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Microsimulation parking choice and search model to assess dynamic pricing scenarios

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ABSTRACT

This article analyses the impact that different parking management policies may have on public roads. Policies were simulated using a new parking model based on two sub models: choice of parking place and search for parking place. The model considers curb traffic and was implemented into a traditional microsimulation traffic software. The parameters for the sub models were estimated from data collected in the city centre of Santander (Spain) and from a stated preferences survey asked to users of parking spaces. The model for testing policies was run on Aimsun simulation software creating a personalised API programmed using Python 3.7. The proposed model was able to dynamically simulate various policies based on charging for on-street parking spaces with fare updates at short time intervals of between 5 and 15 min. A sensitivity analysis was performed on different fare scenarios and considering different levels of information available to the users. As a result, this work demonstrates some benefits of dynamic fares such as reducing searching time, curb induced traffic and emissions as well as a new modal redistribution of parking choice between off-street and on-street supply. On the contrary, dynamic fares implied that users needed to spend a bit more time from their parking location to their destinations.

1. Introduction

Public administrations are aware of the problems generated by the increasing numbers of cars being used in the developed world (European Commission, 2018; OECD, 2019) having attempted to introduce a variety of policies to dissuade people from using them, with various degrees of success (Schmitz et al., 2019). The increasing number of vehicles carries with it associated problems such as congestion, pollution or an excessive use of public space for their circulation and parking (Ortúzar and Willumsen, 2011). The rates of car ownership in many developed countries is even above the 550 vehicles per 1000 inhabitants set by organisations such as the OECD (2019) as the saturation point. These rates represent a problem, not only for traffic management, but also for the management of the various parking systems used in cities. Studies on road occupation indicate that on average vehicles are parked for 90% of the total time they are in the city, which makes the use of urban land dedicated to parking very inefficient (RAC Foundation, 2012). The increased number of vehicles and the long time they are parked is even greater in the central areas of large cities. It has been estimated that if all the parking spaces in the centre of cities like Los Angeles were on the surface it would represent 81% of all the available land (Shoup, 1997). Furthermore, cruising around for free street parking generates induced traffic which can represent 30% of the overall traffic

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Table 1
Parking models.

Model	Type	Purpose	Method	Treatment of space	Search method	Software	Reference
PARK-SIM	Micro	Simulation of parking choice within a group	Discrete events	YES	Queue management	CAD	Young and Thompson (1987); Young and Weng (2005)
SUSTAPARK	Micro.	Simulation of parking choice within a group	Agents/ Cellular automata	YES	Maximisation of utility from 200 m to destination	JAVA onto ArcGIS	Spitaels and Maerivoet (2008); Steenberghen et al. (2012)
AGENT-BASED PARKING MODEL	Micro.	Simulation of on-street parking	Agents	YES	Assignment of search radius and progressive increase of radius depending on availability	MATLAB and MATSim	Waraich et al. (2012)
PARK-ANALYST	Desag.	Calculation of the time dynamic of the parking search	Analytical solution	NO	Analysis of each place until arriving at destination maximising utility and the expectancy of places at destination	–	Levy et al. (2013)
PARK-AGENT 1 y 2	Micro.	Simulation of on-street parking (version 1) and also off-street (version 2)	Agents	YES	Assigns a paid parking place in a defined time after not finding a parking place	Visual Basic/ C programmed onto ArcGIS	Benenson et al. (2008); Levy et al. (2013)

(Shoup, 2006), a figure which can even rise to almost half of all the traffic in specific areas (White, 2007). Such parking activities cause congestion and generate quite high costs in terms of time, which for commercial streets some authors quantify at 0.30 €/h per parked car (Inci et al., 2017).

To face up to these problems practically all large cities have ended up introducing, among other methods, some type of payment system for on-street parking. The economists Vickrey (1954) and Roth (1965) showed the need to charge for parking and established that the fare should be the marginal price resulting from the provision of a free space. However, this payment system has not been implemented in practice and the problem of congestion and parking occupancy (Glazer and Niskanen, 1992) has not been avoided by the fixed parking fares usually implemented in cities (Inci et al., 2017). All these factors have led to the need to implement different strategies to try to reduce the use of public roads usually discouraging the use of the private car (Groote et al., 2016). These policies include new payment systems for parking (Mingardo et al., 2015), park and ride systems (Parkhurst, 2000) or charging for the use of public roads (Leape, 2006), which has seen noteworthy growth over recent years (RPS Group Environmental Consulting Company, 2009). The integrated management of all these policies is complex and has not always resulted in the desired objective of reducing the demand of car access to urban and historic centres (Litman, 2006; RPS Group Environmental Consulting Company, 2009).

Recently, some US cities such as Seattle, San Francisco or Los Angeles have introduced dynamic parking pricing policies (Pierce and Shoup, 2013). These policies allow prices to change depending on occupancy levels, with little change required to the existing infrastructure, making their introduction more attractive because of the multiple benefits they offer. Managing pricing allows the desired occupancy ratios to be reached, coupled with quite successful reductions in cruising traffic and the number of available spaces being offered (Millard-Ball et al., 2014). Fare management can either be done by block or from space to space as in the case of Seattle. The problem with these systems is the rigidity in the price variation as periods of 1 or 2 months to up to a year are required to update the pricing.

In this research a new parking model is proposed. This model has been designed with the objective of being able to simulate dynamic pricing policies and their influence on parking demand, driver behaviour and mobility. In addition, the model is also able to simulate the level of information that users have about parking (Panja et al., 2011), considering whether they are aware of the availability and price of different parking spaces. Therefore, the present research has two main objectives: (a) to develop a combined parking choice and searching model as a tool to evaluate different policies and (b) to assess the effectiveness of introduction real time dynamic parking policies.

There is certain heterogeneity in the parking models proposed in the specialised literature given that these models were designed for different purposes. Generally, according to Levy et al. (2013) there are models which focus on the economic implications of the parking problem (Arnott and Inci, 2006; Arnott et al., 2005) which mainly measure economic parameters and their influence in parking behaviour without considering other spatial characteristics such as the distance from parking space to final destination. On the other hand, some search models consider the complete parking search process, the traffic being generated, the price or the walking distance to destination. Some choice models consider multiple parking alternatives such as off-street parking, the different blocks on the street or different fares. This methodology started to be developed by Thompson and Richardson (1998) who considered the knowledge acquired by users through experience and divided the process into stages, assigning a utility function to journey time, waiting time and fare. They proposed a simple search model applied to two streets. In 2008 the first version of PARKAGENT appeared (Benenson et al., 2008), a search model representing the spatial behaviour involved in the parking process based on a given choice model without considering fares or off-street parking. The first version of SUSTAPARK appeared the same year and defined the parking search process through cellular automata. In this case the model considers the choice of an on-street place or off-street place, as well as variables such as predefined price or occupancy. Gallo et al. (2011) proposed a new methodology to quantify fares, cruising traffic and choice of parking place based on a three stage model where the main limitation was making predictions in areas with little congestion, but considering parking fare variations within their simulation. One year later, Steenberghen et al. (2012) developed improvements to the SUSTAPARK model although some of its limitations such as the fixed search area, or time thresholds to modify the choice of parking type rather than perform a new calculation of utilities, continued to be present. More recently Wareich, Dobler and Axhausen (2012) have developed a search model that considers not only cars looking for somewhere to park but also the rest of the traffic using MAT-Sim model, that is also an agent based model and incorporates variables such as access time to destination and cost. PARKAGENT was another model that was updated by introducing improvements in the choice and possibility of choosing an off-street parking place (Levy et al., 2013). Finally, only one study has been found which uses a parking simulator to establish the price of parking places that achieves an optimal occupancy ratio (Fulman and Benenson, 2017). Table 1 compares the different parking models available.

