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A methodology based on parking policy to promote sustainable mobility in college campuses

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ABSTRACT

Many university campuses are suffering from serious mobility problems resulting from excessive use of the private car by students, teachers and administrative staff. This article proposes a methodology based on a revealed and stated preferences survey aimed at estimating the importance of different variables on users mobility choices in order to simulate their reaction to policies such as the introduction of new modes of transport or charging for on campus parking. This estimation was based on a Mixed Logit model considering the possible presence of heterogeneity in user preferences. The introduction of these results into an optimization model has also allowed us to calculate the optimal parking fare that should be charged which would minimize the number of free spaces on campus or maximize the income received. This methodology has been applied to a case study at the campus of the University of Cantabria (Spain). The elasticities calculated using a Mixed Logit model confirm that setting a fare for parking on campus would be a serious disincentive against private car use in favor of more sustainable transport modes. Furthermore, the optimization model allowed us to calculate the fare that would maximize the income obtained from the parking spaces, an income that could then be used to strengthen the campus sustainable mobility policies.

1. Introduction

Given the high number of journeys drawn to university campuses due to their importance as centers of employment, teaching, research and dissemination, many suffer from problems related to mobility. These problems are basically caused from the over use of the private car by people trying to get to the campus. The use of the car at the installations on a university campus result in many negative externalities like atmospheric and noise pollution along with a general worsening of the overall landscape and environment. These kinds of problems related to non-sustainable mobility and a high dependency on motorized private vehicles have been detected in multiple campuses in the United States (Daggett and Gutkowski, 2003; Shoup, 2008), China (Shang et al., 2007), Europe (Barata et al., 2011; Tolley, 1996) and Western Asia (Aoun et al., 2013).

Research into mobility and the evaluation of parking policies on university campuses is not abundant. This article proposes a complete methodology which will allow different transport policies to be evaluated in order to encourage and empower more sustainable mobility on university campuses. The most noteworthy of these measures is charging for on campus car parking. The proposed methodology has been applied to a case study at the University of Cantabria campus in Northern Spain. This particular campus attracts a total of 14,637 users, including 9,974 undergraduate students, 2,867 post graduate students, 572 administrative staff and 1,224 teaching and research staff (University of Cantabria, 2015).

The proposed methodology will show the importance that different variables have for users when they choose a mode of transport to get to the university campus. This methodology will also allow us to model user behavior when faced with policies introduced to encourage more sustainable mobility, including charging for on campus parking. The tests were based on Revealed Preferences (RP) and Stated Preferences (SP) surveys and discrete choice models with a subsequent optimization model using mathematical programming. The specific aim of this optimization model is to determine the fare that must be paid for on campus parking in order to balance supply and demand and provide finance for encouraging alternative transport modes.

The United States of America is the country where most research has been made to improve mobility around university campuses. An example of this line of research is the study of Balsas (2003), who conducted a survey in eight selected bicycle and pedestrian friendly campuses. His research stressed the importance of seven measures leading to an environment of sustainable mobility: travel demand management (TDM) strategies, organization, planning, facilities, promotion,

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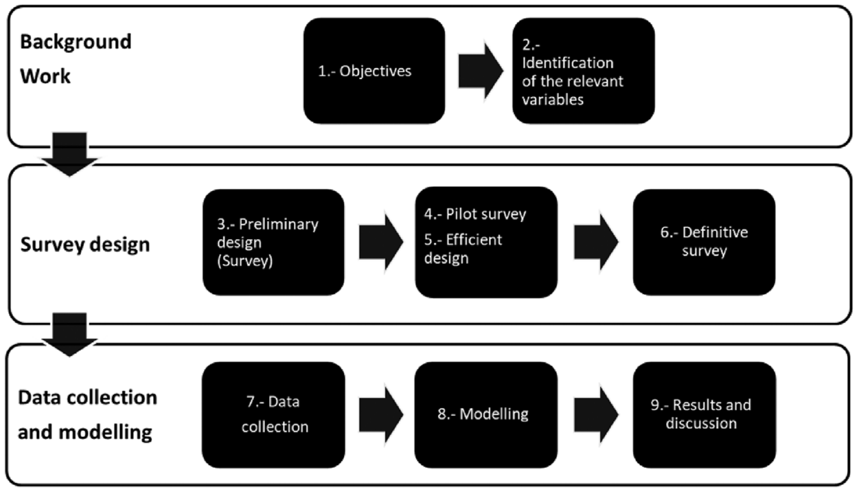

Fig. 1. Proposed methodology.

education and enforcement. The reduction in public transport fares for campus users (e.g. Unlimited Access Programs) have also proven to be effective in helping to reduce parking demand and increase student accessibility to campuses (Brown et al., 2001). Zheng et al. (2009) studied the possible market that could result from a car sharing platform at the University of Wisconsin – Madison as a novel policy to promote sustainable mobility. These authors showed that such car sharing programs have become popular at many US campuses. The authors performed an SP survey to evaluate the weight of different variables in the modal choice of the users and concluded that the transport choices were mainly influenced by previous habits and not so much by other sociodemographic variables such as user income levels.

Shannon et al. (2006) performed a study at the University of Western Australia on the modes of transport used by students and staff to get to the campus. The results of the study led to the conclusion that a reduction in journey times involving more sustainable modes of transport than the car, such as the bus or the bicycle, together with higher parking charges would lead to more sustainable mobility.

