# Capacity Allocation For Parking Choice Models Considering User Heterogeneity

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# Contents

# 1 Abstract

Developing and implementing innovative parking policies is of high importance for authorities, in order to keep the traffic flow and accessibility of attractive destinations at a high level (Benenson and Martens, 2009). These parking issues go hand in hand with the recent upcoming of electric vehicle users. Creating an extensive charging network and supportive electric vehicle environment helps addressing the barriers to use electric cars and is thus a crucial part of the energy transition. By examining Santoña, we seek to glean lessons on the steps towards efficient and innovative policy actions. We found that people differ in taste regarding the time to find a parking spot and the fee that has to be paid. The impact of the fee depends on the income level of the individual and the whether or not someone is a resident of the town. Furthermore, the age of the vehicle is key in the decision process. In this research, we conclude what where a possible underground parking facility is most appropriate. Also, we see that the on-street parking fee should not be higher than 0.7 euros. Regarding power outlets for the electric vehicles, we conclude that up to when one percent of the people use an electric car, the amount of people in queues are agreeable. However, when the amount of electric car users increases to more than that, problems arise. The results of this research can be generalized for policy-making related to parking management.

# 2 Introduction

Cities are an important focal point for our daily travel patterns and traveling by car is preferred by many as it comes with privacy, flexibility and a relatively short travel time. However, there exists no car trip without parking and, consequently, cities struggle with a growing population and a growing number of visitors, resulting in a lack of parking facilities. Developing and implementing innovative parking policies is of high importance for authorities, in order to keep the traffic flow and accessibility of attractive destinations at a high level (Benenson and Martens, 2009). These parking issues go hand in hand with the recent upcoming of electric vehicle users. In 2015, the electric vehicle sales in top electric car markets were already one in every ten new vehicles (Hall and Lutsey, 2017). Therefore, authorities should take into consideration their electric vehicle charging network as expanding their public charging facilities increases the convenience of electric traveling and the user confidence of the driver. Bakker and Trip (2013) showed that the development of public charging infrastructure is correlated with the number of electric vehicles bought. Creating an extensive charging network and supportive electric vehicle environment helps addressing the barriers to use electric cars and is thus a crucial part of the energy transition.

By examining Santoña, we seek to glean lessons on the steps towards efficient and innovative policy actions. It is aspired by many to ease congestions, improve the quality of life of both visitors and local residents, and improve the public charging infrastructure. However, if the congestions and parking problems are not yet solved in smaller towns, how should it be solved in large metropolitan areas? Creating an efficient parking situation in Santoña can act as model and base case for other larger, cities. This paper first identifies parking taste variations and then incorporates these individual preferences into a parking simulation model. Analyzing various types of actions policymakers can choose reveals parking policies which could be more widely embraced to further improve the parking structures of cities around the world. Furthermore, we analyze the effects of improving the public charging infrastructure, in order to keep up with the most recent trend of a growing number of electric vehicles purchased in the rapidly changing vehicle market. Incorporation these results, we are one step closer in creating a favorable policy environment to accelerate electric vehicle adoption.

This research is structured as follows. We first characterize the behavior of potential car parking users based on a stated choice data set provided by Ibeas et al. (2014). This data resulted from a survey which presented eight scenarios containing three alternatives to 197 people, visitors and residents of Santoña. The three alternatives are free on-street parking, paid on-street parking and paid underground parking and differ in the fee that has to be paid, the time until the parking spot is found and the time to walk from the parking space to the destination. Based on the stated choices and the characteristics of the individual decision-maker, a Mixed Multinomial Logit (MMNL) model is used to investigate the parking choice behavior (Ibeas et al., 2014). The estimated coefficients of such a model reveal which factors are important in the decision process and if there are significant taste variations between individuals in various attributes of the model. Furthermore, the subjective values of time are derived from the estimated model. These results combined can be used to set up an efficient parking policy for this town, regarding how the amount of free on-street parking spots, paid on-street parking spaces and the amount of underground parking facilities should be distributed.

Secondly, we create a simulation model focusing on parking in order to lay the foundation for efficient decision-making. This parking model helps to simulate possible scenarios and explore different design and implementation choices, thus helping in decision-making. We incorporate the established means and possible taste variations of the significant elements of the MMNL model into a parking choice simulation. We use an agent-based model to simulate the parking choice process and its effects and we focus on the process of drivers gathering information and subsequently making a parking decision. Within this framework, we distinguish between public, preferred and parking for electric vehicles with a power outlet for charging. Preferred parking is split into parking spots for disabled, women, families and VIP. All on-street parking is divided into free on-street parking and paid on-street parking. The base case is the parking situation with only free on-street parking and we compare this with paid on-street parking and underground parking available as well. We only allow for one underground parking facility as building one is a large investment for a small town like Santoña. Comparing different areas in which the underground parking facility can be build, allows us to determine which area in Santoña is most suitable for an underground parking facility. Furthermore, Santoña is a town of which the economy involves around tourism, especially during summer times. Encouraging the use of electric vehicles is key in the current energy transition process. However, because running out of battery is one of the main problems electric vehicle users face, people are reluctant to visit with an electric car when the availability of charging points within the town is uncertain. Therefore, it is important to determine how many power outlets should be installed in town. Accordingly, we estimate the effects of the recent growth in the use of electric vehicles and thus, the need of more charging points for electric cars, as this has influence on the way the types of parking spots should be distributed. With this information, we set up a favorable policy environment to accelerate electric vehicle adoption.

The remaining part of this paper is organized as follows. Section 3 reviews the relating literature and addresses the possible shortcomings of previously proposed methods. We discuss the data set used and the methodology in Section 4. First, we discuss the set up of the MMNL model used in Section 4.1 and then the implementation of these results into the parking choice simulation in Section 4.3. Accordingly, we evaluate the performances of different parking policies compared to the base case of only free on-street parking in Section 5. Section 6 concludes this paper and Section 7 proposes possible avenues for future research.

## 3 Literature Review

The Mixed Multinomial Logit (MMNL) model has various names and can be found under the name 'random coefficient logit', 'random parameter logit' and 'error components logit'. The last name emphasizes that the error part of the utility function consists of more than one component, which can provide substitution patterns instead of representing random parameters (Brownstone and Train, 1996). The name 'mixed multinomial logit' represents the fact that the probability for a choice is a mix of various logits with mixing distributions that are specified (McFadden and Train, 1997). Because of the generality of this term, we use 'mixed multinomial logit' in this paper. MMNL models have been applied in multiple situations in different forms but their common basis is the integration of the logit formula over the distribution of unobserved random variables (Revelt and Train, 2014). The first MMNL models were used with constant explanatory variables over individuals, with a relatively easy computation of the integral (Cardell and Dunbar, 1980). After that, applications of the MMNL model allowed explanatory variables to vary over individuals, with or without repeated choice. In many cases, the integration computation is done through simulation. Two examples of papers that did not use simulation for this purpose are Ben-Akiva et al. (1993) and Train et al. (1987), which only needed two dimensional integration and therefore were able to apply quadrature (Revelt and Train, 2014).

Previous research provided insights in different aspects of parking policies. Willson and Shoup (1990) state that the amount of solo drivers to work increases when the employer pays for parking. Furthermore, Huber (1962) found that up to 20 percent of the total traffic within the city center can be parking search related traffic. Ergün (1971) based his model on a set of logit models describing the acceptance rates of parking spots in different kinds of blocks, meaning a parking distance from the destination location of less than one, one, two, three and or four blocks or more. Ergün (1971) used only the parkings costs and the parking cost gradient as independent variables. His value of time for walking was estimated between 5 and 11.50 for people parking in the most close block and was estimated to be 4.50 for people parking in all blocks further away. Van der Groot (1982) not only grouped the parking options by location, but by parking type as well. In Axhausen and Polak (1991), the process of searching for a parking spot has been decomposed into different aspects and their valuation, as they noted that choices of different types of parking spots has not yet been investigated thoroughly. They took into account the time searching for a suitable spot, the walk to their destination and the parking cost itself, as is done in this research. Axhausen and Polak (1991) report that the search time for a parking spot should be considered separately from driving when estimating the model. All in all, their results show that the costs for different parking aspects should be identified separately and their relative impacts differ significantly between different purposed for the journey. The authors of (Hess and Polak, 2004) research parking choice behavior also based on a dataset of stated preferences and were the first to use a MMNL model to model parking type choice. The results of Hess and Polak (2004) were different from that of previous research as taking into account heterogeneity led to significantly different conclusions. Their research revealed the presence of taste variation between respondents, when it comes to valuing the aspects of parking related time. We consider heterogeneity between tastes of individuals within our dataset as well.

Before the travel demand simulation model of Warach and Axhausen (2012), many of the traffic simulation models did not include parking. Therefore, Warach and Axhausen (2012) propose a model to be implemented into existing travel demand simulation frameworks. The authors use an agent-based model, as they value the different preferences of people. This model incorporates parking capacity and pricing. Many research has been done with regards to the different aspects of parking. In this research, we use an agent-based simulation model as well, which is a relatively new simulation technique. There are three existing prominent traffic simulators, operating on a microscopic level, which are TRANSIMS, SUMO and VISSIM. However, few are focused on the parking aspect of traffic, although TRANSIMS is recently used for modeling parking (Guo and Sadek, 2013). There has been various research regarding parking behavior of drivers and improving parking policies in general (Geng and Cassandras, 2013). Furthermore, these parking simulations have been applied to study the effects of changes of the parameters within the model and to predict the parking availability and accomplish to get relevant output for parking management.