Moreover, Hilvert et al. (2012) presents an approach based on a Multinomial Logit (MNL) model and a combined stated preference (SP) and revealed preference (RP) survey to parking place choice that includes election between on-street and off-street. This work considers route when parking lot is selected and not considers neither the possibility of park in route if an available space is present nor the adaptation of utilities for dynamic price changes and different user types. Finally, Pel and Chaniotakis (2017) model is presented as a solution to many of the problems detected in the literature. It maximises the utility of multiple spaces, not only the destination, considers the off-street parking alternative as an option rather than a discard option and it can redirect the user in the event of not finding a space at the destination. However, other factors such as real-time response to dynamic fare changes or the combination of different resident, non-resident, informed and uninformed users are not considered.

After analysing these parking models, several shortcomings are detected that have not been covered by them, such as (a) the calibration of the parameters of the utility maximization model using real data collected by a survey (SUSTAPARK). (b) None of the models analyse the utility of multiple parking spaces but only those at the destination, or at most in the same sector (SUSTAPARK) or defined radius of action (MATSIM). (c) Options such as off-street parking are not considered in any of the models analysed, except for the second version of PARKAGENT, but without considering its utility if not simply as a secondary alternative when no parking space is available on the street.

Our proposed parking model (DYNAPARK model) can simulate different policies, and user behaviour in urban areas with and without congestion. This model presents parameters calibrated for the choice model extracted from a driver survey. DYNAPARK differs from previous proposals by being an agent-based microsimulation model (Macal and North, 2006) founded on a user behaviour simulation based on random utility theory (Train, 2003). DYNAPARK can simulate the choices of each driver when choosing the type of parking and the parking space as a function of different variables such as fare, occupancy, type of parking, information available to the user, manoeuvring time, etc. as well as the parking search process involved when the initially selected parking space is not available. The model can redirect the user to a paid car park based on the dynamic calculation of utilities rather than waiting for a time limit, making it more realistic. Finally, DYNAPARK differs from other models in that it can respond in real time to dynamic changes in the fares which can be updated following different strategies.

For testing the second main objective of this research, the proposed model has been applied to a central zone of the city of Santander (Cantabria, Spain) with the aim of calibrating the model and performing different simulations to establish the consequences of various parking policies introducing dynamic fares. DYNAPARK is, therefore, a support tool for decision making in the field of parking policy which aims to improve planning based on the best available evidence.

This article will try to emphasise the advantages offered by a parking search model and the application of dynamic fare policies for the assignment of parking spaces using different methods to offer flexibility in its application to a variety of circumstances and charging policies. The following section will present the main characteristics of the DYNAPARK model, particularly with reference to the choice of parking space and search sub-models. Section 3 addresses the application of the model, the study area and the calibration of the model parameters. An analysis of different parking policies is also presented to simulate their effects on the study area. Finally, the main conclusions drawn from this work are described in the last section.

2. Methodology

The DYNAPARK model is based on two large sub-models: a parking space choice sub-model and a parking search sub-model. Both models are explained below.

2.1. Parking space choice model

The parking space choice sub-model establishes the utility of each homogenous group of available spaces for the following different types of users typically found in a standard city area.

- Residents with their own parking space: users who live in the study area and possess private parking within the area and who therefore do not use the on-street parking spaces that are the main objective of this research.
- Non-residents: this user type wants to perform some activity in the study area and therefore, need to park their vehicle, either in a private car park or in the street. These are the users that are affected by the fares. Two types of users were considered to fall within this category:

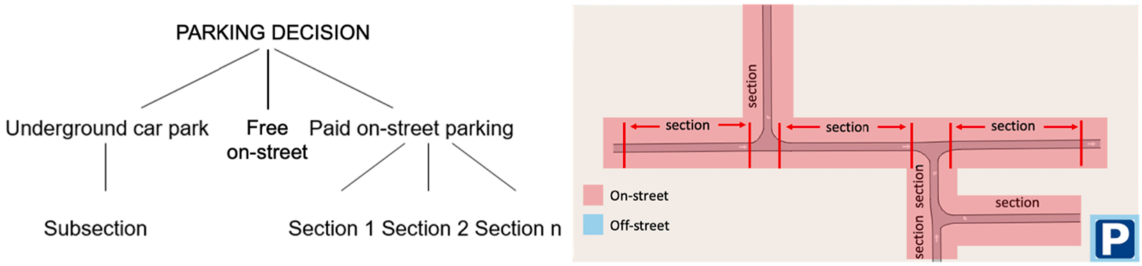


Fig. 1. Schematic showing the choice of parking type and section.

– Uninformed users: these users do not know the parking fare charged in the zone. A price for them needs to be established, which is assumed to be like the other zones in the city. The choice will therefore probably be suboptimal as it is based on limited information. This type of user learns from the situations they encounter in the search process, gaining a greater degree of information over time.
– Informed users: this user type has previous knowledge about the prices charged in each street and they use this information when choosing where to park. They also know the occupation and the free places.

- Users passing by: through traffic where the users do not stop nor have the study area as their destination.

A model also needs to be created to determine the utilities of the different types and sections of parking (a group of parking spaces which could, for example, be in a street) and also for evaluating different parking policies. Discrete choice techniques will be used for the choice of both the type of parking and the section. The first choice refers to the desired type of parking; the user can choose to park from various available types: free on-street parking, paid on-street parking or paid off-street parking. If the user decides to park on the street, they will also have to decide what specific section they want to use from those available to them.

The relationship between the parking type and section can be modelled using two procedures depending on whether they are assumed to be independent or dependent choices. The first-choice level, parking type, is given by a MNL model with different choice alternatives as the following utility functions:

$$V(Free) = \beta_0 + \beta_{TD}TD_{free} + \beta_{TB}TB_{free} + \beta_{OCU}OCU_{free} \tag{1}$$

$$V(on-street) = \beta_0 + \beta_{TD}TD_{on-street} + \beta_{TB}TB_{on-street} + \beta_{OCU}OCU_{\text{on-street}} \\ \beta_{TAR}TAR_{on-street} + \beta_{TMAX}TMAX_{on-street} \tag{2}$$

$$V(off-street) = \beta_0 + \beta_{TD}TD_{off-street} + \beta_{TB}TB_{off-street} + \beta_{OCU}OCU_{off-street} + \beta_{TAR}TAR_{off-street} \tag{3}$$

According to this specification, the choice of paid on-street parking depends on the fare charged (*TAR*), the time to final destination (*TD*), the search time (*TB*), the occupancy of the spaces (*OCU*) and the maximum length of stay allowed (*TMAX*). The choice of free parking depends on the search time (*TB*), the time to destination (*TD*) and the occupancy of the spaces (*OCU*). In the case of choosing off-street private parking (underground car park), the choice will depend on the fare charged (*TAR*), the time to final destination (*TD*), the search time (*TB*) and the occupancy of the spaces (*OCU*). All these variables are consistent with the research of Chaniotakis and Pel (2015) and with the MNL model estimated by Hilvert et al. (2012). To apply the model to cities where there is a limitation on the maximum time spent in the parking space, the model presented includes a parameter that considers this restriction.

Note that equation (2) is only valid in the case of having a single street available for parking. The existence of several alternatives forces to establish a second level of choice (Fig. 1) being necessary to redefine the utility calculation following the formulation developed below. For this reason, at the second-choice level, the parking section, the choice depends on the utility derived from parking in a particular section, expressed by the following expression, with similar parameters and variables to those presented for the choice of on-street type:

$$V(section) = \beta_{TD}TD_{section} + \beta_{TB}TB_{section} + \beta_{OCU}OCU_{section} + \\ \beta_{TAR}TAR_{section} + \beta_{TMAX}TMAX_{section} \tag{4}$$

As mentioned previously, it will also be necessary to model the behaviour of the different types of users, users that are residents and those that are non-residents. The group of residents are differentiated into those who go to a private garage and do not need to be modelled, and those that do not, as between the non-residents with information and those without. The model can assign an on-street parking space to those who have a resident's card, those people allowed to park for free as they live in the zone, and to the non-residents as well as the informed and uninformed users about where the free spaces are, and the fares charged in the different sections. For evaluate different politics, different rates are allowed in each section. The accumulated search time needs to be considered if the users are unable to find a space. Therefore, the utility of a section that represent a specific group of parking spaces between two nodes in a specific street (Fig. 1) expressed by (4) can be modified to take these factors into account:

$$V(section) = \beta_{TD}TD_{section} + \beta_{TB}(\gamma_{user}\, TB_{section} + TB_{accumulated}) + \\ \beta_{OCU}OCU_{section} + \beta_{TAR}TAR_{section} + \beta_{TMAX}TMAX_{section} \tag{5}$$

Table 2
Example of parking scenario choosing from different parking types and sections.

