P = occupancy of the P&R site P.

In order to compute both the dependent and independent variables required to calibrate (1), several data have been adopted.

Characteristics and location of the P&R sites in the metropolitan area of Rome are derived by open data provided by the Mobility Agency of Rome and by the main Rome's public transport operator (ATAC). Actually, P&R sites allow leaving the car free in case of subscription to the public transport service. The collected characteristics of the P&R sites (40 Park & Ride sites with 20'000 parking lots) are dimension, capacity and public transport lines interchange. The definition of the area of each P&R site is essential for the correct computation of the number of vehicles entering or leaving the P&R site.

An extensive collection of geo-referenced data (FCD), carried out by a sample of probe vehicles equipped with an on-board unit (OBU), have been adopted to reconstruct the private vehicles demand and the P&R demand. Specifically, we use a large dataset of FCD by OctoTelematics (Nigro et al., 2017, Liberto et al., 2017) that includes about 150'000 vehicles tracked during the whole month of May 2013 in the metropolitan area of Rome. We organized the information derived by FCD as follows:

- Origin-Destination matrix, containing the number of trips and travel times between each origin-destination pair for each departure time interval;
- Origin-P&R site matrix, containing the number of trips and travel times between each origin- P&R site pair for each departure time interval;
- P&R site matrix, containing information about the occupancy level in every P&R site for each time interval.

The occupancy of the P&R sites in each time interval is a basic information for the P&R model, since if the occupancy is equal to the capacity, it compromises the possibility to receive additional demand. In most of the P&R sites in Rome we found that the occupancy reaches the maximum level between 08:00 and 09:00, and then remains almost constant until 14:00; from this time onwards there is a progressive reduction of the occupancy of the P&R site (e.g. Laurentina P&R site, Figure 2, left).

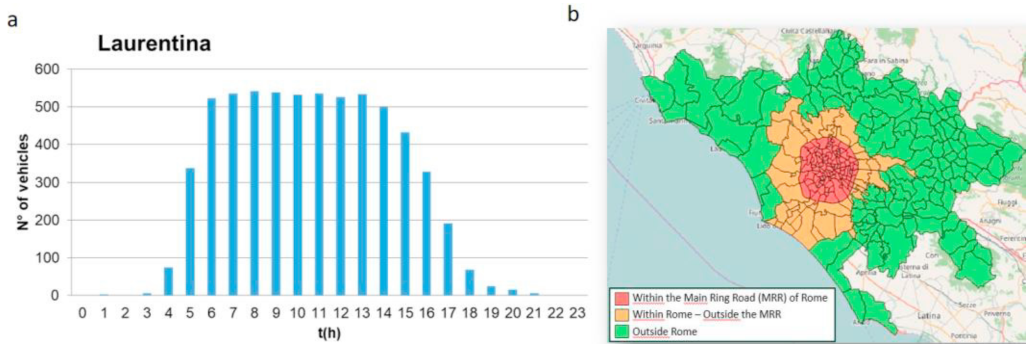

Fig. 2. (a) Example of occupancy level by FCD; (b) zoning system.

The data were subject to a data filtering process to improve their significance for calibration purposes. In the O-D matrix, the trips with a travel time exceeding 4 hours have been deleted. In the O-P&R matrix, the trips with a travel time exceeding 2 hours have been deleted. Moreover, an analysis has been performed on the trips by distance classes of 5 km. For each class, the minimum time and the maximum time used to travel the minimum distance and the maximum distance within the single class have been calculated, by using a maximum speed of 100 km/h and a minimum speed of 10 km/h. In this way, the trips with an average travel time less than the minimum time or with an average travel time greater than the maximum time have been deleted.

The spatial resolution adopted in the study is based on 277 zones (Figure 2, right), 155 urban zones to describe the mobility demand inside the municipality of Rome, while122 zones for the other municipalities within the province of Rome. Adopting this resolution, the linear regression between the trips generated by every origin adopting FCD data and the population statistics provided by census data showed a R^2 correlation factor equal to 0.65 for the urban zones inside the municipality of Rome and equal to 0.82 outside.

The temporal resolution required an aggregation of one hour for each time interval. The trips occurred during the night hours (00:00 h - 04:00 h) are not taken into account, due to the low representativeness of the P&R demand in these hours.