In Portugal, Barata et al. (2011) assessed the parking problems on the campus at Coimbra University. Their study showed that under pricing the parking facility was the main explanatory factor for overcrowding. Using logistic regression, the authors calculated the probability of the campus commuters being willing to pay to have reserved parking on campus. Women, university collaborators and individuals with higher income per capita had a higher probability of being willing to pay for parking. In addition, 73% of car drivers were willing to accept a compensation equivalent to a percentage of the public transport cost in order to reduce their car use.

The literature shows that variables such as waiting time for public transport, the availability of bicycle docking stations, access time from parking space to final destination, travel time and cruising for parking time are clearly significant when explaining modal choice. Among the most commonly used policies for encouraging sustainable mobility on university campuses are (Daggett and Gutkowski, 2003): shared bicycle systems, car share schemes, parking policies and park and ride systems. In some cases car-sharing policies have also been developed in combination with parking policies, allocating some specific parking slots for shared vehicles (Shaheen et al., 2010).

It is worth highlighting that for managing parking policies the most acceptable system found in the research and planning tend towards the direct payment of the parking costs by the user, thereby internalizing the social costs resulting from private car use (Shoup, 2005). This kind of policy removes most cruising time for parking and at the same time encourages the use of alternative and more sustainable modes of transport.

As highlighted by Shoup (2008), university campuses are privileged spaces for the introduction of sustainable mobility policies which can then be used as examples for other institutions and collectives. As many of the university campus users are young people, this increase the probability of encouraging a successful change in favor of more sustainable modes and mobility guidelines.

This research will determine which policies have the greatest capacity to increase sustainable mobility on a university campus. Furthermore, the application of an optimization model will allow us to estimate the parking fare which will provide more funds for financing further measures for promoting sustainable mobility. Considering previous proposals, mainly based on surveys and discrete choice models, this methodology includes the following contributions: a careful identification of the relevant variables to be considered in the models through the use of qualitative techniques (Focus Groups), a calculation of the elasticities to determine the most appropriate policies to discourage the use of the car to access the campus and the application of an optimization model for the estimation of the optimal parking fare within the campus.

2. Design of revealed and stated preferences surveys and their use for data collection

An RP and SP survey will be designed and applied to obtain a clearer image of mobility patterns around a university campus and to model the choices made by the users. This is a key step because the quality and type of data obtained by the survey will condition the rest of the modelling process and the simulation of the results of different policies. It is particularly important to pay careful attention to the design of the scenarios used in the questionnaire of the SP survey so that the experimental design is as realistic as possible. The proposed methodology is made up of the following phases (see also Fig. 1):

1. **Background work.** Clarifying the objectives of the study and the quantitative and qualitative research which will lead to the determination of the main variables influencing mobility for different types of users.
2. **Design and application of the RP and SP survey.** This phase could include the design of a pilot survey. This point is required if the SP survey is to be asked using scenarios chosen based on D-Error indicator as is the case proposed here.
3. **Collection and modelling of the data obtained in the surveys.** Estimation of the discrete choice models and design of an optimal scenario to establish the parking fare.

The following sections will provide a step by step description of each of the phases applied in the methodology with examples from the study case at the University of Cantabria campus.

2.1. Background work. Defining the problem and quantitative and qualitative research

Before designing an RP-SP survey, the variables that may influence choices made by users need to be determined in order to model their mobility behavior. In this case, a thorough bibliographic review was made of the national and international literature (e.g. Danaf et al. (2014)). A series Focus Groups (FG) were also hold (Ritchie et al., 2013) to allow the agents involved to voice their opinions about the different aspects of mobility at a university campus and about the variables they considered to be important when they chose which mode of transport to use.

The participants of the FG were chosen by performing a preliminary characterization survey throughout the university community. The community members were contacted via email and asked to take part in the survey. These users had access to the survey for 5 working days through a web interface. This preliminary survey provided the data summarized in Table 1.

The preliminary survey described above provided a sample of 838 users, of which 50% were male and 50% were female. The average car occupancy was 1.3 people per vehicle. By considering modal choice according to type of campus user (see Table 2) it can be seen how students use the car less and prefer to use the public transport bus service more than the teaching, research and administrative staff do. However, at least 50% of all user types use the private car to travel to the campus. This data led us to the conclusion that it would be better to hold 3 separate FG, one for each of the collectives, given that their mobility patterns, interests and perceptions were different. By holding the three FG we were able to cover better the variety of different campus user profiles, making it a practical recommendation to take before the quantitative collection of information about user mobility.

2.2. Design and application of an RP and SP survey

The data collected in the preliminary survey was used in the design of the RP and SP survey in which the users could choose from the various mobility alternatives to travel to the campus. The literature review and the information obtained from the FG helped us to establish the variables that should be considered in the questionnaire, such as: the fare, travel time, waiting time for public transport, access time to campus and cruising time to find a parking space.

Table 2
Users by transport mode (%).