Many commuter parking models have been built (Benenson and Martens, 2009). Commuter parking models take into account that the commuters or business travelers can avoid all the parking problems at their destination by using another kind of transportation. All car users with a recreational or leisure purpose have more options as they can not only change their way of traveling but their destination as well. In contrast, the model of Benenson and Martens (2009) researches the behavior of people driving home and thus, cannot change either their way of transport and their destination. Thus, they built a model for residential parking in the evenings when there is only a small choice of parking places close to the driver's residence. This model takes into account the fact that every single driver had to find a place for overnight parking and thus, measured the impact of an increase in parking spaces in residential areas. Benenson and Martens (2009) analyzed how residents reacted on different parking situations and policies. As our research includes all kinds of car users, we incorporate part of the assumptions made by Benenson and Martens (2009) in our research.

# 4 Methodology

## 4.1 Mixed Multinomial Logit Model

We characterize the parking preferences of people of Santoña, a Spanish town of approximately 10.000 inhabitants, with data gathered by Ibeas et al. (2014) in 2007, in order to find the importance of the variables considered when making parking choices. Ibeas et al. (2014) conducted a parking choice stated preference experiment and the participants were either residents of the town or visitors. The individuals participating in the experiment were contacted on the streets of Santoña and were at that moment parking or starting a journey. The responses of the survey created a sample of 197 respondents providing 1576 observations.In the stated preference experiment, each individual was offered a series of choices. Each scenario proposed consisted of three kinds of parking types. These parking categories are free on-street parking (FSP), paid on-street parking (PSP) and paid parking in underground car parks (PUP). Per experiment, each category varied in access time to parking (AT), access time to destination (TD) and parking fee (FEE). AT and FEE have three levels of variation, whereas TD differs only between two values. At the time of the survey, parking was free everywhere and there was no underground facility. Thus, FSP is thus seen as the base case. The defined scenarios are described in Table 1.

Table 1: Stated preference scenarios on the AT, TD, and FEE variables

| | FSP | | | PSP | | | PUP | | |
|---|---|---|---|---|---|---|---|---|---|
| Scenario | AT | TD | FEE | AT | TD | FEE | AT | TD | FEE |
| 1 | 10 | 10 | 0 | 10 | 10 | 0.6 | 5 | 10 | 0.8 |
| 2 | 10 | 15 | 0 | 10 | 15 | 0.6 | 5 | 10 | 0.8 |
| 3 | 15 | 15 | 0 | 10 | 10 | 0.8 | 5 | 10 | 0.8 |
| 4 | 15 | 10 | 0 | 10 | 15 | 0.8 | 5 | 10 | 0.8 |
| 5 | 15 | 15 | 0 | 10 | 10 | 0.6 | 5 | 10 | 1.5 |
| 6 | 15 | 10 | 0 | 10 | 15 | 0.6 | 5 | 10 | 1.5 |
| 7 | 10 | 10 | 0 | 10 | 10 | 0.8 | 5 | 10 | 1.5 |
| 8 | 10 | 15 | 0 | 10 | 15 | 0.8 | 5 | 10 | 1.5 |

Table 2: Sample Composition

| Attribute | Percentage |
|---|---|
| Gender | |
| Male | 73.10 |
| Female | 26.90 |
| Age | |
| $< 24$ | 11.68 |
| 25-34 | 30.46 |
| 35-44 | 20.81 |
| 45-54 | 16.75 |
| 55-64 | 13.71 |
| $> 65$ | 6.60 |
| Place of residence | |
| Santoña | 53.30 |
| Outside Santoña | 46.70 |
| Income level | |
| $<$ 600 Euros | 20.22 |
| 600-1500 Euros | 55.19 |
| 1500-2500 Euros | 21.86 |
| $>$ 2500 Euros | 2.73 |
| Age Vehicle | |
| $\leq$ 3 years | 62.44 |
| $>$ years | 37.56 |

The individual was informed about the components of each parking category and was asked to choose the one he preferred. Each individual provided responses to eight choice experiments. A MMNL model is used on the stated preference data to forecast the impact of various parking policies. The variables gathered by the survey characterizing the individuals entering the survey are given in Table 2 (Ibeas et al., 2014). Furthermore, the data contains information on the age of the vehicle the individual is using, noted as whether the car is either less than three years. It is also stated what the origin and the destination of the trip of the individual answering the survey is, which can be either in or out town. Ibeas et al. (2014) indicate an income level less or equal to 900 euros a month as low income, less or equal to 1800 euros as medium income and higher than 1800 euros as high income. Ibeas et al. (2014) also provide the purposes of the individuals participating in the stated preference experiment (Table 3).

Table 3: The travel purposes in percentages

| Purposes | Residents | Visitors |
|---|---|---|
| Home | 24.76 | 9.78 |
| Work | 33.33 | 35.87 |
| Shopping | 9.52 | 17.39 |
| Leisure | 14.29 | 26.09 |
| Other Purposes | 18.10 | 10.87 |

To model the survey responses and to aim at a highly accurate real world representation, the MMNL model is used, which is able to approximate any random utility model to any degree of accuracy (Train, 2003). Unlike the logit model, it allows for random preference variation, unrestricted substitution patterns and over time correlating unobserved factors (Train, 2003). Furthermore, it resolves the limitation of the probit model as it is not restricted to only normal distributions. The MMNL model allows for both types of taste heterogeneity and explicitly accounts for the repeated choice nature of the survey conducted by Ibeas et al. (2014). Consequently, the main advantage of the MMNL model is the ability to discover random taste variations across otherwise identical individuals as well as deterministic taste variation across groups of agents, such as different journey purposes and cost elasticity as a function of income (Hess and Polak, 2004)).

In the survey, a person $n$ (N=197) faces for each scenario t (T=8) a choice between three alternatives (I=3). The MMNL model expresses the choice probability that person n chooses alternative i in the form (Train, 2003):

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta \tag{1}$$

where $L_{ni}$ is the logit probability evaluated at parameters $\beta$ is as follows, under the assumption that the utility function is linear in $\beta$ (Revelt and Train, 2014):

$$L_{ni}(\beta_n) = \frac{e^{\beta_n' x_{ni}}}{\sum_j e^{\beta_n' x_{ni}}} \tag{2}$$

where $f(\beta)$ is a density function. We derive the MMNL probability, Equation 1, based on random coefficients. Thus, the utility of person n from alternative j is as given by (Revelt and Train, 2014):

$$U_{nj} = \beta_n' x_{nj} + \epsilon_{nj}, \tag{3}$$

where $x_{nj}$ is a vector of observed variables relating to alternative j, $\beta_n$ is the unobserved coefficient vector for person n which represents the taste of person n, and $epsilon_{njt}$ is the unobserved random term vector. These coefficient are different for each person in the population with density $f(\beta)$. We specify the distributions of each coefficient to be normal, $\beta \sim$ N(b, W), and estimate b and W. We imply by assuming normal distributions that the signs of the coefficients can vary between the individuals.To account for individual tastes, we express the coefficient vector such that $\beta_n = b + \eta_n$, where $b$ is the mean of the population and $\eta_n$ is the deviation from this mean representing individual taste.

The aim is to estimate the population parameters describing $\theta^*$, the distributions of the individual parameters. It is not possible to calculate the maximum likelihood function, Equation 4, exactly, as we cannot calculate the integral part analytically. Therefore, we estimate the MMNL model with maximum simulated likelihood (MSL). MSL only differs from maximum likelihood in that the probabilities that are used are simulated instead of exact (Train, 2003). The log-likelihood function we maximize is the following:

$$LL(\theta) = \sum_n lnP_n(\theta) \tag{4}$$

where $\theta$ is a vector of parameters and $P_n(\theta)$ is the probability of the observed choice of observation n. We sum over N independent observations. We use 200 Halton draws per individual during the simulation (Ibeas et al., 2014). The maximum likelihood estimator is the value of $\theta$ that maximizes Equation 4. The matlab codes used for the maximum likelihood estimation are based on the codes of Train (2016) and also provide the potential correlation among the alternatives.

## 4.2 Willingness to Pay

In order to measure the trade-offs between travel time and cost, we estimate the subjective values of time to find an empty parking spot and the subjective values of time to access the final destination. We interpret these values as the willingness-to-pay for savings in travel time within the parking choice model (SVT), expressed in euros per hour. SVT are interesting measures for welfare changes. Under the assumption that the utility function derived in the MMNL model is linear and additive in the marginal utility parameter, the SVT is the ratio between the estimated parameters for travel time and for the travel cost, $\theta_t$ and $\theta_c$ respectively (Armstrong and Ortúzar, 2001):

$$VT = \frac{\theta_t}{\theta_c} \tag{5}$$

However, the $\theta_t$ and $\theta_c$ are both random variables of which the values depend on the sample given. Therefore, the SVT calculated in 7 is a random variable of which the distribution is unknown as well. Consequently, we replace these values of $\theta_t$ and $\theta_c$ by constructed confidence intervals. Results obtained with the t-test method provide accurate and good confidence intervals for the SVT (Armstrong and Ortúzar, 2001) and thus, we will use this method in our research and derive the mean values of the intervals with the estimated intervals. Accordingly, we derive the test statistic t, which is asymptotically normal distributed, by the following equation(Armstrong and Ortúzar, 2001):

$$VT = \frac{\theta_t - VT\theta_c}{\sqrt{Var(\theta_t - VT\theta_c)}} \tag{6}$$

The lower and upper bounds needed for the interval are computed as follows (Armstrong and Ortúzar, 2001)

$$V_{S,I} = (\frac{\theta_t}{\theta_c}\frac{t_c}{t_t})\frac{t_t t_c - \rho t^2}{t_c^2 - t^2} \pm (\frac{\theta_t}{\theta_c}\frac{t_c}{t_t})\frac{\sqrt{(\rho t^2 - t_c}t_t)^2 - (t_t^2 - t^2)(t_c^2 - t^2)}{t_c^2 - t^2} \tag{7}$$

where $t_c$ and $t_t$ are the derived test statistics for $\theta_c$ and $\theta_t$, respectively, and $\rho$ is the estimated correlation coefficient between $\theta_c$ and $\theta_t$. These intervals allows for consideration of the lower and upper limits of the benefits that can be obtained from saving travel time.