Section 1	Section 2	Underground
Fare: 1 €/hT. search: 5 minT. to destination: 3 minProb. space: averageT. maximum stay: 2 h	Fare: 1.5 €/hT. search: 3 minT. to destination: 1 minProb. space: averageT. maximum stay: 3 h	Fare: 2.5 €/hT. search: 0 minT. to destination: 4 minProb. space: average

Table 3
Attributes and levels specified in the SP survey design.

Alternative	Fare (€/h)	Search time (min)	Time to destination (min)	Expected occupancy (%)	Max. allowed stay (h)
Section 1	0	3	1	30	1
	1	5	3	60	2
	3	10	6	90	4
Section 2	0	3	1	30	1
	1	5	3	60	2
	3	10	6	90	4
Underground	1	0	2	20	
	2	3	4	40	
	5	5	7	60	

The introduction of the dummy parameter γ_{user} allows us to consider an expected search time equal to 0 in the case where the user is informed and knows he will find a space in that section. On the other hand, when the variables $OCU_{section}$ and $TAR_{section}$ are modified, they adopt values in real or historical network standard time and introduce variations affecting the different users, informed or not, considering their behaviour in the model.

Therefore, the choice of section depends on the fare (*TAR*), the time to destination (*TD*), the parking search time (*TB*), the occupancy of the section (*OCU*) and the maximum length of stay allowed (*TMAX*), as well as on the type of user (γ_{user}) as mentioned above.

Finally, the combined choice of the type of parking and section consists of the specification of a Hierarchical Logit (*HL*) model in which the utility of the on-street alternative depends on the maximum expected utility of the related alternatives, in other words, on the different parking possibilities available in the sections. These two connected choices can be schematized as shown in Fig. 1. In this case, the utility of parking in the street will be given by the expected maximum utility (*EMU*), or:

$$V(on-street) = \frac{1}{\lambda}EMU = \frac{1}{\lambda}ln\left\{\sum_i e[\lambda V(section_i)]\right\} \tag{6}$$

Where λ is the scaling parameter of the distribution of the error terms within the nest and *i* is the group of sections within the on-street parking alternative (or a certain subgroup of them), which may show some level of correlation.

This second type of modelling, using HL means that the different parking sections available for on-street parking can show a certain level of correlation as they can have some common characteristics in terms of their systematic utility and their random errors.

2.2. Survey design

A survey was asked to extract the required values for the parameters of the parking choice model being presented. The methodology used for designing the survey involved three large steps in accordance with those suggested by Hensher et al., (2015).

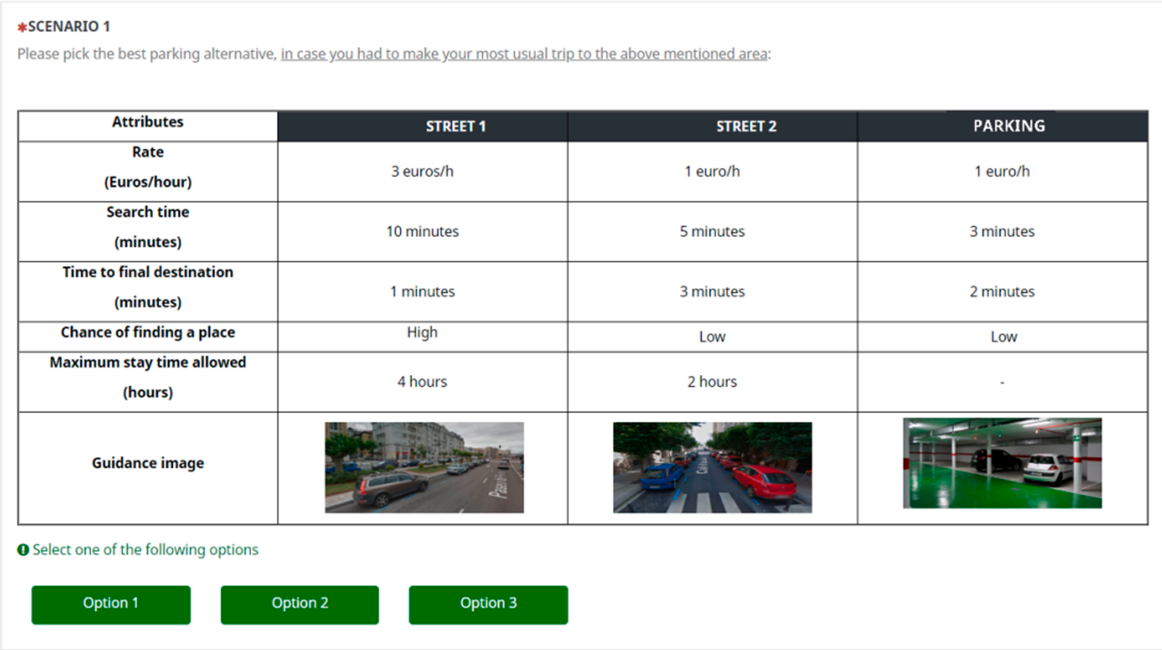
1. Definition of the model and the problem to be solved, including the identification of the attributes and alternatives.
2. Design of the experiment to be solved using the survey.
3. Design of the survey to be asked to the users which will provide the desired parameters.

2.2.1. Definition of the model

The problem to be addressed and the model to be used need to be established before designing the specific survey and questionnaire. This research needs to estimate the parameters of a choice model for parking type and section. This requires a SP survey which, given the configuration of the study area, will present three choice alternatives in each scenario: two hypothetical sections of on-street parking, along with the off-street underground car park alternative (see Table 2). Each one of the alternatives will be defined from the following attributes: (a) Parking fare (€/h); (b) Time required to find the section (min); (c) Time to get to the destination from the parking section (min); (d) Probability of finding a space: High (ocup. $<$ 40%), Average (ocup. 40%–80%) and Low (ocup. $>$ 80%); and (e) Maximum allowed length of stay in the section (hours)

2.2.2. Experimental design

The second step in the chosen methodology consists of creating the experimental design. The design of the survey levels can be consulted in Table 3. Realistic levels were chosen to conform to the actual real situation and avoid large increases in fares or times


*SCENARIO 1

Please pick the best parking alternative, in case you had to make your most usual trip to the above mentioned area:

Attributes	STREET 1	STREET 2	PARKING
Rate (Euros/hour)	3 euros/h	1 euro/h	1 euro/h
Search time (minutes)	10 minutes	5 minutes	3 minutes
Time to final destination (minutes)	1 minutes	3 minutes	2 minutes
Chance of finding a place	High	Low	Low
Maximum stay time allowed (hours)	4 hours	2 hours	-
Guidance image			

Select one of the following options

Option 1 Option 2 Option 3

Fig. 2. Example of a LimeSurvey scenario interface.

required to find a space, reach the destination or the maximum stay allowed.

The survey should establish the relative weight of the attributes in the utility function of the choice model addressing the parking type and place. Once the relevant alternatives, the attributes and the levels of the attributes have been decided, then the method used for the design can be chosen. Among the possible methods available for the design are complete factorial design, fractional factorial design, orthogonal design, and efficient design.

An experimental design is efficient when the combination of the values of the variables is the result of the application of an optimization algorithm that minimizes an indicator like D-Error related to the standard error of the estimated parameters. The application of a complete factorial design would not be recommended as it would produce so many scenarios that the interviewee would become tired of the survey and not want to continue and, given the advantages mentioned above of efficient designs, this study has opted to use efficient experimental design.

