On-street parking search time modelling and validation with survey-based data

Sylvain Belloche a*

aCerema, 25 Avenue François Mitterrand CS 92803, Bron cedex 69674, France

Abstract

Multimodal journey planners tend to develop in cities so as to help a traveller to choose the most appropriate mode or modal combination according to the foreseen journey. However, multimodal journey planners do seldom take into account the time needed to park a car whereas it includes waiting and transfer times for public transport. This results in an underestimation of car travel time favouring this mode when compared to others such as public transport. In literature, car parking is mostly seen in a strategic point of view, dealing with the impacts assessment of parking policies. There is little knowledge about modelling the user's behaviour and the time needed to park a car. Axhausen et al. (1994) have experimented modelling off-street parking search time in Frankfurt. The model appears robust, but it has not been experimented for on-street parking.

Therefore, the focus of this paper is on modelling on-street parking search time. The modelling starts from Axhausen's proposal for off-street parking, but specificities of on-street parking allow for taking into account several models to estimate on-street parking search time. These models are then confronted to a survey done in several districts of Lyon. The results of this confrontation give interesting conclusions about on-street parking search time modelling, validation and further research needs in order to improve the model robustness.

1. Introduction and literature review

Several modes of transportation are available in a city, enabling a traveller to choose one or a combination of several of them to achieve a journey. In order to help these travellers in their choice, multimodal journey planners...
have been developed during the last past years. These planners often give as a result to a user's request the time needed to the traveller to achieve the foreseen journey, and the mode or the modal combination that is to be considered. However, if a journey planner does take into account transfer times or waiting time for public transport, it seldom takes into account the time needed to park a car. The main reason for that is the little knowledge about the car parking issue and the lack of models that give an accurate estimation of parking search time, especially when considering on-street car parking. However, there is evidence that the car parking search time is far from being inconsiderable: a survey in a few districts in three French cities shows that the average on-street car parking search time is often higher than several minutes, e.g. 10 minutes in the Commerce district in Paris (Gantelet & Lefauconnier, 2006). Moreover, the literature review of twentieth-century cruising for parking studies (Shoup, 2006) indicates that the average searching time goes from 3.5 to 13.9 minutes. Therefore, this parking search time may influence the journey planner result, and consequently the traveller's choice when considering the modal alternatives to achieve a journey.

If car parking search time has to be taken into account so as not to favour the car in comparison with other modes, few models dealing with on-street car parking search time have been suggested in the literature, and even fewer have been validated thanks to on-field data. Indeed, the car parking search time is the result of individual experiments and therefore depends either on individual strategies or on parking-related variables. As for individual strategies, Polak & Axhausen (1990) have classified them in seven categories, with five of them dealing with on-street parking. The strategy in which drivers are supposed to circle around their destination to find a vacant on-street space is often admitted to be the most used strategy when on-street parking is full (Spitaels & Maerivoet, 2008), and the longer the driver searches, the greater the radius of the circle goes (Gantelet & Lefauconnier, 2006). Other strategies, such as looking for an on-street space next to the destination before going to an off-street facility or choosing illegal parking are other strategies in use (Polak & Axhausen, 1990). The driver's knowledge of the district, the destination and the trip purpose (Spitaels & Maerivoet, 2008) (Hualiang et al, 2002) also have an influence on the on-street parking strategy and search time.

On-street parking search time may also depend on parking-related variables, such as the occupancy ratio, the parking capacity (i.e. the number of parking spaces in the vicinity of the destination), the turnover rate and the place fee (Spitaels & Maerivoet, 2008). As suggested by Polak & Axhausen (1990) but also by Hualiang et al (2002), these variables are dynamic, depending on the time and the day of arrival of a driver, and therefore quite difficult to measure in practice (Spitaels & Maerivoet, 2008). Other parameters may influence the search time, such as traffic conditions (Polak & Axhausen, 1990), but a few studies show that the average search speed is nearly constant at about 10 to 12 km/h (Benenson et al, 2008) (Levy et al, 2012).

On-street parking space search also differ from off-street parking space search in at least two ways. First, and even if a few experiments have recently been carried out, there is seldom information given to drivers about vacant spaces in the street: drivers have therefore to find a vacant space by themselves quite always, and according to Hualiang et al (2002), this lack of information influences significantly the parking search time. Second, illegal parking is to be considered since it is noticed in practice in surveys (Gantelet & Lefauconnier, 2006) (Benenson et al, 2008) and considered as a strategy (Bifulco, 1993), especially for short stays (Spitaels & Maerivoet, 2008).