Mode	Students	Administrative staff	Teaching and research staff
Car	50.2	77.2	74.4
Bus	19.2	8.6	6.3
Walking	11.4	7.4	13.1
Bike	0.8	0.6	1.1
Other	18.4	6.2	5.1

The second step taken in the design of the RP and SP survey was to decide the correct sample size. From a statistical point of view, the determination of the sample size mainly depends on the variability of the parameters considered in the population and the required precision level (Ortúzar and Willumsen, 2001):

$$n = \frac{CV^2 Z_\alpha^2}{E^2} \quad (1)$$

Where CV is the coefficient of variation of the variable of interest, Z_α is the value of the Normal standardized distribution for the required confidence level and E is the error level expressed as a proportion.

Considering a 90% confidence level and a 10% error, the sample size would therefore be given by $271CV^2$. Previous studies in the field and the data provided by the preliminary survey have shown that the CV of the relevant variables such as travel time, waiting time for the bus or cruising time for a parking space have a CV close to 1 meaning that a sample size of 200 individuals would be enough considering also the limited resources.

A small pilot survey of 30 individuals was performed before designing the definitive RP and SP survey. This smaller survey helped to correct any possible deficiencies detected in the design of the questionnaire. The data obtained were also used to estimate a Multinomial Logit model which provided some preliminary parameters used to calculate the definitive experimental design (Bliemer and Rose, 2005; Rose and Bliemer, 2009).

The experimental design asked to the users was chosen based on an efficiency criterion dependent on the minimization of the D-error indicator, in other words, on the minimization of the determinant of the variance-covariance matrix obtained from the parameters calculated from the pilot survey.

$$D - error = (\det \Omega)^{1/k} \quad (2)$$

This type of efficient design selects the optimal group of scenarios so

Table 1
Variables obtained from the preliminary sample of university campus users.

1) User and trip Characterization	2) If the bus mode is used
Gender Age Income level: < 900 euros (€), 900-1500€, 1500–2500€ or > 2500€ Possession of driving license Type of user: student, teaching/research staff or administrative staff Trip origin Trip destination Most frequently used mode of transport Most common time of day for making the trip	Typical travel time Typical waiting time Typical time from origin to initial bus stop Typical time from destination bus stop to final destination. Qualitative score for the public transport connection between home and campus: Very good, Good, Average, Bad or Very bad
3) If the car is used	**4) If a combination of train and bus is used**
Typical travel time Chosen parking location Time required to find a parking place Time parked Usual vehicle occupancy	Qualitative score for the connection between train and bus: Very good, Good, Average, Bad or Very bad

that the parameters of the estimated models present the smallest possible standard errors in contrast with the classic orthogonal designs which are centered on the minimization of the correlation between attributes (Hensher et al., 2005).

Based on the data from the preliminary survey and the Focus Groups five possible choice alternatives were considered for traveling to the university campus:

1. Use the car as the mode of transport and park at the campus.
2. Use the car as the mode of transport and park at a park and ride space with a free shuttle service to the university.
3. Use the car as the mode of transport and park in the streets near to the university.
4. Use the bus as a mode of transport.
5. Use the bicycle as a mode of transport.

All the alternatives were available when the survey was asked with the exception of the second alternative because the university did not have a free shuttle bus service for users of the park and ride car park. The bus is available for both, the inhabitants of the city through 4 lines of the urban transport network, and the inhabitants of the main centers of the region through several intercity lines. In addition, the university campus has available two public bicycle hire points.

The RP section addressing user characterization and data collection was the same used in the preliminary survey (see Table 1). The levels of the attributes and the labels chosen for the experimental design of the SP survey can be seen in Table 3. Three levels were set for each attribute. In the cases of the alternatives involving car use (alternatives 1, 2 and 3) the travel time was calculated as being the same as provided by the interviewee in the RP survey, as well as the time taken increased by 15% and the time taken increased by 30%. In the case of the bus alternative, travel time was calculated based on a commercial speed of 15 km/h and 10 km/h in the case of the bicycle. Therefore, in the cases of the travel times taken by the different modes of transport available to the user, the values of the variable in the SP survey depend on the times provided by the user in the RP survey (i.e. pivot design (Ortúzar and Willumsen, 2011)). In order for the scenario values to be calculated in real time, the survey was asked using mobile devices. The remaining levels were set as fixed based on the information obtained in the FG and the preliminary survey.

Fig. 2 shows a schematic map of the different available parking alternatives on and around the university campus. When the study was being performed there were 1,473 free parking spaces available on the campus. Near the campus there are several residential areas in which it is possible to find free parking slots, although during the peak hours these streets may have a high occupancy rate, which forces drivers to cruise for parking.

Table 3
Attribute levels and labels used in the experimental SP design (fare given in € and time in minutes).

Alternative	Fare	Travel time	Waiting time	Cruising time for parking	Access time
1 – CAR CAMPUS	0	Stated	–	1	–
	0.8	+15%		3	
	1.6	+30%		15	
2 – CAR SHUTTLE BUS	–	Stated	2	–	–
		+15%	4		
		+30%	10		
3 – CAR SURROUNDINGS	–	Stated	–	1	3
		+15%		3	8
		+30%		15	15
4 –BUS	0.5	Stated	4	–	–
	1	+15%	7		
	1.5	+30%	15		
5 - BIKE	0	Stated	–	–	2
	0.5	+15%			6
	1.5	+30%			10

The number of scenarios in a labeled design can be calculated using L^{MA}, where L is the number of levels, M the number of alternatives and A the number of attributes (Hensher et al., 2005). In this case, a complete factorial design would have 3^{14} scenarios. The algorithm for the efficient design resulted in 9 choice situations or scenarios.