2.2.3. Design of the survey instrument

The final part of the survey design consists of implementing the questionnaire. The questionnaire is developed from the efficient experimental design, establishing the choice situations that each interviewee will have to face when asked to choose where they are going to park.

An early decision to make in the design of the questionnaire is how to register the choice of each interviewee in each scenario. The possible options are: 1) picking the preferred alternative, 2) selecting the best or worst alternative and 3) ranking all the alternatives. In this research the authors opted for the preferred alternative option as it requires less effort on the part of the interviewee, and in this choice context it can provide enough information to estimate the discrete choice models required for the parking simulator.

Another important factor in designing the questionnaire is how to collect the information. The most common methods are (Fowler, 2013; Rea and Parker, 2014): user interception survey, telephone survey, on-line survey and postal survey.

The on-line survey was chosen given the speed of digitally registering the information. Furthermore, the form has been designed in such a way that the information can be collected from users who have travelled and parked at some point in the study area as well as from users who were parked there. In the latter case, the survey would become an interception survey, although performed using digital methods (Tablet). Fig. 2 shows a scenario from the survey as it is presented to the interviewees using the online survey software interface LimeSurvey.

2.3. Design of the search model

As mentioned previously the DYNAPARK parking search model is based on agents and considers a variety of factors to assign different utilities to each of the sections. As opposed to the parking search systems referred to in Table 1, in this case numerous factors are considered for running the model.

The different simulations and runs of the model are made using the Aimsun application developed by the TSS company to provide the required base for simulating the behaviour of vehicles that travel from an origin centroid to a destination centroid along the

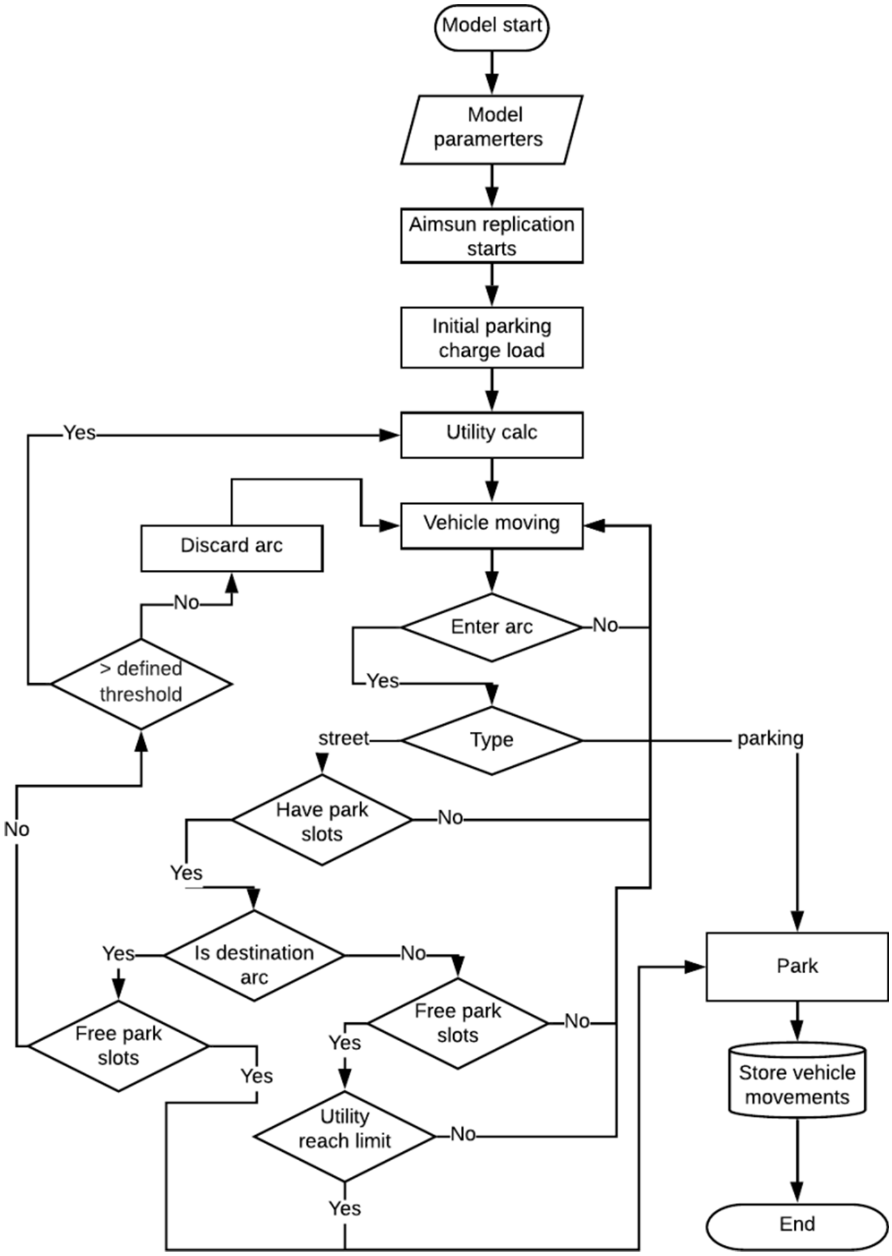


Fig. 3. Flow diagram showing the application working.

network defined in the software. The way of interacting with the vehicles through the API of this software allows the simulation to be controlled by making changes in real time to the running of the model. The Python programming language was used to make real time changes to the parameters, extract behaviour patterns and define the objectives of the model introducing all the variables to be considered because its versatility and scalability allows for direct interaction with the simulation.

The demand for the different sections used in the model was set using the method proposed by authors such as Gillen (1978), or, more recently, Weinberger and Hampshire (2016) for San Francisco, who showed that as users approached the commercial and business centres they had greater difficulty in finding somewhere to park. Therefore, the distribution of the user demand for the desired parking sections follows equation (7), according to the number of commercial premises it contains with respect to the total for the zone.

$$P_{parking_{section}} = \frac{Commercialpremises_{section}}{Commercialpremises_{zone}} \tag{7}$$

Other parameters which are present in the model, such as the length of time parked or the expected search time, are not represented

Fig. 4. The study area in central Santander.

by a unique value which could be common to all users. When these times need to be calculated, a normal distribution function is applied centred on a given time and with a typical deviation also defined as a model input parameter.

The search model works iteratively to find the best available parking section for each user by considering that, although the maximum utility is found on a certain link, maybe the user will accept inferior utilities to those desired when there is a high level of congestion.

The model is started by introducing traffic demand data which include both through traffic and traffic heading for the zone. The vehicle stopping points are set by assuming that the parking spaces are located along the entire link (section) and each vehicle stopping point is randomized along it. Once a vehicle is going to travel to the interior of the zone, a vehicle distribution pattern needs to be chosen. This is achieved by considering the number of commercial and business premises present along each of the links. The parking areas have been clustered at the different centroids and all the vehicles have been distributed proportionally to the number of businesses, given that greater activity implies greater demand (Gur and Beimborn, 1984).

The model was run for each of the vehicles in accordance with the following sequence (Fig. 3):

1. Assignment of user type: as described in Section 2 the users fall into two categories. On the one hand, informed users with knowledge about prices and available spaces along each street and this changes the calculation of the utility they will find in each of the sections as per equation (5). On the other hand, those users who have no previous knowledge and for whom the parameter γ of equation (5) takes a value of 0. The drivers without information do not know the real time pricing or occupancy of the spaces and they are assigned the medium price of the dynamic regulated city parking system for the calculation of utilities at their first parking attempt. After this first attempt, the model supposes that they know the actual occupation rates of the sections.
2. The vehicle enters the control network: each vehicle is assigned an ID which it keeps throughout its time in the area. At this point the model assigns the destination centroid following the probabilistic distribution described in (7) and the vehicle starts to travel towards its destination.
3. Calculation of utilities: the utilities of the different alternatives are calculated for on-street parking in each of the different on-street sections and then for underground parking. The vehicle chooses the centroid which maximizes utility, and it moves towards it.
4. Search for a parking space: during this phase of the model the user is found inside the network looking for a parking space. Three possible situations may occur:
   a) The user finds a free parking space whilst travelling to the chosen section: the relative utility of the free space with respect to the chosen destination is evaluated. If the convenience of the free space falls within a defined range (one of the input parameters of the model), then a parking manoeuvre begins.
   b) The user arrives at the section providing maximum utility and parks in a free space.
   c) The user reaches the parking section but cannot find a free space: the destination centroid is dynamically changed, requiring that the microsimulation model updates the new route for the vehicle. Depending on the number of previous attempts, two cases may occur:
      i. If a predefined threshold of iterations has been reached, the model performs a new calculation of utilities to decide whether to park on-street or off-street.