Models in literature often simplify these differences and specificities. Axhausen et al (1994) have introduced a very simple model that gives the search time function for off-street parking: see equation (1) below, where \( t \) is the average search time experienced by drivers, \( a \) is a structural parameter, \( \text{Occ} \) is the estimated occupancy of the parking facility and \( K \) is the total capacity of the facility. This model can be easily transposed to on-street parking since it only considers the occupancy ratio and a structural parameter \( a \).

\[
t = \frac{a}{1 - \frac{\text{Occ}}{K}}
\]

The model has been confronted to on-field data in Frankfurt, but only for an off-street parking facility (Axhausen et al, 1994).
If the occupancy ratio $T_{Occ}$ is defined by the estimated occupancy divided by the total capacity, equation (1) becomes equation (1’):

$$t = \frac{\alpha}{1 - T_{Occ}}$$  \hspace{1cm} (1’)

Bifulco (2005) introduced a similar model, but the occupancy ratio is seen as a time-dependent variable.

Other models are based on the assumption that vacant spaces are rare and can be compared to random events: therefore, in a probabilistic analysis, the negative exponential law seems a good approximation of the search time distribution (May & Turvey, 1985) (Arnott & Rowse, 1999). This exponential distribution has been confronted to survey results in London with quite good results. However, the survey was only based on 48 individual experiments, thus limiting the model validation. Another search time function has been introduced by Tong et al (2004): this function links the search time to the power of 4 of the ratio of the effective total parking time with the available total parking time for defined spaces to, but no explanation about this power of 4 is given in the paper.

Based on this literature review, the paper presents the different models that may be valid to deliver an accurate on-street parking search time. In order to assess the models validity, a survey has been carried out in several districts in Lyon. The characteristics and the methodology of this survey are introduced afterwards. The results of the confrontation between survey data and the models results are then presented. In conclusion, the paper summarises the main results and discusses about their limits and future possible work.

2. Modelling on-street parking search time

The few models presented in the literature seem first coherent, except for the unexplained model using the power of 4 (Tong et al, 2004). However, models have not been validated nor calibrated with on-street parking search time data, apart from the model using the exponential law for the search time distribution. However the validation was carried out with very limited survey results. Axhausen et al (1994) formulation has the main advantage of using only one variable, the occupancy ratio, which is not too difficult to measure on field nor to determine for on-street parking. The same goes for Bifulco’s. For the negative exponential law, the on-street parking search time is a function of the probability of finding a vacant space. Therefore, the on-street parking search time is also directly linked to the occupancy ratio in this formulation. An explicit formulation between the on-street parking search time and the occupancy ratio is given below (2).

$$t = \alpha e^{-\beta T_{Occ}}$$  \hspace{1cm} (2)

where $t$ is the average search time experienced by drivers, $\alpha$ and $\beta$ are two structural parameters and $T_{Occ}$ is the occupancy ratio in the district.

However, the occupancy ratio does not take into account the illegal parking strategy which is specific to on-street parking. In order to take a better consideration of the parking demand in a district, illegally parked vehicles have to be added to the estimated occupancy. Hence, another variable, the parking congestion ratio $T_{cong}$ may be used instead of the occupancy ratio. This congestion ratio is defined as the number of all parked vehicles (including illegal parked cars) in a district divided by the total parking capacity. Equation (3) gives the congestion ratio with $Occ$ is the occupancy in the district (legally parked vehicles), $I$ the number of illegally parked vehicles in the district and $K$ the total space capacity in the district:

$$T_{cong} = \frac{Occ + I}{K}$$  \hspace{1cm} (3)
Unlike the occupancy ratio, the congestion ratio may exceed 100%. If so, the number of parked vehicles exceeds the total number of legal spaces. Axhausen et al formulation is no longer valid because of the asymptote for $\text{Occ} = K$, i.e. for an occupancy ratio of 100%. In order to solve this problem, another parameter is included in Axhausen et al formulation.

Axhausen et al formulation becomes equation (4), and the exponential formulation becomes equation (5) below:

$$t = \frac{\alpha}{\beta - T_{\text{Cong}}}$$

$$t = \alpha e^{-\beta T_{\text{Cong}}}$$

Hence, we have four potential explicative models described by their own on-street parking search time function. Table 1 sums up the model names and associated formulations.