## 4.3 Parking Choice Model

By incorporating the results of the MMNL model together with the SVT into a parking choice simulation model, we aim to simulate the parking choices of individuals. Accordingly, an agent-based model is used, as this is suitable to research the effect of different parking policies. An agent-based simulation is a system where the individual components within this system, the agents, and the behavior of those agents are described as autonomous and unique entities (Railsback and Grimm, 2011). Macal and North (2010) adds to the following properties of an agent: self-contained, self-directed and with a state varying over time. In this simulation, the agents are also heterogeneous, as we want to incorporate the preference differences revealed by the MMNL model previously discussed. These agents are able to interact with other agents and with the local environment. Railsback and Grimm (2011) state that the approach based on an agent-based model allows for studying the behavior of individuals, the diversity of all kinds of behaviors and thus, the group behavior of all these individuals together. Agents are at the core of the agent-based simulation and thus, particular characteristics of these agents can be changed. Hence, with an agent-based simulation we can explore, based on changes from the agent's perspective, possible scenarios and different parking choices and facility designs, helping in policy-making. In this paper, agents represent individual drivers entering Santona. The agents within the model are rational and aim to arrive at their destination in a way that results in the highest utility possible. The agents within the simulation do not have a private parking place at their disposal. After arriving at the destination, the car is parked for a certain time at the parking spot. Thereafter, the agent leaves the parking spot and thus, the simulation.

The characteristics of drivers are as follows: resident/visitor, male/female, not disabled/disabled, VIP/non-VIP, alone/family, and electric/non-electric car. The distribution of these characteristics varies between certain experiments, in order to compare changes in population and in use of electric vehicles. An increase in electric vehicle drivers is especially an important aspect which effects will be measured. The town Santoña is divided into nine areas as shown in Figure 1 and thus, all the possible destinations of agents within such an area are gathered, in order to simplify the simulation process. When choosing this set of areas there is a trade-off between a large enough set such that the agent is able to consider parking spots with a larger distance to the destination, and a set that is not too large such that performance will not be too slow. The width and height of each area within the map is approximately 350 meter, based on the distance within most of the parking related walking distances lie (Benenson and Martens, 2009). Each agent entering the simulation process is assigned one of these nine destinations. As areas 1,2 and 3 are all areas in which only warehouses are build, we assume that only people with as purpose 'work' and 'other leisures' as purpose to be assigned that destination (Table 3). Given their purposes, the destinations are randomly assigned to the agents entering the system. Another assumption we made is that the rate of cars arriving in the system changes over time, as most rush hours and traffic jams are in the morning and late afternoon.Therefore, we use an arrival rate that is distributed following a non-homogeneous Poisson process and thus, is piecewise constant on a set of data-independent intervals (Henderson, 2018).

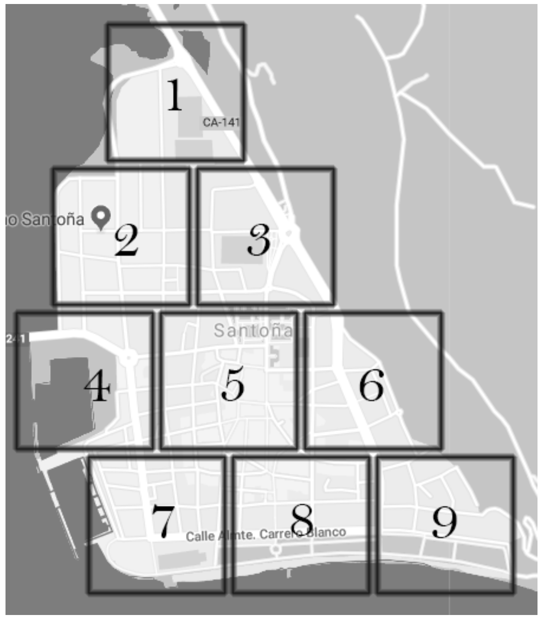


Figure 1: Division of the map of Santoña

The basic parameters of the simulation model are discussed now. The simulation encompasses at least a period of a week and starts at midnight. We run the model for a number of scenarios. We assume that Santoña does not have an underground parking facility yet Ibeas et al. (2014). We base the number of parking spots in Santoña on the map of the town. Combining our assumption that the average length of a car is four meters with the estimation that each area has on average 3 streets of full length (350 meters) on which on-street parking is available, we set the initial number of parking spots equal to 260 cars per area, resulting in 2340 on-street parking spots overall. In their research, Benenson and Martens (2009) state 20 percent of all feasible parking spots in the neighborhood they researched was unoccupied during the day, which is in our case would be 468 unoccupied on-street parking spots. Furthermore, they found that daytime visitors occupy another 20 percent of all parking spots. Because Santoña is a far more touristic town than the neighborhood Benenson and Martens (2009) investigated, we assume 30 percent during Winter and 40 percent during Summer, resulting in 702 and 936 parking spots needed for visitors, respectively. Using the approximately 50-50 distribution of residents and visitors of the survey of (Ibeas et al., 2014), we thus assume that the same amount of spots are needed for residents. Benenson and Martens (2009) assume that 75 of all daytime visitors leave uniformly between 5pm and 9pm. We combine this with the survey results of (Ibeas et al., 2014) that 20 percent of all visitors indicated home or 'other purposes' as purpose of the car journey. Consequently, we assume that 80 percent of all visitors' duration of stay is between half an hour and seven hours (and thus, we also assume that daytime visitors arrive not earlier than 10am). We assume that all residents with another purpose than home or 'other purposes' stay between half and hour and four hours. Furthermore, we assume that the remaining 20 percent of the visitors and all residents as well, the ones with as purpose home or 'other purposes' will stay between 7 and 12 hours with a uniform distribution (Table 4).

Table 4: Length of the stay

| Purposes | Residents | Visitors |
|---|---|---|
| Home and Other Purposes | 7-12 hours stay | 7-12 hours stay |
| Work, Shopping and Leisure | 0.5-4 hours stay | 0.5-7 hours stay |

In addition, (Benenson and Martens, 2009) found in their survey that 60 percent of the on-street parking spots is occupied by residents at the end of the day (5pm), which would result in approximately 1404 occupied by residents on-street parking spots in our simulation at 5pm. As Santoña is a touristic town during Summer and differs in occupancy in Summer from Winter, we assume two different non-homogeneous Poisson processes. We based these processes on the discussed findings of (Benenson and Martens, 2009). Accordingly, we assume that during Winter approximately 2 x 702 $\approx$ 1404 individuals on average are within the system and during Summer approximately 2 x 936 $\approx$ 1872, during daytime. This results in Figure 2, describing the people within the simulation during a one week period. Here it can be seen that both during Winter and Summer, the amount of people staying overnight is approximately 550. During Summer, the peak of people within the system is approximately 2100, and during Winter approximately 1600. The $\lambda$(t), the instantaneous arrival rate of cars at time t, per day ($0 \leq t < 24$) corresponding to the assumed number of people within the system is shown in Figure 3.