Table 4
Simulated scenarios using the DYNAPARK model.

	Sc. 1	Sc. 2	Sc. 3	Sc. 4	Sc.5
Apply parking model		X	X	X	X
Apply fixed fare		X		X	
Apply dynamic fare			X		X
Apply current fare		X	X		
Apply high fare				X	X

Table 5
Parameters obtained in the choice model.

Variable	Parameter		Z
Fare (€/h)	−0.49092		−11.67
Search time (min)	−0.06744		−2.80
Time to destination (min)	−0.06881		−2.53
Occupancy (%)	−0.00880		−3.17
Max. allowed t. of stay (h)	0 0.26111		4.70
Underground constant	1.33220		6.85
Street Nest	1		n/a
Log-Likelihood		−503.608	
Log-Likelihood (Null)		−632.801	
Log-Likelihood(Constants only)		−621.219	
McFadden PseudoR-squared		0.189	

ii. Otherwise, the model assigns the next section of maximum utility to the user.

5. Computing the new fare: if the model is applied to a situation of dynamic fare charging, whenever a time set by the modeller in the input parameters has passed, new parking fares depending on actual occupancy are calculated for each of the streets where the model is being applied.
6. Parking: during this phase, once the user has found a space, the vehicle is stopped for the time it takes to perform a standard parking manoeuvre and afterwards disappears from the network.

2.3.1. *Model input parameters*

The model was run using the Aimsun software API which allowed certain parameters to be introduced to enable the simulation of different policies and user behaviour to evaluate their effects on the network. The required parameters were as follows: parking manoeuvre time; minimum time parked; maximum time parked; initial occupancy; range of parking fares; range of occupancy; standard on-street fare; underground parking fare; average search time and deviation; maximum relative utility; time to update fares; and, finally, the percentage of informed users.

3. Practical application

The DYNAPARK model has been applied to evaluate different parking pricing policies in a central area of Santander, Spain (Fig. 4). This area has been chosen because the existence of different parking alternatives such as: regulated paid on-street parking, private parking and paid off-street private parking. Different scenarios have been proposed and are detailed in Table 4 by varying the fares and the application or not of dynamic pricing.

The parameters for the model were found by asking a SP survey to frequent and infrequent users of parking in the chosen area. In total were obtained 576 observations which provided the parameters presented in Table 5, estimated using maximum likelihood. The estimated model for these replies shows no significant correlation between sections so λ in equation (6) is equal to 1 and therefore the proposed model collapses and needs to be re-estimated as a MNL model. As can be seen, all the parameters are significant and have a correct sign. All the variables are significant at least at a level of confidence of 95%.

The simulations were then performed using the different scenarios proposed in Table 5. The simulation parameters defined above had to be input to run the different scenarios (Section 2.3.1). Table 7 shows the parameters for each of the scenarios.

The values chosen for each of the model input parameters were based on various criteria. Some of the input data, such as maximum allowed time of stay and the standard fare, were taken from the municipal parking regulations (Ayuntamiento de Santander, 2014). Other parameters, like the price per hour of underground parking, were available from these businesses and are public knowledge. On the other hand, the increasing number of sources of online information have provided further data, for example, the average vehicle parking time was found from an analysis in the Open data of Santander website (Ayuntamiento de Santander, 2021). Fig. 5 shows the network of active sensors available in the study area which detect whether a parking space is occupied or free. With these data, the profile of vehicle arrivals and departures at the parking spaces can be obtained, after evaluation of 5383 parking manoeuvres in the study area with a mean stay of 65.76 min and a deviation of 25.59. A normal distribution with this data has been used as input for the

Fig. 5. Parking sensors present in the study area.

Table 6
Model input parameters for the different scenarios.

Variable	Units	Scenario 1	Scenario 2 (Scenario 4)	Scenario 3 (Scenario 5)
Time parked	sec.	Model not applied, each user moves to their final centroid and finds a parking space	22.3	22.3
Minimum time parked	sec.		300	300
Maximum allowed stay time	sec.		7200	7200
Initial occupancy	%		95	95
Fare range for on-street parking	€/h		When the current fare is applied, dynamic fares are not required	[0.5,1,1.75] ([1,2,3.5])
On-street occupancy range	%			[60,80,100]
Generic on-street parking fare	€/h		0.75 (1.45)	1 (2)
Off-street parking fare	€/h		1.60 (2.75)	1.60 (2.75)
Average search time	sec.		240	240
Search time deviation	sec.		120	120
Minimum relative utility	%		90	90
Fare updating time	min.		15	15
Informed users	%		Not applicable	50

model. In addition, the number of users residing in the area has been defined thanks to the information provided by the parking meter operator and these spaces have been blocked once the vehicle is parked. Other data mentioned in Section 2.3.1 referring to the average search time (Antolín, 2019; Belloche, 2015), has been taken from the bibliographic review.

The input data for the fare and occupancy ranges in the scenarios with dynamic fares charging was based on experiences performed in other cities (Pierce and Shoup, 2013) and with the analysis of the SP survey carried out introducing the variation in prices as a function of occupancy ranges instead of using a fixed price. The time taken to update the prices has been fixed in such a way that, considering the search time, a driver will not be affected by changing prices once a parking section has been chosen. Finally, the percentage of informed users is defined by the average number of users who employ applications for payment of on-street parking fares (de Unamuno, 2020). Further scenarios were simulated using the values chosen for the various parameters and using duplicated fares to simulate their effects (Scenarios 4 and 5). Table 6 resumes all model input parameters.

4. Results

After defining the parameters for each of the 5 comparison scenarios, the model was run for one hour using traffic data based on real measurements taken from traffic counters located in the city. Rush hour traffic demand for using regulated parking, from 11:00 to 12:00 was used for a working day, with 300 s of warm up to set an initial demand in the system. Each scenario had 15 replications to obtain results that faithfully represent reality. The number of 15 replications is not a random choice, multiple studies for traffic microsimulation determines that number above 10 simulations seem to be sufficient for minimize variance error (Burghout, 2004; Fries et al., 2017; Lu et al., 2014). Also, variance evolution of the main parameters was studied and help to determine the optimum number of replications between 10 and 15 such the literature and the Aimsun manual propose. The average run time for each of the 15 simulations are shown in Table 7 and were obtained from calculations made on a machine with an i5 processor and 8gb of RAM.

The longer simulation time is clearly seen after introducing user behaviour into the choice and search for parking from scenario 1 to

Table 7
Scenario run time in seconds.