We noted a remarkable variability between the values of average access times to the different P&R sites, with a maximum travel time equal to 1 hour and a minimum travel time of 10 minutes. Considering all the P&R sites, an average access time of 24 minutes and a standard deviation of 12 minutes have been calculated. Instead, the distribution of the distances travelled from the origin to the P&R sites showed that the average distance travelled is equal to 11 km with a standard deviation of 6 km. All these values are compatible with the case of the city of Rome.

Further information used for the calibration of the model concern the level of service provided by the public transport and expressed by its travel times and number of transfers for every origin-destination or P&R site-destination trip, for every time interval. These data have been obtained adopting CSA routing algorithm with the introduction of specific variations that permit to take into account also pedestrian path to change stop or vehicle (Biazzo et al., 2017).

3. Results

3.1. Calibration and validation of the RF

Before starting the calibration process, the following filtering criteria have been adopted on the explanatory and on the independent variables to be adopted into the model:

- Origin of the trips where G_O^{Park} and G_O, as derived by FCD, are equal to zero have been deleted, since it implies that no monitored flow started the trip from that origin in that time interval;
- Any outlier has been removed. Specific outliers have been found on the variables x_1, x_4, x_6, x_7 as they showed unexpected corresponding values of the P&R share;
- if any correlation (Pearson coefficient higher than |0.7|) is founded between the independent variables (x_1, x_2, ... , x_n), a choice has to be done in terms of the variable to be adopted. This was the case of x_2 and x_2_bis, as well as x_3 and x_3_bis, where the high correlation suggested the adoption of only x_2 and x_3;
- a minimum threshold of 0.5% has been introduced on the P&R share computed by FCD. Lower values may derive by a poor reliability of the FCD detection rate rather than a low propensity to the P&R mode.

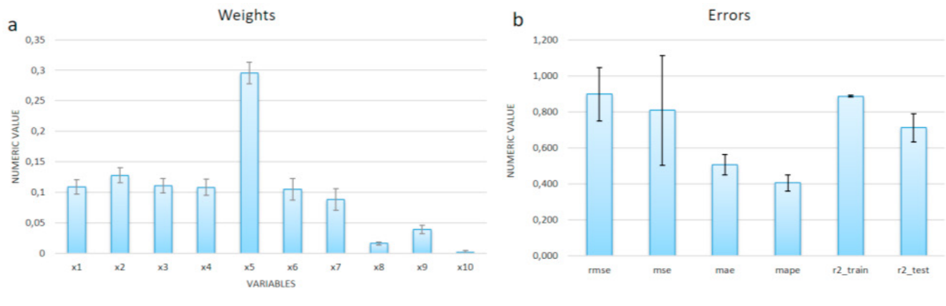

Fig. 3. (a) Average and standard deviation of the weights; (b) Average and standard deviation of the errors for both the calibration and the validation phase.

The aim of these criteria was to provide a database as clean as possible to the forecasting method.

The final database counts for 832 elements and 10 independent variables. It has been divided according to a cross-validation method into two subsets: 70% used to train the model (training data set) and the remaining 30% (validation data set) to evaluate its predictive capability; 1'000 extractions of the training and test datasets have been conducted in order to derive the average results. The calibration of the model by RF generated the weights (feature's importance) relative to the importance of each independent variable (Figure 3, left): this allows establishing which variable has the higher predictive power in the model. The weights are expressed as a percentage, thus the sum of the weights is equal to 1. The average occupancy of the P&R sites (x_5), followed by the impedances on private and public transport reported the higher weights. Instead, the lower effects are reported by the dummy variables x_8 about the location of the zone and x_{10} about the starting time of the trip.

In order to evaluate the goodness of fit of the model, several statistics have been computed on the test datasets. Figure 3 (right) reports the average values of these statistics together with their standard deviation. It is possible to note an average percentage error between the model and the data of about 40% with a correlation (R^2) in the test phase of about 0.75.