In the simulation model, we distinguish between free on-street parking, paid on-street parking and underground parking. We set the amount of on-street parking spaces equal for all areas and allow the percentage paid and free parking to change, in order to model different situations. At the time of the survey, there was no underground parking facility yet. Therefore, we only allow for one underground parking facility for the whole town. This is because building an underground parking

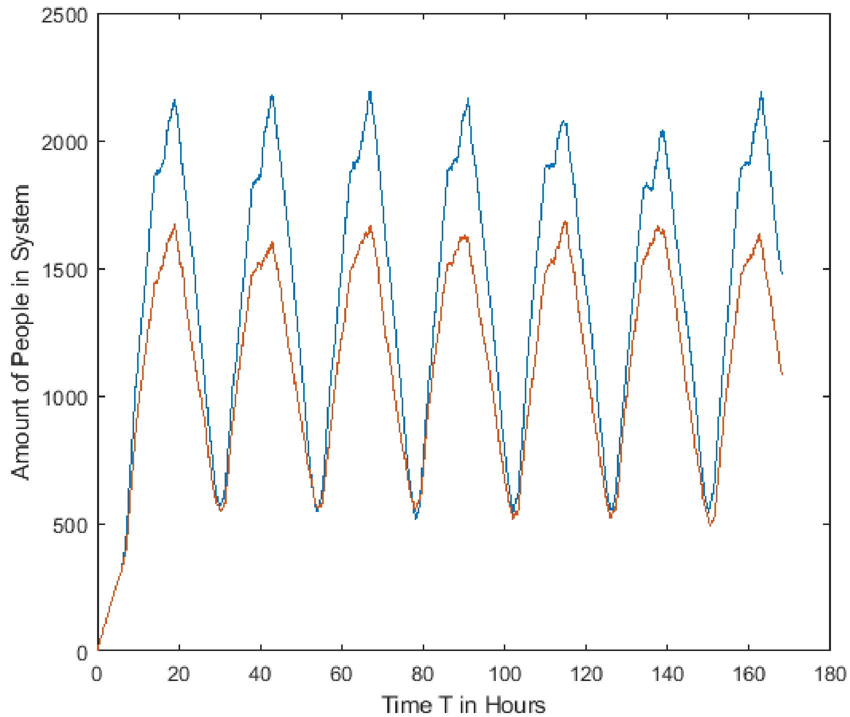


Figure 2: People within the system, during Summer (blue) and Winter (red)

facility is an intensive projects which might include high prices of land and construction costs, and thus, we assume that the local authority will only build one underground car park at a time. To test the effects of this facility and which area is best suited to build the underground parking in, we allow the number of spots and the area of the underground parking to change between different simulation situations. Furthermore, we distinguish between three kinds of parking types within the parking model, namely, public parking, reserved parking and electric parking. Public parking is free to use for everyone and therefore, all individuals can park there. Reserved parking is reserved for a specific group of agents. This type is divided into four sets, parking for women, parking for disabled people, parking for VIP's and parking for families. The electric parking spaces are parking spots with a specific characteristic, as we take into account electric vehicles needing a power outlet for charging. Preferred parking spots and power outlet charging spots have the same distribution across free on-street, paid on-street and underground parking.

For each simulation run, the user is asked for certain input. The amount of on-street parking spots per area, as well as the distribution of free and paid parking spots, is asked. Additionally, the

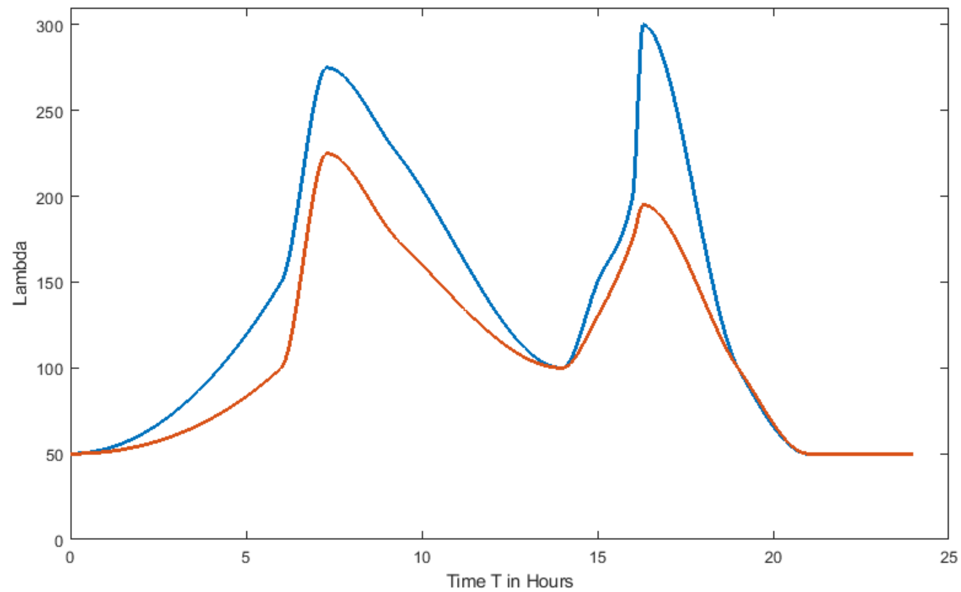


Figure 3: Distribution of lambda, during Summer (blue) and Winter (red)

amount of parking spots available in the underground parking and the area in which the underground parking is situated should be given as input. Furthermore, the distribution of public, preferred and charging outlet parking spots, equal for on-street and underground parking, is user input. Lastly, the parking fees for paid on-street parking and underground parking are asked.

For each decision of each agent, the parking choice algorithm is based upon the framework described in Warach and Axhausen (2012) and is explained in Figure 4 and Figure 5. Based on given percentages for women, disabled, VIP's, families and electric vehicle drivers, the incoming agent is randomly assigned its characteristics. In addition, the length of stay of this particular agent is determined, as is the destination, both based on uniform distributions. The first step is to look for available parking spots within the area of destination. To focus the study on electric vehicle convenience improvement, we only allow electric vehicle drivers to park in parking spots with a power outlet within their area of destination (time to destination (TD) is zero). When such a parking spot is not available for the electric driver, the agent queues up in the shortest queue within the destination area. For each available and allowed, accordingly to the agents characteristics, parking space, the utility is calculated. Then, the spot with the highest utility is chosen. When there is no such parking spot available, the driver will look in one of the neighboring areas. This area is randomly chosen from the set of neighbors of the destination area (TD is one). The same parking search then happens in all neighboring areas until a suitable parking spot is found. When all the neighboring areas of the destinations have been searched through without successfully finding a parking spot, the neighbors of the searched through areas are entered until parking is possible (TD is two). When there is still no suitable parking spot found within those areas, all the neighbors of the areas with a TD value of two are searched through (TD is three). Whenever the agent cannot park in Santoña, the agents utility gets a penalty in terms of access time to the parking space and access time to destination from the parking space and then leaves the system. Every time an area is searched through unsuccessfully, the access time to destination increases by one. The access time from the parking spot until the destination is determined by how much areas the agent has to go through when going to the destination area.