Scenario 1	Scenarios 2 and 4	Scenarios 3 and 5
376	522	562

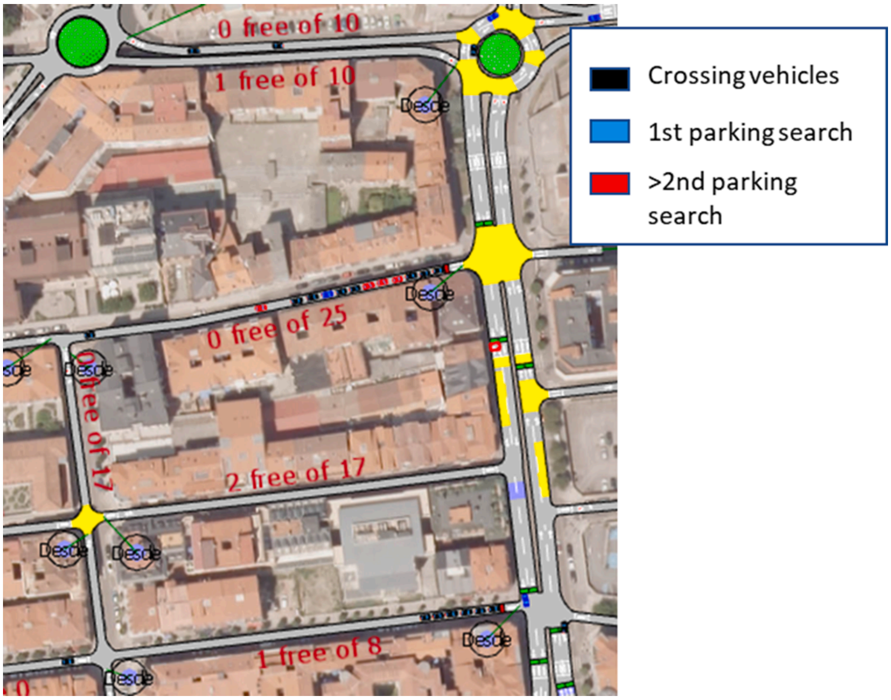


Fig. 6. Image of the search model working.

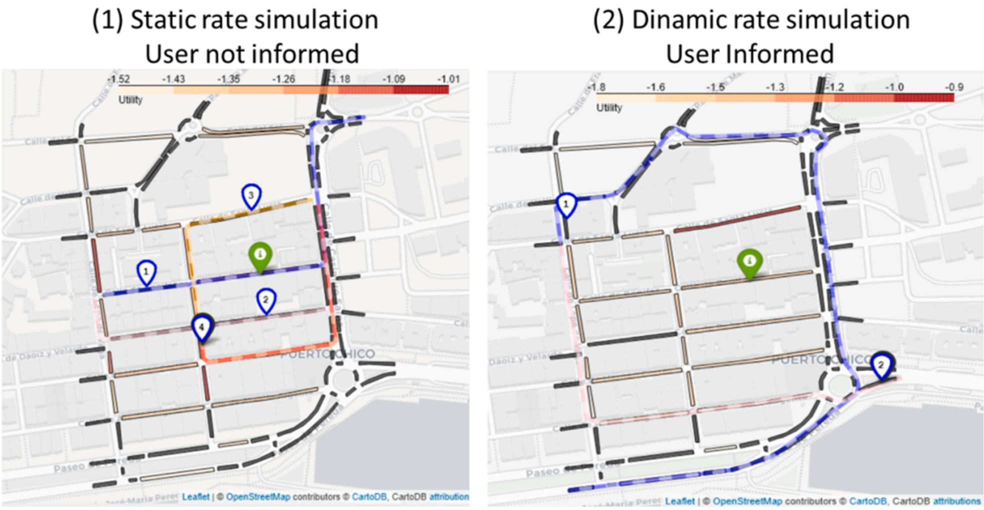


Fig. 7. Comparison between routes followed by real and simulated vehicles.

2 and to 3. These increases were 49% for the worst of the studied cases given that the processing time per vehicle is approximately 0.08 s. This slows down the normal functioning time of the simulation software but does provide richer results about user behaviour. These times do not show excessively significant increases compared to the benefits from the data provided by the simulation. In comparison, other authors like Tan et al. (2005) found increased run times of 600% when the demand for parking increased by 400%. In the case of

Table 8
Results of the simulations for various indicators.

Indicator	Units	Sc. 1	Sc. 2	Sc. 3	Sc. 4	Sc. 5
Average queue - Car	veh	8.64	28.96	24.75	36.06	14.35
Average queue - Car- park	veh	2.71	24.57	20.67	32.74	8.81
Fuel consumption - Car	l	180.2	201.32	203.11	208.68	191.21
Fuel consumption - Car- park	l	24.43	91.24	78.56	97.27	56.29
Density - All	veh/km	24.19	27.39	28.33	28.62	26.33
Density - Car	veh/km	4.18	7.18	6.60	8.20	5.08
Density - Car- park	veh/km	20.02	20.22	21.74	20.43	21.26
Total travel distance - All	km	1023.7	1143.45	1140.94	1118.14	1126.55
Total travel distance - Car	km	922.97	885.17	911.44	877.33	926.03
Total travel distance - Car- park	km	100.73	258.28	229.5	240.81	200.52
Emissions - Car - CO2	g	57315.73	65401.47	64851.58	68396.36	60877.09
Emissions - Car - PM	g	18.15	19.60	19.68	19.64	18.81
Emissions - Car- park - CO2	g	12471.3	34854.07	29870.2	37127.71	22352.2
Emissions - Car- park - PM	g	4.42	10.13	8.49	10.20	7.39
Delay time - Car	sec/veh	25.89	57.66	52.5	68.5	35.85
Delay time - Car- park	sec/veh	19.11	250.46	226.4	275.25	101.64
Travel time - Car	sec/veh	15.03	23.07	22.67	25.9	17.92
Travel time - Car- park	sec/veh	80.40	309.00	215.40	380.40	137.40

Table 9
Comparison of results between scenarios 2/3 and 4/5.

Parameter	Var. 2/3 (%)	Var. 4/5 (%)
Average queue - Car	−14.54	−60.21
Fuel consumption - All	−3.72	−19.10
Density - All	3.43	−8.00
Total travel distance - All	−0.22	0.75
Delay time - Car	−8.95	−47.66
Delay time - Car- park	−9.61	−63.07
Delay time - All	−9.28	−55.37
Travel time - All	−16.01	−47.35

the DYNAPARK model, the demand for vehicles, considering those that change their destination after not finding a place to park, grows by 812 vehicles inside the network to an average, in scenario 2, of 2767 vehicles, representing an increase of 240%. This figure corresponds to an increased run time of 360%, thereby improving on the expected calculation times for the results compared to the previously mentioned work.

Figs. 6 and 7 show the results of running the model with the simulation software. As this is an approach that does not exist in the base microsimulation model, a system of visualization has been created for the different types of vehicle and available parking spaces. The visualization that was created (Fig. 6) shows 3 types of users on the network, those who are just passing through the zone, those who have newly arrived on the network and are looking for a parking space for the first time and those who are generating traffic related with looking for a parking space. This visualization provides a visual reference of the effect of the traffic being generated by searching for parking and their influence on the network. Fig. 7 shows an analysis of the routes followed by drivers searching for parking one followed by an informed driver and other simulated for an uninformed driver. This information allows the workings of the model to be finely tuned by checking several of the results. The simulated uninformed drivers followed patterns of movement which were similar to those followed in reality according to survey responses, driving around the final destination and trying to park as close as possible (green point in Fig. 7.1). The informed users parked in places that were further away from their final destination, the fare being more important than distance and a greater percentage of them go to private car parks. The image clearly shows the reduced amount of movement of these drivers in the zone.

The results were compared numerically by analysing various output parameters from the microsimulations such as: fuel use, average queue generated, vehicle density, total distance travelled by the vehicles, flow, journey time, vehicles on the network, velocities and emissions generated, all are parameters which provide us with a specific view to compare the scenarios. The emissions of pollutants were compared using the model described in the work of Lizasoain-Arteaga et al. (2020). The results obtained for each of these indicators are shown in Table 8 where some of the results are disaggregated for the cars in transit and the cars that have parked, identified as “park”.

Two expected effects were produced. On the one hand, scenario 1 shows some of the theoretically more beneficial results in all the extracted factors. However, this scenario deliberately excluded traffic searching for somewhere to park, which makes the results unrealistic, but it does demonstrate the influence of the traffic generated by looking for somewhere to park (Shoup, 2006), as shown by the increases in the indicators for scenarios 2, 3, 4 and 5 compared with scenario 1. Comparing the results of the different scenarios with those provided by scenario 1 shows how some factors like the length of time cars are on the network increases significantly by up

Table 10
Results of different indicators in the scenarios with users who have parked (The percentage variation with respect to Scenario 2 is given in brackets).