Respondents ranked the three most preferred alternatives in order. The definitive survey was answered by 200 people with 1,800 effective observations. The survey was performed in the morning (9:00–14:00) over four weekdays. The sample was composed of 88% students and 12% from other groups (administrative staff and teaching/research staff). Considering the respondents by gender, 48% were male and 52% female. These percentages were very similar to those obtained in the preliminary survey.

3. Modelling and results

The data obtained in the SP survey can be used to model user preferences and simulate their modal choices for traveling to the campus under different scenarios. The modelling was performed using discrete choice models based on random utility theory (Hensher et al., 2015; Train, 2009). According to the hypothesis of this theory, each individual associates a level of utility, depending on their personal preferences, with each alternative, with a greater probability of choosing the one that maximizes their utility. The total utility is split into two parts, a systematic component known to the modeler and another unknown random component:

$$U_{ni} = V_{ni} + \varepsilon_{ni} \tag{3}$$

Where V_{ni} is the systematic utility for user n in alternative i and ε_{ni} is the random component.

The most widely known discrete choice model is the Multinomial Logit model (MNL). The MNL model starts from the hypothesis that random errors in the alternatives are independent and identically distributed (IID). Furthermore, in the MNL model the estimated parameters are identical for all the population, even though systematic variations in user taste can be introduced through the interaction of the characteristics of the alternatives with the socioeconomic characteristics of the users. More recent discrete choice models like Mixed Logit (ML) (Hensher and Greene, 2003) are able to consider the presence of a distribution of preferences among the population by introducing random parameters. These random parameters should be set by specifying a type of random distribution defined by two parameters to be estimated: the mean and the standard deviation. The probability that user n will choose alternative i can therefore be expressed as (Train, 2009):

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta \tag{4}$$

Where $L_{ni}(\beta)$ is the logit probability evaluated at the parameters β and $f(\beta)$ is a density function. Therefore, the probability given by the ML model is a weighted mean of the logit formula evaluated for different values of β with weightings given by the density function $f(\beta)$. It is this function that allows us to capture the heterogeneity in the tastes of the population.

The specification of the ML model for the five available alternatives is shown in equations (5)–(9).

$$\begin{aligned} U_{CAR-CAMPUS} &= \theta_{ASC_{CAR}} + \theta_{FARE_{CAR}} \cdot FARE_{CAR} + \theta_{TT} \cdot \mathrm{TT}_{CAR} + \theta_{ST_{CAR}} \cdot ST_{CAR} \\ &\quad + \theta_{OCCUP_{CAR}} \cdot OCCUP_{CAR} \end{aligned} \tag{5}$$

$$\begin{aligned} U_{CAR-SHUTTLE\ BUS} &= \theta_{ASC_{SHUTTLE\ BUS}} + \theta_{TT} \cdot \mathrm{TT}_{CAR} + \theta_{WT_{SHUTTLE\ BUS}} \\ &\quad \cdot \mathrm{WT}_{SHUTTLE\ BUS} + \theta_{OCCUP_{CAR}} \cdot OCCUP_{CAR} \end{aligned} \tag{6}$$