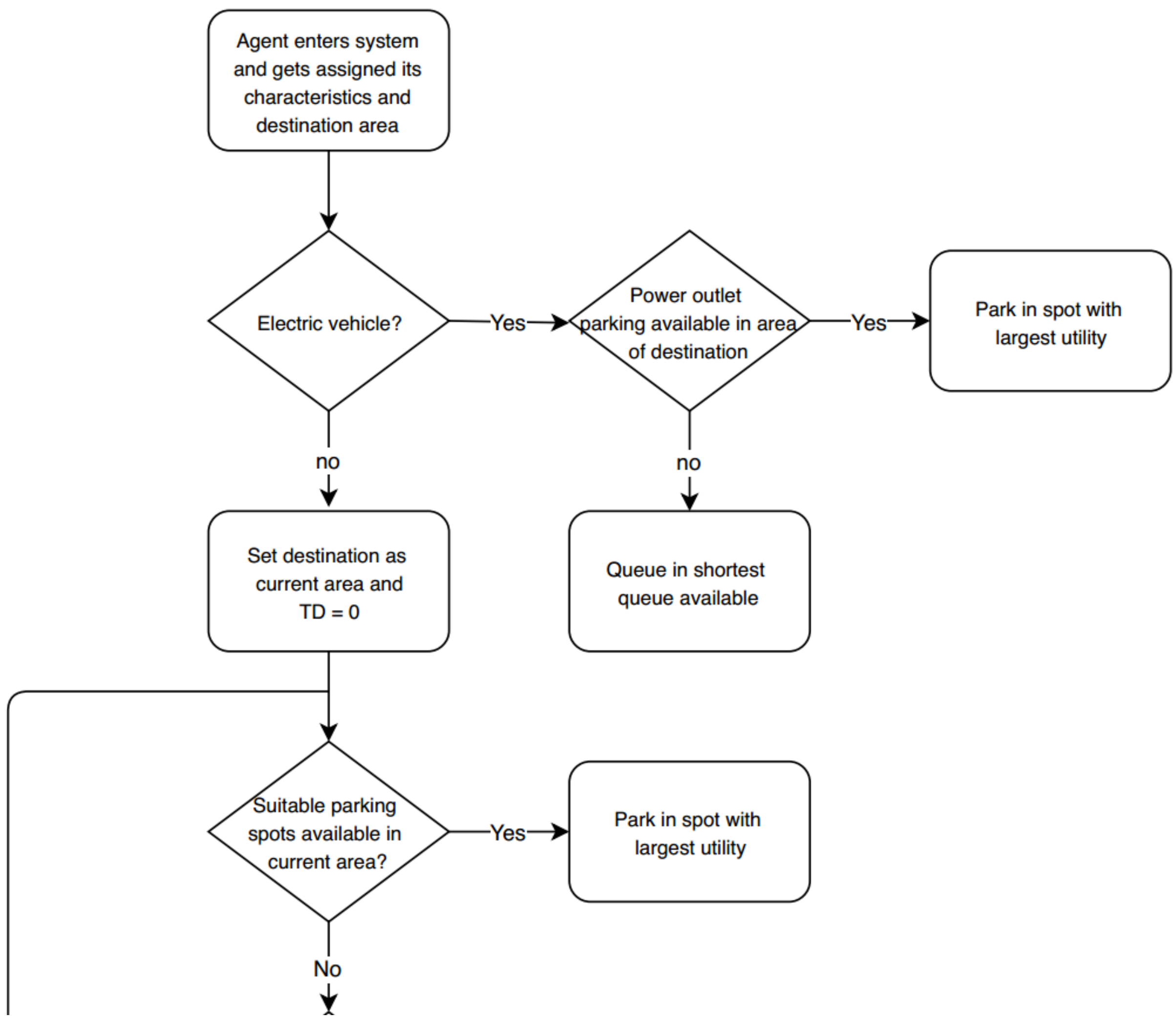


Figure 4: Parking Choice Algorithm Part 1

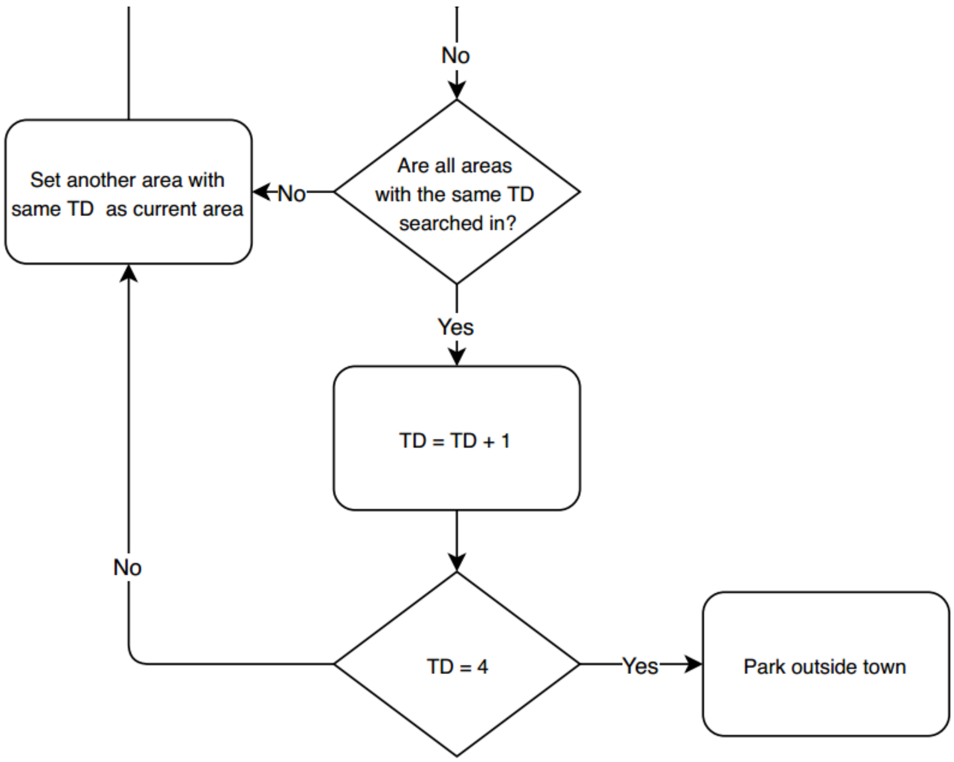


Figure 5: Parking Choice Algorithm Part 2

The utility for each parking spot for a particular agent within the system is derived according to Equation 3. The access time to parking (AT), the access time to destination (TD) and the fee that has to be paid (FEE) are important factors of the utility, as can be seen from the results of the MMNL model (Ibeas et al., 2014). Furthermore, whether the age of the vehicle used is less than three years (AGE is one if car age is less than three years) and whether the agent is parked in a paid on-street parking spot ($B_{PSP}$) or in an underground car park ($B_{PUP}$) are significant factors as well. As shown in Section 5, the population has a heterogeneous preference for access time to parking and how much fee has to be paid. We take this into account in our utility calculation as well. Because normal distributions are used in the MMNL model, we derive the coefficients for the access time to parking and the fee that has to be paid by generating a random value from their normal distributions, called $BN_{AT}$ and $BN_{FEE}$ respectively, for each separate agent. The coefficients used in the simulation in Equation 8 are based on the results of Ibeas et al. (2014) and thus, the coefficient for the access time is normally distributed with mean -0.788 and standard deviation of 1.064, whereas the coefficient for the fee is normally distributed with mean -32.328 and a standard deviation of 14.168. All coefficients can be found in Table 5.

$$U_n = \beta_{B_{PSP}} B_{PSP} + \beta_{B_{PUP}} B_{PUP} + \beta_{AT} AT + \beta_{FEE} FEE + \beta_{TD} TD + \beta_{ORG} ORG + \beta_{AGE} AGE \quad (8)$$

# 5 Results

## 5.1 Mixed Multinomial Logit Model and Willingness-to-Pay

First, assume that all parameters are random and then allow for fixed parameters to be in the model. This resulted in the specification of the MMNL model in Tabel 5. In the model, only the access time and the level of the fees have a significant random variability. Therefore, it is shown that the preferences for the access time to the parking spot and the fees that have to be paid for the parking spot are heterogeneous for the population. Thus, the coefficient for the access time is distributed as $\beta_{AT} \sim$ N(-0.51, $0.69^2$) and the coefficient for the fees as $\beta_{FEE} \sim$ N(-24.14, $10.58^2$). This means that every individual within the population places another weight on the importance of these variables. It has to be taken into account that the coefficients for FEE and AT are correlated and thus, the heterogeneity of both coefficients is partially due to this. It is interesting to note that the values of the coefficients for AT and TD are quite similar, whereas only the deviation of the coefficient of AT is significant.

Table 5: MMNL model estimation

| Variables | Mean | SE | St Dev | SE |
|---|---|---|---|---|
| Fixed | | | | |
| TD | -0,4566 | 0,1568 | - | - |
| Origin | -5,6311 | 2,8099 | - | - |
| AgeVeh $\leq$ 3 | 3,2704 | 2,6654 | - | - |
| $B_{SPS}$ | 7,7265 | 1,4965 | - | - |
| $B_{PUP}$ | 27,5163 | 5,5320 | - | - |
| Random | | | | |
| AT | -0,5142 | 0,1754 | 0,6943 | 0,4131 |
| FEE | -24,1426 | 5,4107 | 10,5807 | 2,3347 |

The variable AgeVeh $\leq$ 3 is the dummy variable for people driving a car of which the age is is less than 3 years (1) or more (0). This variable has a positive coefficient, which implies that people with a relatively new car place more weight in leaving them in a safe place. In addition, the variable origin is defined as the base case and is dummy variable that specifies, in case of free on-street parking, if the journey is internal (1) or external to town (0). The negative sign of the coefficient implies that when the journey is internal to town, utility is abstracted from the choice of free on street parking. This is especially important for the cases where people were parked in an underground parking and hence, are always handicapped when having to choose for free on-street parking as then, it will always have 5.63 less utility. $B_{SPS}$ and $B_{PUP}$ are the choice specific constants for the paid on-street and paid underground parking alternatives, respectively. Ceteris paribus, all people prefer underground parking over the two other alternatives. Furthermore, we investigated how the income level of the decision-maker influences the way the fee that has to be paid is valued. We can conclude that people with a lower income place more weight on the fee that has to be paid then the people with a higher level of income.

We distinguish between income groups and between residents and visitors when calculating the subjective values of time, as the means of the SVT intervals differ significantly between income high/medium and low income groups and between residents and visitors. The SVT, the means of the confidence intervals, are thus computed based on these groups and are shown in Table 6. The given values are interpreted as the willingness to pay in order to save either time looking for a parking spot or time to reach the destination from the parking spot in euros per hour. It is shown that people with a higher income, as well as visitors, are willing to pay more in order to save time.

Table 6: Subjective Values of Time

| | | | SVT (Euros/h) | |
|---|---|---|---|---|
| | | Income | AT (Mean) | TD(Mean) |
| Paid On-Street Parking | Resident | Low | 1,2200 | 0,5170 |
| | | Med-High | 1,6927 | 0,7201 |
| | Visitor | Low | 1,5980 | 0,8720 |
| | | Med-High | 2,6582 | 1,1347 |
| Underground Parking | Resident | Low | 1,1641 | 0,5047 |
| | | Med-High | 1,7368 | 0,8718 |
| | Visitor | Low | 1,4664 | 0,8123 |
| | | Med-High | 2,6582 | 1,1996 |

### 5.2 Parking Choice Model

We start by investigating in which area the underground parking should be. We run the simulation multiple times, each time specifying in which area the underground parking is, while keeping all other variables equal. We set the capacity of parking spots in the underground parking facility to 40, which is relatively a large amount for an area of 230 parking spots available in total. The results are shown in Table 6 and represent the average access time to a parking spot (AT) and the average time to the destination (TD) for an individual, measured over a one week period. The red and the blue line both represent the base case where there is no underground parking available. In Figure 6 we see that no matter where the underground parking facility is placed, the AT and the TD decrease by approximately ten percent at least. Area 8 and area 9 both seems most appropriate to build the underground parking facility in, as both have the lowest values for AT and TD. This could partly be a result of the assumption that only people with a 'work' or 'other leisures' purpose are only able to have area 1, 2 and 3 as destination area. Because when choosing area 9 results in the lowest AT and TD, the area of the underground parking facility is set to area 9 for the following simulation situations.