Parameter	Sc. 2	Sc. 3			Sc. 4	Sc. 5		
User type	Grouped	Informed	Uninformed	Grouped	Grouped	Informed	Uninformed	Grouped
Average distance travelled	1018.42	761.92 (-25.19)	865.75 (-14.99)	813.84 (-20.09)	1023.77 (0.53)	662.9 (-34.91)	747.16 (-26.64)	705.03 (-30.77)
Average distance to destination (m)	138.6	180.39 (30.15)	164.83 (18.92)	172.61 (24.54)	138.91 (0.22)	182.14 (31.41)	163.43 (17.91)	172.78 (24.66)
Average attempts to park	2.98	1.38 (-53.69)	1.72 (-42.28)	1.55 (-47.99)	3.02 (1.34)	1.04 (-65.1)	1.36 (-54.36)	1.2 (-59.73)
Average search time (min)	479.8	356.11 (-25.78)	395.78 (-17.51)	375.95 (-21.64)	595.18 (24.05)	190.96 (-60.2)	218.15 (-54.53)	204.56 (-57.37)
Users of off-street parking (%)	24.62	29.78 (20.96)	33.47 (35.95)	31.63 (28.47)	23.78 (-3.41)	32.43 (31.72)	36.85 (49.68)	34.64 (40.7)
Users who park in a section that is not that of maximum utility (%)	44.84	17.57 (-60.82)	22.25 (-50.38)	19.91 (-55.6)	44.84 (0)	17.38 (-61.24)	23.29 (-48.06)	20.34 (-54.64)

to 224%. Clearly an increased number of vehicles will result in a relative rise in fuel consumption, estimated at around 69%. These results show, therefore, the benefits of adding an extra layer of microsimulation of vehicles in cities to consider all the manoeuvres carried out by drivers trying to park and also of simulating in a realistic way different policies and parking scenarios. This aspect supports research being done on the influence of cruising traffic on general mobility in urban areas.

Once the influence of the parking search itineraries and parking manoeuvres has been demonstrated in the simulations, the results of applying a dynamic charging system can be analysed and compared with a traditional charging fare system by comparing scenarios 2 (actual fare) and 3 on the one hand and scenarios 4 and 5 with higher charges on the other. Table 9 contains comparison between the output variables from the simulation after applying the dynamic fare charging system. The results obtained from scenario 3 are compared with those from scenario 2, and similarly those from scenario 4 are compared with the results from scenario 5 with the higher charges, where the differences are even greater in terms of policy differentiation. All the studied indicators show improvements in the data when dynamic fare is applied and even more in the maximum fare (scenario 5).

The differences in average queuing and the clear fall in fuel consumption between the scenarios are striking, particularly when the policy implies a price rise. The presence of informed users within the dynamic scenarios facilitates a better distribution of the parking spaces which, in turn, favours the observed reductions. The introduction of dynamic fare charging results in two phenomena, reduced fuel consumption and consequently reduced emissions. Quantifying the savings made in this zone in the most significant case, the drop between scenarios 4 and 5 represents about 70 fewer litres of fuel being consumed per hour, a saving of around 0.20€ for each user and parking space in the analysed case, resulting from the introduction of dynamic fare charging and the increase in fees. The model also shows that because of the variability in charges drivers are parking further from their destination, increasing their access times to their desired activity. Between dynamic scenario 3 and real scenario 2 there is a difference of 35 m in the access distances to destination, 172.61 m for the dynamic scenario and 138.6 m for the actual situation. If the fares are increased, this distance goes from an average distance to access final destination of 138.91 m in scenario 4, compared with 172.78 m in scenario 5. The further distance is due to the increased weight the users place on parking in cheaper or free places and the rise of off-street parking use, as the dynamic fare charging somewhat penalizes being closer to their final destination, nevertheless the overall results are very positive for the rest of the variables.

Applying the API of the microsimulation software and the Python programming language to the 15 iterations for each of the scenarios provided comparative results for drivers who parked in scenarios 2/3 and 4/5 as a function of user type, as shown in Table 10. Note that scenarios 2 and 5 do not contemplate any differentiation between informed users and uninformed users so the results have been grouped together.

The indicators clearly show the difference between types of users within the same scenario and between the fare policy. The average distance travelled by each user falls between the dynamic scenarios and those with static fare charging. Slightly related to the distance travelled, we can analyse the average number of attempts a user makes to park in a street or square. This indicator falls significantly in the group of users with dynamic rates to nearest 1, in the case of the cheapest dynamic fare charge for informed users, who mostly drive directly to available spaces or private car parks, the use of which also reflects a clear variation. Their use rises to rates of 35% for informed users in scenario 5, or around 32% in the case of lower fares as found in scenario 3, 8 more points than static fares. On the other hand, users in the case of static rates decide to park later than those on dynamic rates ("static" users coming to the car park make an average of 4 to 5 attempts to park on the street before going, compared to 2 or 3 in the case of dynamic fares), which leads to an increase in the distribution of the type of parking in the case of dynamic rates. Therefore, a high rejection of paid off-street parking is found because of the high cost involved, whereas with the dynamic fares informed and uninformed users make greater use of the service. Another of the related indicators is the search time, which is found to be around 8–10 min in the case of the system without dynamic fare charging, a similar time to that found in the survey performed by Antolin (2019). Note that the increase in the informed users' distance to destination which is partly due to their use of off-street private parking and travelling to parking areas that are further away but cheaper. Therefore, a high rejection of paid off-street parking is found because of the high cost involved, whereas the informed users make greater use of the service.

It is also important to analyse the data and how it evolves throughout the simulation period. In this case there are two basic factors that explain the importance of introducing the new proposed methodologies. On the one hand, the parking model, as shown by the

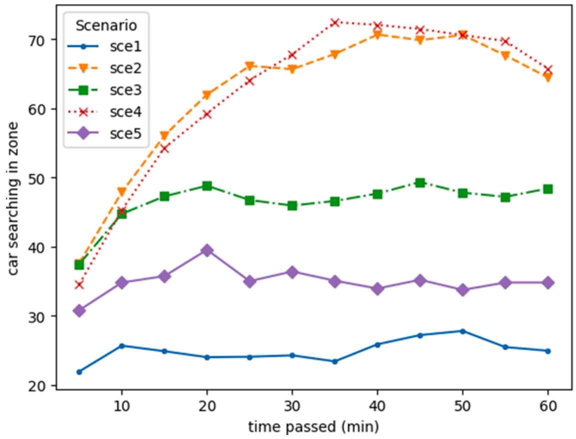


Fig. 8. Sum of vehicles inside the zone searching parking.

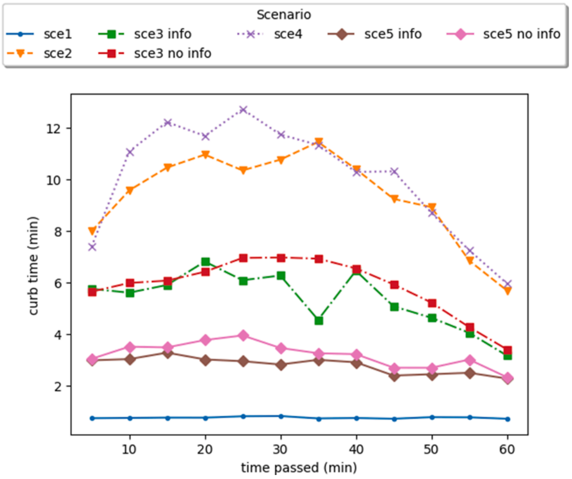


Fig. 9. Evolution of search time during simulation.

graph of vehicles trying to park inside the zone (Fig. 8), reveals the clear difference between the evaluated scenarios. On the other hand, the dynamic fare charging has found differences of up to 40 vehicles inside the zone while running the model. This latter factor regarding the policies evaluated is due to the lower accumulation of users during the dynamic scenarios, when there is also greater convergence between the fares charged for parking on and off street, which explains the increase in users choosing to park in underground car parks. This difference is also defined by the change in the queues that are generated, as shown at the beginning of Table 9. Moreover, an analysis of the data considering the emission of pollutants was performed. The changes in the presence of four of the observed pollutants have been seen to follow similar trends, as shows in Table 8. One of the main pollutants found to be a result of traffic circulation, NOx (Beevers et al., 2012; Kurtenbach et al., 2012), is seen to follow a similar trend in scenarios without dynamic pricing, where the emissions are an average of 50% greater than those scenarios with dynamic pricing. (SEE Fig. 9.)