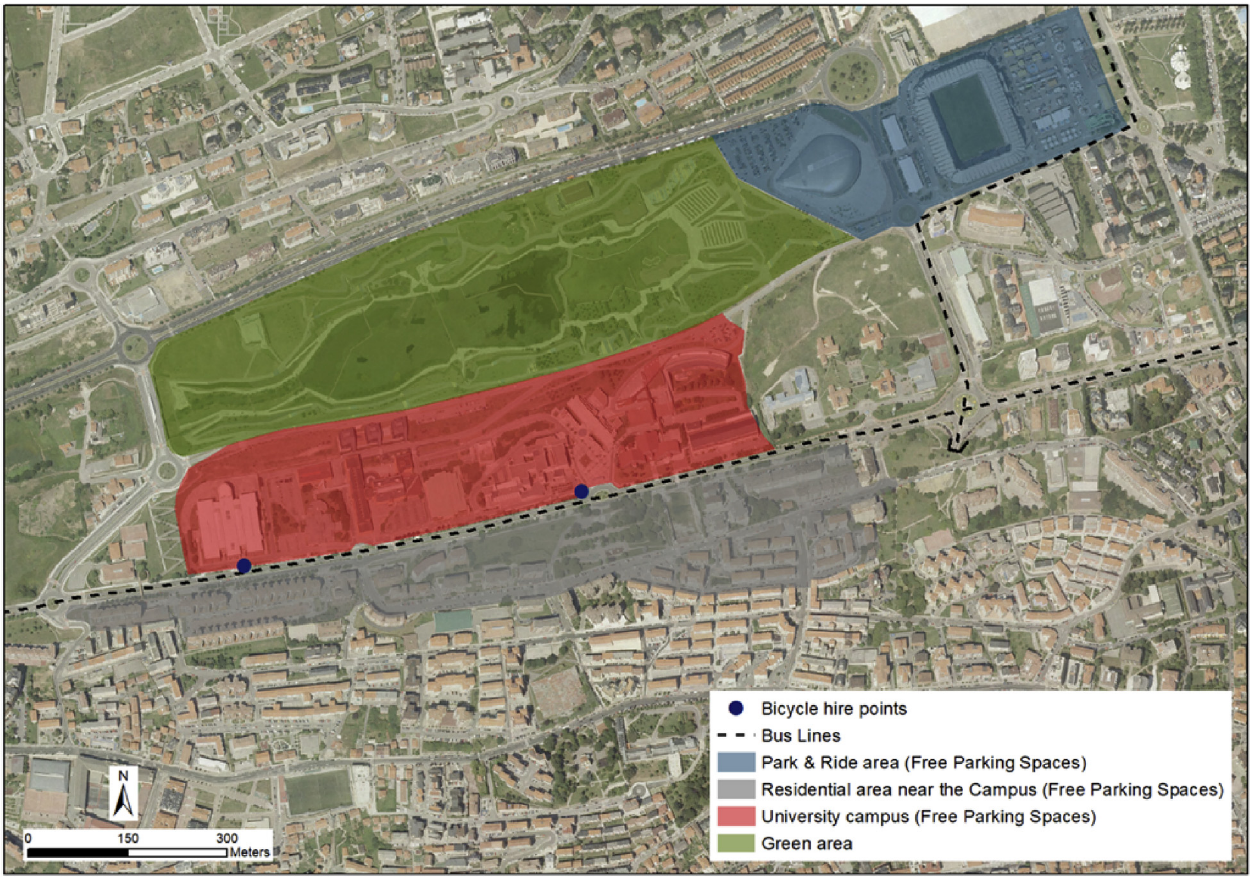

Fig. 2. Mobility alternatives on the campus and its surrounding area.

$$U_{CAR-SURROUNDINGS} = \theta_{ASC_{CAR-SURROUNDINGS}} + \theta_{TT}\cdot \mathrm{TT}_{SURROUNDINGS} + \theta_{ST_{SURROUNDINGS}}\cdot ST_{SURROUNDINGS} + \theta_{OCCUP_{CAR}}\cdot OCCUP_{CAR} \quad (7)$$

$$U_{BUS} = \left(\theta_{FARE_{BUS}} + \theta_{FARE_{BUS/MINC}}\cdot MINC\right)\cdot FARE_{BUS} + \theta_{TT}\cdot \mathrm{TT}_{BUS} + \theta_{WT_{BUS}}\cdot WT_{BUS} \quad (8)$$

$$U_{BIKE} = \theta_{ASC_{BIKE}} + \theta_{FARE_{BIKE}}\cdot FARE_{BIKE} + \theta_{TT}\cdot \mathrm{TT}_{BIKE} + \theta_{AT_{BIKE}}\cdot AT_{BIKE} \quad (9)$$

Where θ_{ASC} are the specific constants of the alternatives. The other parameters can be interpreted following the abbreviations shown in Table 4. The ML model was estimated using simulated maximum likelihood by means of a Halton sequence of 100 draws. Bhat (2001) has shown that this procedure gives more accurate results than a random simulation with 1,000 draws. The parameters that were finally estimated in the model are summarized in Table 5.

Table 4
Description and name of the attributes.

Name	Description	Unit
FARE	Cost of parking the car or travelling by bus or bike (in the case of the bike-sharing system)	Euros (€)
TT	Travel time	Minutes
WT	Waiting time for the bus	Minutes
ST	Time to find a parking space	Minutes
AT	Access time to the Campus from the parking spot (car or bike)	Minutes
$OCCUP_{CAR}$	Variable that quantifies the number of persons occupying the car	–
MINC	Binary variable that identifies the individuals in the medium household income level (1200–2500 €/month).	1/0

Table 5
Resulting parameters from the Mixed Logit Model.

Parameter-Alternative	Coefficient	*t*-test
Non – random parameters		
ASC_{CAR}	1.609	37.16
$ASC_{SHUTTLE\ BUS}$	0.630	3.54
$ASC_{SURROUNDINGS}$	−0.059	−1.13
ASC_{BIKE}	−2.501	−12.88
$FARE_{CAR}$	−1.300	−11.07
ST_{CAR}	−0.042	−3.38
$OCCUP_{CAR}$	0.383	6.76
$WT_{SHUTTLE\ BUS}$	−0.075	−5.62
$ST_{SURROUNDINGS}$	−0.082	−11.10
WT_{BUS}	−0.024	−2.69
$FARE_{BIKE}$	−0.655	−6.21
AT_{BIKE}	−0.066	−3.59
Random parameters		
TT	−0.037	−4.25
$FARE_{BUS}$	−0.366	−4.07
Systematic variations of the average value of parameters		
$FARE_{BUS}$*MINC	0.202	2.34
Standard deviation of the random parameters		
Ts TT	0.037	4.25
Ts $FARE_{BUS}$	0.366	4.07
Log-Likelihood	−3,912.70	
Log-Likelihood (Constants only)	−4,959.22	
LR test	2,093.04	
$\bar{\rho}^2$	0.211	

Given that the specific constants in SP data reproduce the choice shares in the sample and not the real market shares, they need to be estimated following the procedure proposed by Hensher et al. (2005). Initially the model is estimated as usual, but in a second step all the parameters are fixed except for the specific constants which are weighted by the real market shares obtained from the RP survey.