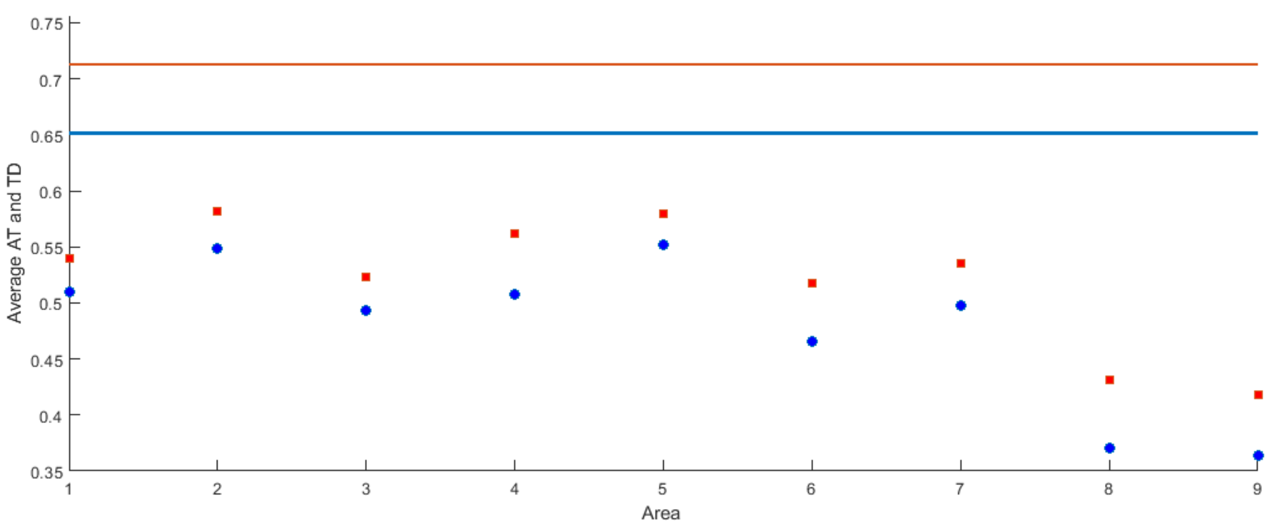


Figure 6: Access times to parking spot (blue) and to destination (red) for different facility areas

Secondly, we look at the impact of adding more or less spots to the underground parking facility. We set the fees for on-street parking and underground parking to 0.6 and 0.8, respectively. Table 7 shows the average access time to the parking spot and the average time to the destination for different amounts of parking spots in the underground parking facility. This is also measured over a one week time period. With less than 50 parking spots available, the TD is on average higher than the AT, which could be a result of the people driving electric cars queuing up for a power outlet in their area of destination. Figure 7 shows that the AT and TD decreases fastest on the interval between 20 and 80 spots. However, when more than 100 parking spots are build, the At and TD are not decreasing anymore. The slight differences in values for AT and TD when over 100 spots are created, can be the result of randomness in the simulation. Furthermore, the average utility per agent is shown in Table 8, also measured over a one week time period. The steepest increase in the average utility per individual is on the interval between 20 and 80 parking spots as well. This high payoff for creating parking spots should be kept in mind in the decision-making process for the underground parking facility. When more than 80 parking spots are created, the utility still increases but with a lower rate. Based on these result, it is recommended to build between the 40 and 100 spots, depending on the building and investment costs. For further simulation runs, we set the amount of parking spots in the underground facility to 80.

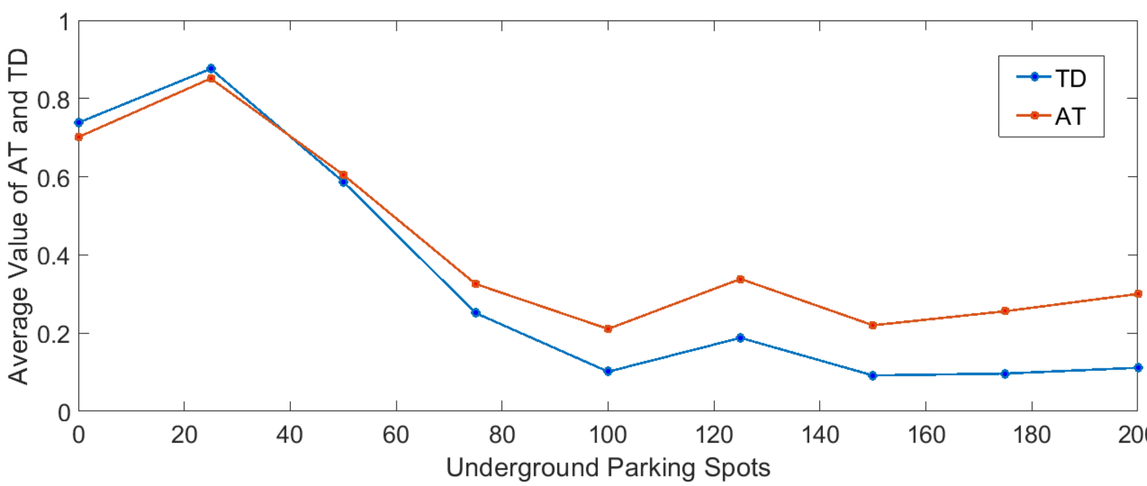


Figure 7: Access times to parking spot (red) and to destination (blue) for different amount of parking spots

Now, we analyze the impact of the fees on the utility of the individuals entering the system and the impact of the fees on the revenue of the local authority. In Figure 9 it is shown that when the underground fee is fixed at 0.8 and the on-street fee is increasing from 0 to 1.5, the utility is decreasing by 200 percent. The same holds for an underground fee fixed at 1.5. There is no significant difference between the decrease when the underground fee is fixed at 0.8 or is fixed at

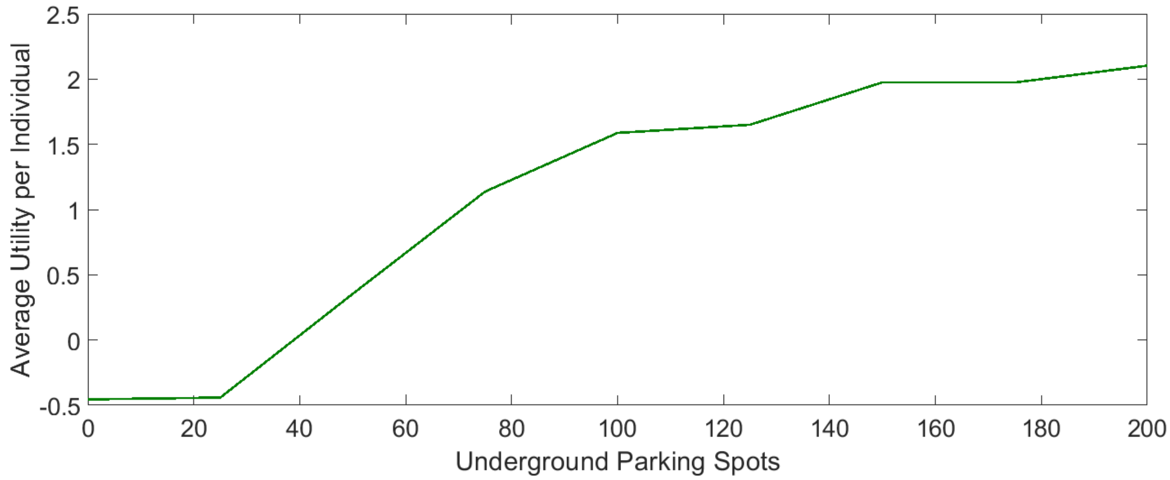


Figure 8: Average Utility per individual for different amount of parking spots

1.5. Both line cross the zero utility line when the on-street fee is between 0.6 and 0.7. Accordingly, we can recommend to set, independently of the underground parking fees, the on-street parking fee not higher than 0.7, in order to avoid negative utilities. Furthermore, Figure 9 shows that when the on-street parking fees are fixed, the average utility per person only decreases one or two percent when the underground parking fees increase from 0 to 1.5. The revenues that can be obtained by setting these fees are shown in Figure 10. In this figure as well, there is only a slight increase in revenue when the underground fees go up. In addition, the revenues increase significantly when the on-street parking spots increase. These results can be interpreted as that more people use the on-street parking than the underground parking.

Lastly, we focus our research on electric cars. Electric vehicles still outnumber public charging stations by more than six to one, indicating that most drivers rely primarily on private charging stations (Global EV Outlook 2017). It is key to ensure that public power outlets are accessible and available for the amount of people willing to drive an electric vehicle, especially when visiting a remote town such as Santoña. According to the Global EV Outlook 2017, the magnitude of growth of electric cars was the equal to the growth in publicly accessible chargers in 2016. Every town and every city needs to adapt their parking infrastructure to satisfy the growing need for power outlets. We assume that there is one electric parking spot per area and one in the underground parking lot. This is relatively a lot compared to other towns. In other words, there is one power outlet per 260 parking spots and there are ten electric charging outlet available within the town. Given the fact that electric cars outnumber the number of outlet charging spots, we assume that there are at least