3.2. Sensitivity analysis

The model has been subject to several tests for its evaluation. Firstly, a sensitivity analysis is conducted on the parameters of the RF, specifically the number of trees that make up the RF (higher number of trees implies higher stability of the model, but higher computational times) and the maximum depth reached by each tree (higher maximum depth, higher the risk of overfitting). Several RFs were built, in which the number of trees have been modified between 50 and 2'000, evaluating the average error between model and data, as well as the standard deviation. The same analysis has been performed by varying the maximum depth of random forests between 10 and 500 levels. The analysis showed that the variability of the result decreases as the number of trees increases (Figure 4, left) and a clear difference between the RF with 10 depth levels and the others (Figure 4, right). The optimal parameter values for the RF have been then set as 1'000 number of trees and 20 as the maximum depth.

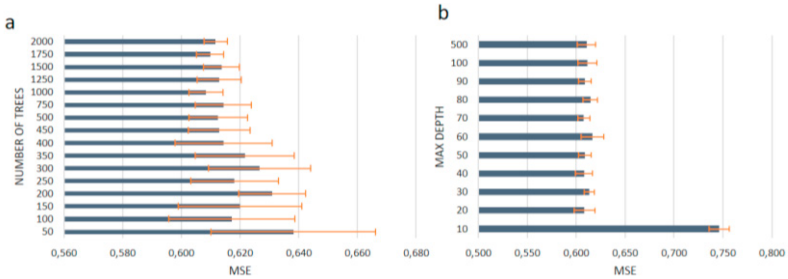

Fig. 4. (a) MSE for different number of trees; (b) MSE for different maximum depth.

Then, fixed the optimal parameter for RF, a sensitivity analysis is performed modifying the values of two of the most important independent variables and analyzing the results of the model in terms of estimated P&R share.

The variables adopted for this sensitivity analysis were x_1 (impedance on private transport) and x_5 (average occupancy of the P&R sites). Thus, several changes in the P&R sites access time and in the parking occupancy level have been applied on three specific zones of Rome. Results underline a higher elasticity of the model for an increase of x_1 up to 50% (i.e. a reduction of P&R share of one percentage point is modelled if the average access time to the P&R sites changes from about 10 minutes to about 20 minutes). Instead, the P&R share is less sensitive to variation of x_1 higher than 50%. About the parking occupancy, results report as expected a nonlinear trend between x_5 and the P&R share indicating that a given P&R share can correspond to both a low occupancy state (high capacity available, filling phase of the P&R site) and a high occupancy state (no more capacity, no more demand).

4. Implication of electric vehicles in the RF model and further research

The P&R model has been calibrated and validated on the actual mobility scenario in Rome, where penetration rate of electric vehicles is almost zero (0.02% of private vehicles circulating in the whole province of Rome, OpenData MIT). However, the most interesting variables usually explaining the P&R behaviour has been introduced adopting an aggregate data driven approach. Actually, P&R sites in Rome are freely available for subscribers to the public transport service and this is the reason why no monetary cost is introduced in the model.

Considering the increasing number of electric vehicles, several policies can be considered to push the electric cars to the P&R choice. These policies can be quantified through an economic benefit due to a discount on the public transport subscription and/or to a discount in the electricity bill. The discount in the electricity bill is even more realistic in case the electric vehicle, parking in the P&R site, give back part of its energy to the electricity grid (Vehicle To Grid). The energy fed into the grid is paid to the user directly in the electricity bill together with an economic incentive (i.e. the discount on the electricity bill) for making available its energy.

In the P&R model, the policies can be incorporated with an additional function linking the increase in the P&R share with the economic incentive I:

$$(\mathrm{G_O^{Park}} / \mathrm{G_O})|\mathrm{Dt} = f(\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_n) + \mathrm{I}(\text{Economic benefit €}) \tag{9}$$

where Economic benefit € = g (discount on public transport subscription; discount on the electricity bill)

A first estimate of the possible discount on the electricity bill has been computed in the hypothesis of night-time charging at home of the electric vehicle, an average access and egress distance to/from the P&R site of 10 km and a safety threshold to not leave the vehicle completely without energy. Not being able to refer to similar cases in the literature, for the unit price of energy, we referred to the value adopted for domestic users actually producing energy through photovoltaic panels and feeding it into the energy network (Article 6, LD n. 387/03). The discount estimate resulted in approximately 500€ for one year. Further research will be required to evaluate the willingness of accepting the policy by road users, as well as how the policy can influence the mode choice and specifically, the P&R share.

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