As can be seen in Table 5, the estimated parameters have the expected sign and are statistically significant to a 95% confidence level. The only exception was the specific constant of alternative 3 (Parking in the surrounding area) which was not significantly different from zero according to the *t*-test. The likelihood ratio (LR) test showed the model had a clearly better goodness of fit to the data than the constants only model.

The specified ML model presents two random parameters in the variables Travel time and Fare for the bus alternative. Therefore, in both cases there is evidence of the presence of variability in user tastes. This heterogeneity resulted in a truncated triangular distribution for both variables which removes the presence of counterintuitive positive signs in the random parameters (Hensher et al., 2015). In the case of alternative 4 (Bus) this heterogeneity was explained because average income individuals (1,200–2,500 €/month) showed a reduced preference for the fare, meaning they gave less weight or importance to the cost of traveling by bus than the other people in the sample.

The variable $FARE_{CAR}$ showed no significant variation in taste, although it was clearly significant and its parameter had a high value. Finally, apart from the variables specified in equations (5)–(9) the car occupancy level ($OCCUP_{CAR}$) was introduced into alternatives 1, 2 and 3. The different estimations that were performed showed that occupancy was an influential factor as it increased the utility of the alternatives involving the car, which was almost certainly due to the students sharing the costs of travelling to the university.

Table 6 presents the direct and cross point elasticities estimated for each of the variables of the alternatives using sample enumeration. The elasticities represent the percentage of change in the choice probability of each alternative if the corresponding variable is increased by 1%. These results allow us to state that the fall in the probability of choosing to park on campus is high if the parking fare is increased (−0.45), a much higher effect than found with increases in the bus fare (−0.1) or for using the public bicycles (−0.3). Therefore, a paid parking policy seems to be the way forward as the most effective way of promoting sustainable mobility on campus, even though the users could continue to use the car and attempt to park on the surrounding streets (alternative 3). However, the time required to find a parking space around the campus surroundings was also clearly significant with an elasticity of −0.3.

Other measures aimed at reducing bus travel time (elasticity of −0.24) and especially bicycle travel time (with an elasticity of −0.69) could also encourage sustainable mobility on campus. Shorter bicycle travel times could be found by constructing and improving bike lanes from residential areas to the campus. A connection can also be seen between increased bus journey times and increased demand for bicycle use (crossed elasticity of 0.33). Overall, any penalization of car usage can have a positive impact on the choice to use other alternatives, especially increasing the on campus parking Fare given its significant positive crossed elasticity, around 0.2, for the cases of both the bus and the bicycle. For this reason the on campus parking fare will be the centre of our attention for the final part of the proposed methodology. The application of this type of policy is consistent with the broader mobility plan adopted by the city council of the area where the campus of the University of Cantabria is located. The mobility plan of the city aims to encourage sustainable mobility through the enhancement of walking, bicycle and public transport modes while discourage the use of private motorized vehicles using policies such as paying for parking and construction of Park-and-Ride facilities (Ayuntamiento de Santander, 2010).

4. Optimal scenario for parking fares

An optimization model is presented below to determine the fare that must be paid to park on the campus. The objective function has considered two cases:

- Case 1: maximize the number of occupied parking spaces or minimize the number of free spaces:

$$MinZ = P_a - P_o \tag{10}$$

- Case 2: maximize the income per parking space:

$$MaxZ = FareU \cdot P_o \tag{11}$$

Where:

P_a: Total paid parking spaces
P_o: Occupied paid parking spaces
FareU: Parking fare

These occupied paid parking spaces are calculated as:

$$P_o = \sum_i D_i \cdot P_{1,i} \cdot \frac{1}{O_{CAR}} \tag{12}$$

Where:

i: user class (2 classes: whether they belong to the middle income category or not)
D_i: trip demand for each class of user
$P_{1,i}$: probability that users from class i will choose alternative 1 (in which they make use of the on campus paid parking spaces)
Ocar: average car occupancy

The probability of choosing alternative 1 is calculated using a MNL model based on the ML model estimated in the previous section. This model has the following well known functional form.

Table 6
Demand elasticities for the ML model.

Attribute (Alternative)	1. Car + park in campus	2. Car + shuttle bus	3. Car + park in the surroundings	4. Bus	5. Bike
FARE (Car + park in campus)	−0.445	0.233	0.284	0.196	0.217
TT (Car + park in campus)	−0.225	0.133	0.157	0.079	0.032
ST (Car + park in campus)	−0.102	0.063	0.072	0.031	0.025
TT (Car + shuttle bus)	0.098	−0.261	0.134	0.048	0.019
WT (Car + shuttle bus)	0.072	−0.190	0.085	0.042	0.031
TT (Car + park surroundings)	0.070	0.080	−0.365	0.045	0.016
ST (Car + park surroundings)	0.054	0.063	−0.303	0.046	0.044
FARE (Bus)	0.027	0.024	0.036	−0.093	0.184
TT (Bus)	0.075	0.063	0.093	−0.241	0.332
WT (Bus)	0.022	0.019	0.028	−0.073	0.145
FARE (Bike)	0.001	0.001	0.002	0.009	−0.298
TT (Bike)	0.003	0.002	0.003	0.020	−0.690
AT (Bike)	0.002	0.001	0.002	0.009	−0.335

Table 7
Demand elasticities for the MNL model.