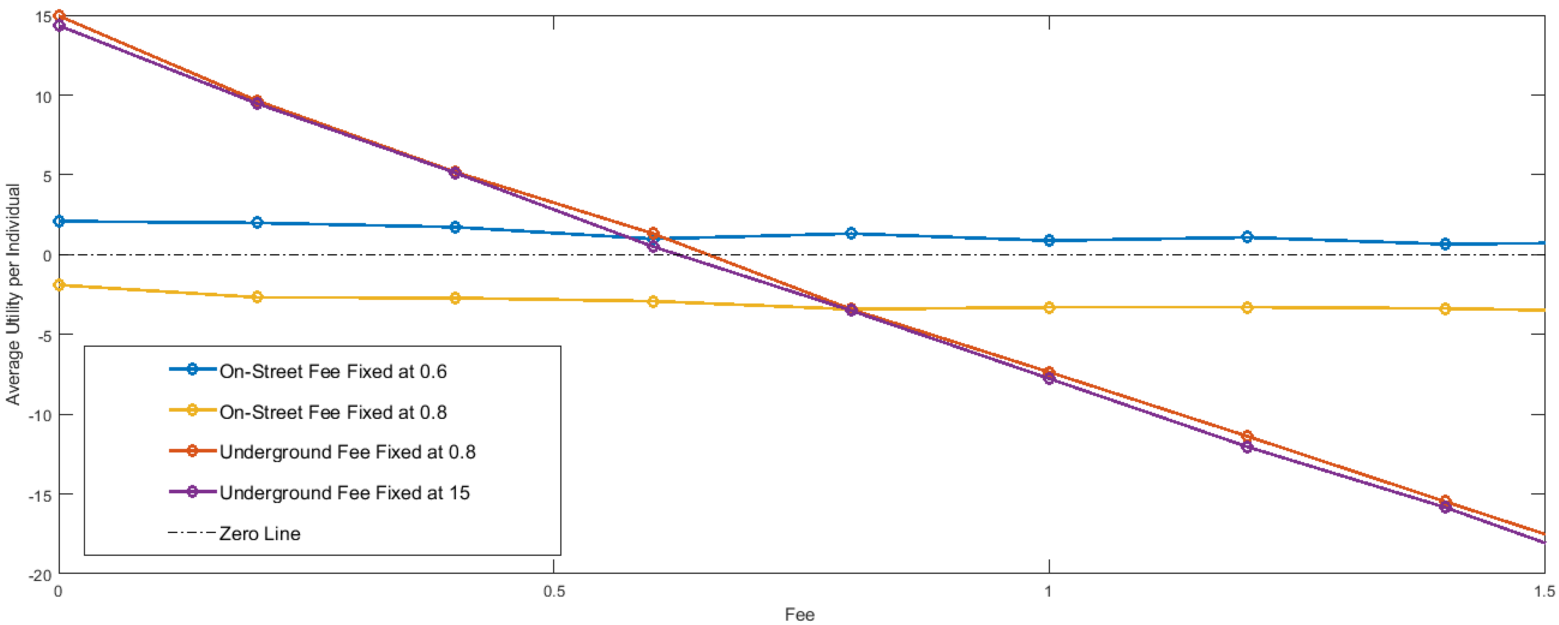


Figure 9: Average utility per person when the fee goes up

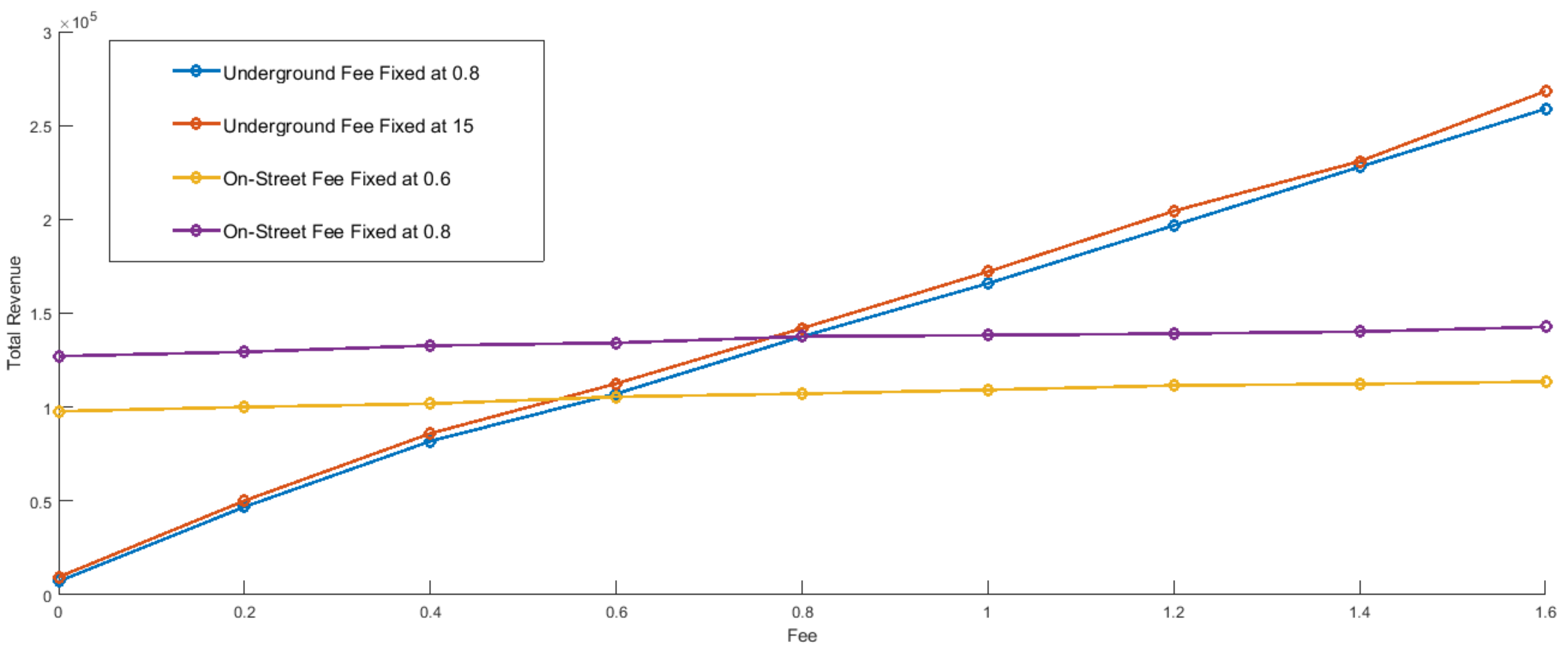


Figure 10: Revenue when the fee goes up

six times more electric car users on average. However, this means that three percent of the car users use an electric vehicle. The results of the simulation with these assumptions are shown in Figure

11. This figure shows, over a one week period, the amount of people using an electric car at time t (in red) and the amount of people queuing up for an electric power outlet. In this graph, is can be seen that with these assumptions, there are always at least ten people queuing up for a power outlet. However, as three percent is a high amount to assume, this results will not represent reality. But this figure shows how the queues develop over time and gives a good insight in the effects of the growth in electric vehicle drivers.

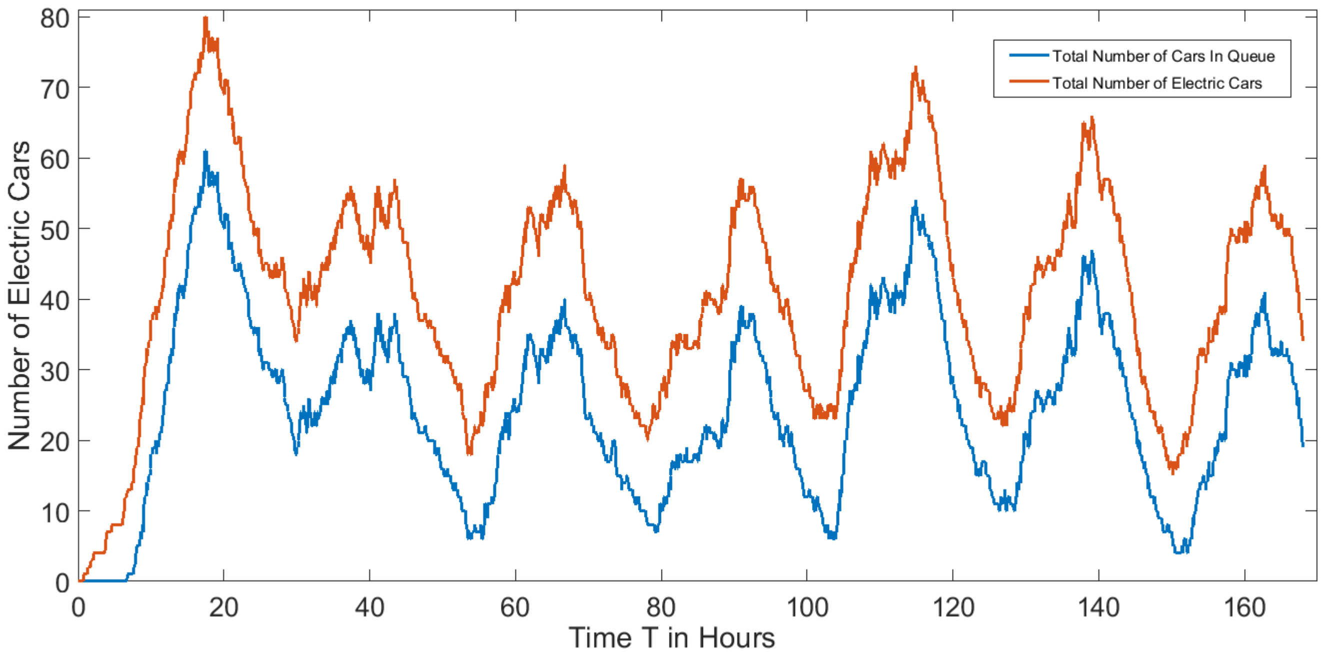


Figure 11: People queuing up

Furthermore, we analyze what happens when the amount of people driving an electric car increases. We keep the amount of parking spots equal to one per area and one in the underground parking lot and vary the percentage of people using an electric vehicle from zero to ten percent. In the following figure, Figure 12 we see how the amount of people with an electric vehicle that has to wait in queue grows as the percentage of the people using electric cars increases. The blue line represents when the simulation runs for a one week period and the red line represents when the simulation runs for a three week period. The two lines diverge when more than approximately four percent of the people are driving an electric vehicle. This can be interpreted as that the queues are accumulating and thus increasing over time when there are over four percent of the people using an electric car. After this, the average over one week increases by approximately 100 percent, whereas the average over three weeks increases by 600 percent. This demonstrates and stresses the importance of adjusting to the growing amount of electric vehicle users.