Comparing the results by different types of users, which is the case of the comparison of search times (Fig. 8), once again reveals the ample differences between the main scenarios in favour to apply dynamic pricing strategies. Remarkable differences are shown between dynamic and not dynamic rates specially, one more time, when rates are increased. Mean time in scenario 5 and scenario 2 and 4 diverges in approximately 8–10 min on average. Moreover, in this case user behaviour for standard fares is similar and searching times with higher fares are the same. The average search time generated by the model can be seen to approach the search times found by authors such as Arnott et al. (2005), of around 7.8 min when standard tariffication policies are applied. More recent studies like Chaniotakis and Pel (2015) also obtain this range parking times in their surveys. Furthermore, the search time data for informed users in dynamic pricing systems is a similar that on the predictions shown in the work of Caicedo et al. (2012), which found that informed users had a 10% advantage over uninformed users.

After having applied the policies evaluated in scenarios 2–5, a positive trend in the occupancy rates have been observed with dynamic fares. In both cases, during the simulation there are about 6 spaces available in the total area. The most positive aspect observed refers to the redistribution of user behaviour. With the increase in the use of off-street parking (growth of around 8% with

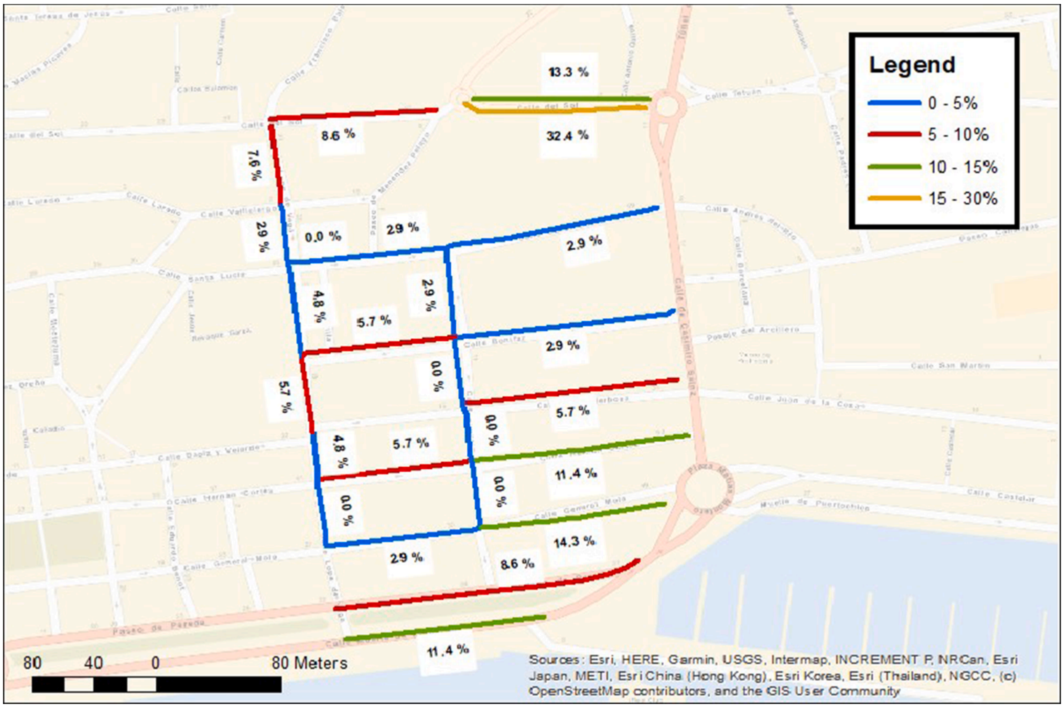


Fig. 10. Variation of the final fare charged with the initial fare charged in each section.

dynamic fares and higher prices), with simulated occupancy rates, variables such as density, search time and total traffic in the area studied are improved.

The final analysis was performed on the dynamic pricing data (scenario 5) to spatially represent 3 factors: the percentage changes in the fare charged in each section, the average fare charged in each section and the variation between the initial and final fare charged. These indicators can be used to check how the zones with greater demand have more traffic. The first factor, relative to the number of times the fare has changed in each section with respect to the total number of possible changes (75), show that the outer sections have changed fare the most during the simulation. This high variability explains that the average fare is also the most economical and so the variation between the initial price of 3.50€ and the final price will be the greatest (Fig. 10). On the other hand, the sections with the most demand, coinciding with the highest number of iterations, present a more constant fare with minimal variations in the prices being charged. In this case maintaining the highest fare of the 75 possible without changing it throughout the running of the model.

5. Conclusions

This research has presented an agent based scalable parking choice and search model with the main objective of evaluating the introduction of real time dynamic fares in on-street parking. For this purpose, a simulation tool has been written in the Aimsun model using python programming language and introducing curb parking into a traditional microsimulation model. This has allowed us to take advantage of all the characteristics of this kind of tool to evaluate different parking scenarios. Furthermore, the model has been applied to a specific study area to simulate on-street parking scenarios with and without real time occupancy using dynamic pricing.

The main conclusions of the work could be resumed in these main aspects: (a) The influence of curb traffic need to be considered when a traffic microsimulation model is implemented. Traffic density has been shown to increase by around 50%, as reflected by White (2007) in their study of New York City, a fact that reveals the need to simulate this kind of traffic to obtain realistic estimations. (b) The benefits of applying dynamic fares in parking zones are significant in terms of search times, attempts to park and fuel consumption. (c) Once dynamic fares were applied, users are penalized in terms of distance to destination and higher cost of paying for parking. (d) Parking mode distribution changed when dynamic fares were applied. Off-street parking choice rate increased up to 8 percentual points.

Other aspects observed in this study are about users who are informed about pricing and occupancy rates and have been introduced into the network and their behaviour has been modelled using a space utility parameter in the choice model. This analysis has found some positive results for the introduction of policies which provide users with greater information and has verified predictions made by previous research (Panja et al., 2011). The results obtained show significant improvements in search time, with reductions of between 60% and 80% from the introduction of dynamic pricing. These new fares have also resulted in lower occupancy rates after only one hour of simulation.

One of the possible challenges observed in the research could be to reach the 85% occupancy level recommended in the literature as an important level to improve overall traffic (Pierce and Shoup, 2013; Shoup, 2006). Instead, with the evaluated policies, dynamic pricing achieves a persistent number of free spaces that is sufficient to reallocate some users to off-street parking options and significantly improve traffic in the area by decreasing the number of cars looking for parking, the density of cars or the search time needed.

The development of this model and the application of dynamic pricing opens a whole new range of research possibilities within this field to detect the optimal parking fares and to study, in the future, the influence of new forms of mobility as could be generated by the rise of autonomous vehicles and their abilities to self-park.

CRediT authorship contribution statement

Andrés Rodríguez: Conceptualization, Software, Validation, Investigation, Data curation, Writing – review & editing. **Rubén Cordera:** Conceptualization, Validation, Investigation, Writing – review & editing, Supervision. **Borja Alonso:** Conceptualization, Validation, Writing – review & editing. **Luigi dell'Olio:** Formal analysis, Writing – review & editing, Funding acquisition. **Juan Benavente:** Software, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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