Attribute (Alternative)	1. Car + park in campus	2. Car + shuttle bus	3. Car + park in the surroundings	4. Bus	5. Bike
FARE (Car + park in campus)	−0.451	0.238	0.285	0.202	0.231
TT (Car + park in campus)	−0.149	0.087	0.103	0.056	0.024
ST (Car + park in campus)	−0.102	0.063	0.073	0.033	0.026
TT (Car + shuttle bus)	0.061	−0.178	0.085	0.034	0.014
WT (Car + shuttle bus)	0.069	−0.199	0.083	0.044	0.033
TT (Car + park surroundings)	0.045	0.053	−0.242	0.031	0.012
ST (Car + park surroundings)	0.054	0.065	−0.307	0.047	0.047
FARE (Bus)	0.025	0.023	0.032	−0.078	0.104
TT (Bus)	0.056	0.049	0.068	−0.169	0.223
WT (Bus)	0.023	0.022	0.030	−0.073	0.137
FARE (Bike)	0.001	0.001	0.002	0.008	−0.293
TT (Bike)	0.002	0.002	0.003	0.013	−0.483
AT (Bike)	0.002	0.001	0.002	0.009	−0.343

$$P_{j,i} = \frac{e^{\theta \cdot U_{j,i}}}{\sum_k e^{\theta \cdot U_{k,i}}} \tag{13}$$

Where:

j: alternative
k: group of all the available alternatives
$U_{j,i}$: utility function for alternative j and user type i
θ: parameter to be estimated

The utility functions have been specified as detailed in equations (14)–(18). Note how the parameters and the elasticities (see Table 7) are very similar to those obtained in the ML model estimated in the previous section. This is especially true in the cases of key variables for the optimization process such as $\mathrm{FARE_{CAR}}$ and $\mathrm{ST_{SURROUNDINGS}}$.

$$\mathrm{U}_{CAR-CAMPUS} = 1.748 - 1.297 \cdot FARE_{CAR} - 0.024 \cdot \mathrm{TT}_{CAR} - 0{,}042 \cdot ST_{CAR} + 0.381 \cdot OCCUP_{CAR} \tag{14}$$

$$\mathrm{U}_{CAR-SHUTTLE\ BUS} = 0.683 - 0.024 \cdot \mathrm{TT}_{CAR} - 0.075 \cdot \mathrm{WT}_{SHUTTLE\ BUS} + 0.381 \cdot OCCUP_{CAR} \tag{15}$$

$$\mathrm{U}_{CAR-SURROUNDINGS} = 0.073 - 0.024 \cdot \mathrm{TT}_{SURROUNDINGS} - 0.081 \cdot ST_{SURROUNDINGS} + 0.381 \cdot OCCUP_{CAR} \tag{16}$$

$$\mathrm{U}_{BUS} = (-0.167 + 0.160 \cdot MINC) \cdot FARE_{BUS} - 0.024 \cdot \mathrm{TT}_{BUS} - 0.023 \cdot WT_{BUS} \tag{17}$$

$$\mathrm{U}_{BIKE} = -2.452 - 0.651 \cdot FARE_{BIKE} - 0.024 \cdot \mathrm{TT}_{BIKE} - 0.066 \cdot AT_{BIKE} \tag{18}$$

The constraints being considered are:

- Limit the maximum on campus parking fare (3 euros maximum).

$$FareU \leq 3 \tag{19}$$

- Each and every one of the probabilities must be values greater or equal to zero and lower or equal to 1.

$$1 \geq P_{j,i} \geq 0 \quad \forall_{i,j} \tag{20}$$

- The sum of the probabilities of each alternative for the same class of user should add up to 1.

$$\sum_j P_{j,i} = 1 \quad \forall_i \tag{21}$$

- Occupied parking spaces must not number more than current supply.

$$P_a \geq P_o \tag{22}$$

The objective functions of both cases will therefore be specified as:

$$MinZ = P_a - \sum_i (D_i \cdot P_{1i}) \cdot \frac{1}{O_{car}} \tag{23}$$

$$MaxZ = FareU \cdot \sum_i (D_i \cdot P_{1i}) \cdot \frac{1}{O_{car}} \tag{24}$$

The results obtained were identical using both objective functions. The optimal fare is 1.83 euros providing a total income of 2,701.48 euros. With this parking fare the occupancy of the available space is complete; all 1,473 spaces are filled (see the horizontal black line in Fig. 3). Therefore, any fare charged under 1.83 euros will guarantee filling the available supply but at the cost of lower total income, whereas any fare charged above 1.83 euros will reduce occupancy and thus also implies a lower overall income.

However, a sensitivity analysis of the ST variable (see also Fig. 3) shows how the optimal fare varies depending on cruising time for finding a parking space off campus. This data provides an idea of the parking fare policy to follow as a function of the difficulty in finding off campus parking. In this way, the fare should rise as more time is required to find a parking space off campus. This means that, if you want to prevent that the residential areas near the campus are affected by a spillover effect, it would be advisable to combine the parking fare system within the campus with a parking fare system in these residential areas. This would help to prevent residents and businesses in areas close to the campus from being affected by the mobility management policies of the University. Even so, it has been detected in other study areas that these spillover effects may be lower than expected if most users choose to change their mode of transport (Melia and Clark, 2017).