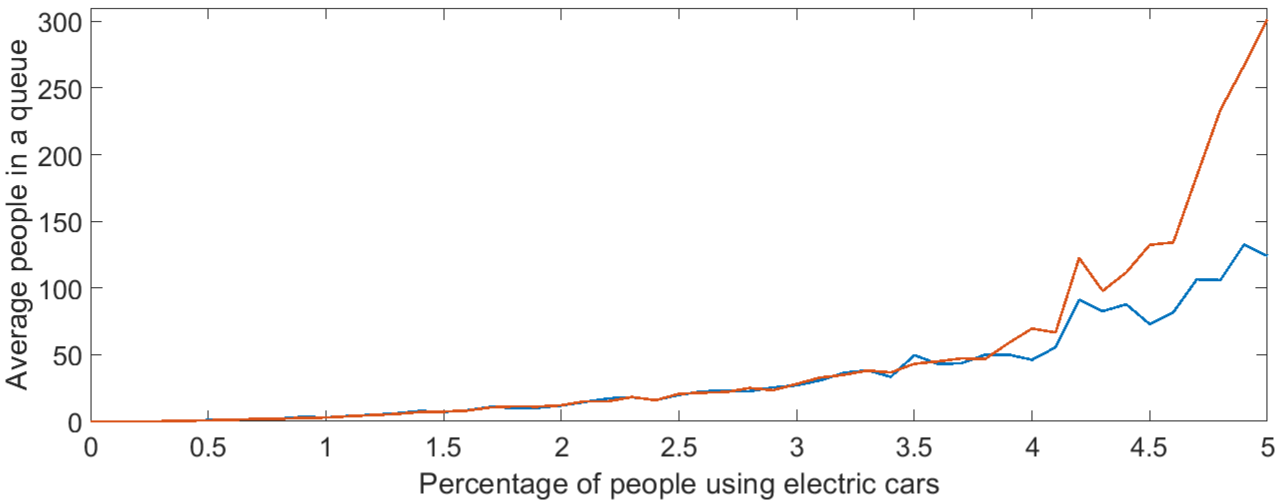


Figure 12: Average number of people in a queue over a one week (blue) and three weeks (red) period

## 6 Conclusion

In this paper, we aimed to investigate the different aspects of parking policies and thus, the results give an insight in the importance of parking fees and the time to search for parking spots, as well as the influence the characteristics of people have on the choices people make. This paper was focused on the Spanish town Santona, as this town frequently suffers from parking problems and thus, is in need of a better parking policy. The results of the MMNL model applied are consistent with previous findings in the parking choice area (Hensher and King, 2001) and showed that people have different preferences for fees that have to be paid and time to access the parking spot. It is interesting to note that the values of the coefficients for the access time to the parking spot and the time from the parking spot to the destination are quite similar, whereas only the deviation of the coefficient of the access time to the parking spot is significant. This can be explained by the fact that it can take a lot of time to find a parking spot in a busy area, but will take less time when this is done in a quiet area. The results also show that it should be taken into account that the more people with a relatively new car, the more underground parking spots are important as they prefer to keep them in a relatively safe place.

Furthermore, when building an underground parking facility, area 9 seems to be most appropriate in the case of the town Santona. However, more factors than the aforementioned factors in the results section should be taken into account. Some areas are more costly to build in and these construction costs can be significant in deciding which area is best suited for an underground parking facility. In addition, we showed that it it is recommended to build between the 40 and 100 spots, depending on the building and investment costs. Regarding the fees for the paid on-street parking spots and underground parking spots, the on-street fees are recommended not to be higher than 0.7. In contrast, it is hard to draw conclusions regarding the underground parking fees.

Charging infrastructure is indispensable for electric vehicles and in order to contribute to the growth of electric vehicle use, we investigate the effect of a growing percentage of electric car drivers on the queues for the power outlets. When assuming one power outlet spot per area and one underground electric vehicle spot, therefore ten spots in total, and three percent of people using such cars, we see that the queues are increasing fast. This demonstrates the need of power outlet in such a small town as Santoña, as tourists should be able to visit without not being able to charge their car. We can also draw the conclusion that when the percentage of people using electric vehicles grows over one percent, queues are accumulating over time and hence, are not disappearing anymore. On the other hand, the average number of people queuing up is only slowly increasing until one percent electric car use. As there are still relatively little people using electric cars, the town Santoña has therefore time to adjust for changing times. All in all, the deployment of the charging infrastructure should be tailored to the evolution of the electric car use growth. To conclude, "the transition to electric cars began only a decade ago and is gaining momentum. It holds promise for a low-emission future, provided that such dynamism can be sustained over the coming decades" (Global EV Outlook, 2017). The results of this research give a good insight of the precautionary measures small towns should make to adjust and make car trips for electric car users as convenient as possible.

## 7 Discussion

The data is limited to the survey responses of 197 people in a small town. With larger sample sizes, more reliable conclusions can be drawn. Thus, research in this area can be easily extended by data of larger, more dense cities. However, the basis for parking adjustment are on a small level and thus, the results of this research are important to learn about the implications of different parking policies. Furthermore, The parking choice model is limited to agents knowing a set of parking spots and choosing the one resulting in the most utility. Therefore, this model only includes parking choice decisions of people that are already familiar with the parking situation of the destination. The parking choice model can be extended by including the process of searching for parking spots, resulting in a decision making process of an agent that travels through a traffic simulation.

The results for the electric vehicle use increase are not realistic enough in the sense that not every electric vehicle driver always needs a power outlet and in our parking choice simulation, they are restricted to those spots in their area of destination. Therefore, the results are too extreme. In further research, the battery levels of these cars should be taken into account. Furthermore, simulations always give a lot of room for improvement and hence, research can be done in many aspects of parking choices with this simulation system.

# Bibliography


Armstrong, G. R., P. and J. Ortúzar. Confidence interval to bound the value of time. *Transportation Research part E*, 37:143–161, 2001.

Axhausen, K. and J. Polak. Choice of parking: Stated preference approach. *Transportation*, 18: 59–81, 1991.

Bakker, S. and J. Trip. Policy options to support the adoption of electric vehicles in the urban environment. *Transportation Research Part D: Transport and Environment*, 25:18–23, 2013.

Benenson, I. and Martens. Parkagent: An agent-based model of parking in the city. *Computers, Environment and UrbanSystems*, 32:431–439, 2009.

Ergün, G. Development of a downtown parking model. *Highway Research Record*, 369:118–134, 1971.

Geng, Y. and C. G. Cassandras. New "smart parking" system based on resource allocation and reservations. *IEEE Transactions on Intelligent Transportation Systems*, 14:1129—-1139, 2013.

Guo, H. S., L. and A. W. Sadek. A novel agent-based transportation model of a university campus with application to quantifying the environmental cost of parking search. *Transportation Research Part A: Policy and Practice*, 50:86–104, 2013.

Hall, M. M., D. and N. Lutsey. Electric vehicle capitals of the world. *The International Council of Clean Transportation*, 2017.

Henderson, S. Estimation for nonhomogeneous poisson processes from aggregated data. *Operations Research Letters*, 3:375–382, 2018.

Hess, S. and J. Polak. An analysis of parkng behaviour using discrete choice models calibrated on sp datasets. *ERSA Conference Paper, European Regional Science Association*, 2004.

Huber, M. Street travel related to local parking. *Highway Research Record*, 41, 1962.

Ibeas, A., L. dell'Olio, M. Bordagaray, and J. de Ortúzar. Modelling parking choices considering user heterogeneity. *Transport Research Part A*, 70:41–49, 2014.

Macal, C. and M. J. North. Tutorial on agent-based modelling and simulation. *Journal of Simulation*, 4:151–162, 2010.

Railsback, S. F. and V. Grimm. Agent-based and individual-based modeling: a practical introduction. *Princeton University Press*, 2011.

Revelt, D. and K. Train. Mixed logit with repeated choices: Households' choices of appliance efficiency level. *Review of Economics and Statistics*, 80:1–11, 2014.

Train, K. Mixed logit. *Cambridge University Press*, Chapter 6:138–154, 2003.

Train, K. Mixed logit with a flexible mixing distribution. *Journal of Choice Modelling*, 19:40—-53, 2016.

Van der Groot, D. A model to describe the choice of parking places. *Transportation Research*, 16A: 109–115, 1982.

Warach, R. and K. Axhausen. Agent-based parking choice model. *Transportation Research Record: Journal of Transportation Research Board*, 2319:39–46, 2012.

Willson, R. and D. Shoup. Parking subsidies and travel choice: Assessing the evidence. *Transportation*, 11:141–157, 1990.