5. Conclusions

This article has presented a methodology for implementing parking and mobility policies to promote sustainability in college campuses. The methodology has been applied in a case study at a university campus in Northern Spain. The combination of the data obtained from the RP and SP surveys with the application of discrete choice and optimization techniques has shown how the on campus parking fare is a fundamental variable not only for reducing the demand for travelling by private car but also to reinforce and finance alternative and more sustainable transport modes. Furthermore, an optimization model has been used to estimate the optimal fare which maximizes income or occupancy of parking spaces on campus. The estimated model shows that a fare of 1.83€ with a cruising time for parking off campus lower than 15 min guarantees that the on campus car parks are full and the overall income is optimal. The tariff could even be increased if the off campus cruising time increases, although the ideal situation would be to combine the on campus charging policy with further policies introducing a fare for parking on the surrounding streets and thereby provide even more incentives to use more sustainable alternative modes

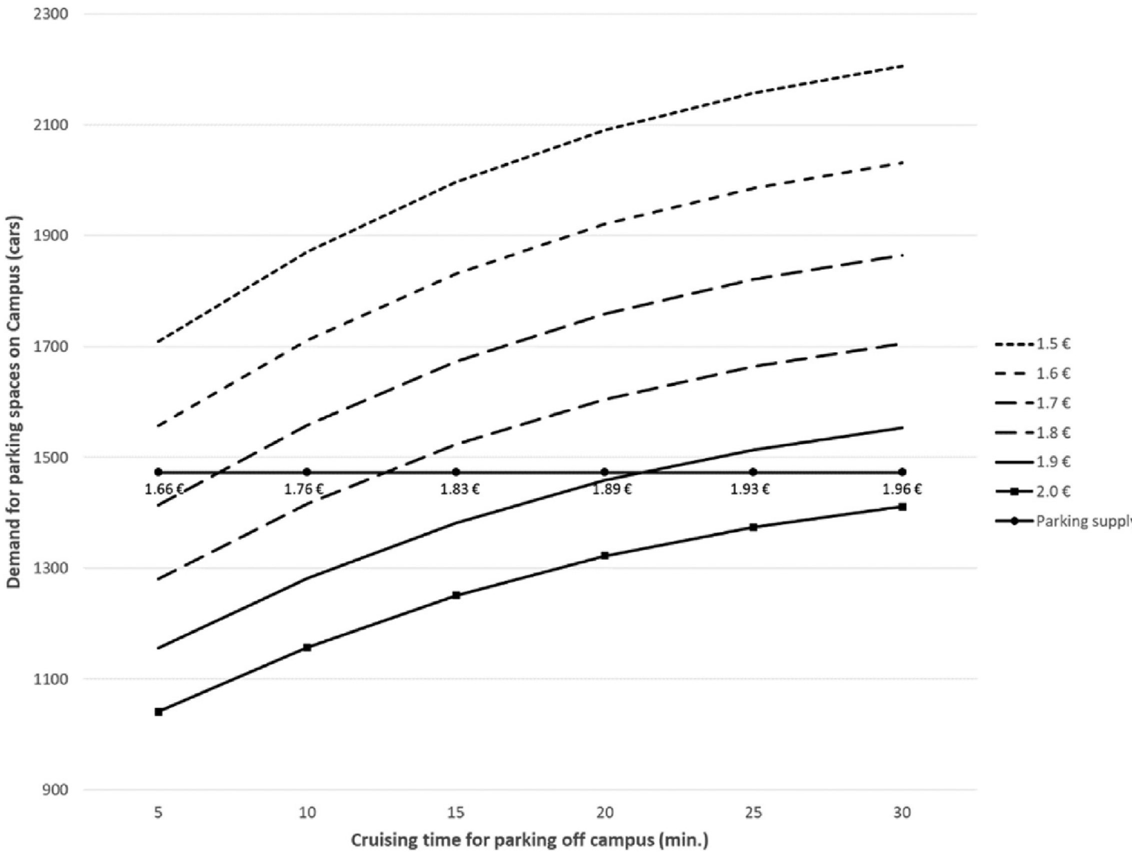

Fig. 3. Demand for parking spaces at different fare levels and cruising times for parking off campus.

of transport.

The financial income from charging for on campus parking could then be invested in other policies promoting sustainable mobility such as new bicycle infrastructure or public transport offering a free shuttle service from external car parks to the campus. Therefore, charging for on campus parking is definitely the key policy that could change the travel patterns of the users and increase the utility of using alternative transport modes. The implementation of this policy could also be eased by taking advantage of the new technologies available in smart cities (Russo et al., 2016) such as smartphone payment systems.

This methodology has been applied to modelling a whole series of parking and sustainable mobility measures aimed at improving the internal and external mobility system associated with the Las Llamas Campus of the University of Cantabria. However, this policy could be applied with few modifications to other university campuses and even to other installations which attract a great many people (hospitals, industrial estates, technology centers, etc). It is worth pointing out here that this work has also served as the basis for the preparation of a methodological Guide for creating Mobility Plans for University Campuses in Spain.

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