<table>
<thead>
<tr>
<th>Model name</th>
<th>Formulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Axhausen</td>
<td>Equation (1')</td>
</tr>
<tr>
<td>Axhausen-congestion</td>
<td>Equation (4)</td>
</tr>
<tr>
<td>Exponential</td>
<td>Equation (2)</td>
</tr>
<tr>
<td>Exponential-congestion</td>
<td>Equation (5)</td>
</tr>
</tbody>
</table>

3. Survey in Lyon: methodology and results

3.1. Survey methodology

In order to validate the different formulations above, a survey has been led in Lyon in 2008.

The methodology of the survey follows the French national guidelines for on-street parking search time surveys, which is close to park-and-visit surveys (May and Turvey, 1985): a car is driven to a chosen address of a district and the time needed to find a vacant space from this address is then recorded. This operation is done several times so as to get an average search time. As indicated by Polak and Axhausen (1990), this approach provides good estimates of the search time distribution. However, there are two main drawbacks to this methodology: first, since there are different on-street parking search strategies, the driver in charge of the experiment may not be representative of the population of on-street searchers. Second, a cut-off time is almost always introduced so that the survey does not take too long. In the survey done in Lyon, the cut-off for searching is 20 minutes, 5 minutes more than in the survey done in London. Beyond that time, the driver stops searching and the search time is said to be equal to 20 minutes. The survey has been led in 10 districts in Lyon, and for each district, 10 periods have been surveyed. 923 individual measures of the on-street parking search time have hence been recorded, leading after data qualification to 896 usable results.

Figure 1 below gives the 10 surveyed districts and their localisation within Lyon city. Figure 2 gives the surveyed area for district 1. In this area, there are 310 on-street parking spaces.
Fig. 1. Localisation of the Lyon 10 surveyed districts. The city limits are represented in yellow.

Fig. 2. Area surveyed for district 1. The departure point is where the driver starts searching for a vacant space within the district.
3.2. Survey results

For each measure, the space location, the space payment mode (free, metered or mixed), the parking time and the traveled distance to find a vacant space have been noted. These observations have been used to determine the search time and the search speed. As for the search speed, the coefficient of determination of the linear relation between the search time and the traveled distance is 0.73 \((n=896)\). The search speed value is 9.87 km/h. This value is consistent with literature findings.

The occupancy and congestion ratios have been measured by on-field persons and updates have been provided every hour.

Table 2 below gives the surveyed districts, the minimum and the maximum occupancy and congestion ratios and gives the average and the maximum search time. Except for district 5, the minimum search time is always equal to zero.

Since these individual measurements reflect one random selection, they have been then aggregated to get average on-street parking search time for each period and for each district. 98 average search times have been obtained by this aggregation. Figure 3 below represents these average search times in function of the measured occupancy ratio. These results illustrate the non-linear relation between the occupancy ratio and the search time.

Table 2. Surveyed districts, measured occupancy and congestion ratios and average and maximum search time.

<table>
<thead>
<tr>
<th>District number</th>
<th>District name</th>
<th>Payment mode</th>
<th>Occupancy ratio</th>
<th>Congestion ratio</th>
<th>Search time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Minimum</td>
<td>Maximum</td>
<td>Minimum</td>
</tr>
<tr>
<td>1</td>
<td>Presqu'île</td>
<td>Metered</td>
<td>0.86</td>
<td>0.98</td>
<td>0.99</td>
</tr>
<tr>
<td>2</td>
<td>Massena</td>
<td>Metered</td>
<td>0.85</td>
<td>0.96</td>
<td>0.88</td>
</tr>
<tr>
<td>3</td>
<td>Freres Lumiere</td>
<td>Metered</td>
<td>0.51</td>
<td>0.86</td>
<td>0.54</td>
</tr>
<tr>
<td>4</td>
<td>Place Guichard</td>
<td>Metered</td>
<td>0.79</td>
<td>0.94</td>
<td>0.81</td>
</tr>
<tr>
<td>5</td>
<td>Part-Dieu</td>
<td>Free</td>
<td>0.83</td>
<td>0.95</td>
<td>0.95</td>
</tr>
<tr>
<td>6</td>
<td>Croix-Rousse</td>
<td>Mixed</td>
<td>0.77</td>
<td>0.93</td>
<td>0.78</td>
</tr>
<tr>
<td>7</td>
<td>Montchat</td>
<td>Free</td>
<td>0.84</td>
<td>0.92</td>
<td>0.87</td>
</tr>
<tr>
<td>8</td>
<td>Belges</td>
<td>Free</td>
<td>0.85</td>
<td>0.95</td>
<td>0.89</td>
</tr>
<tr>
<td>9</td>
<td>Charpennes</td>
<td>Free</td>
<td>0.90</td>
<td>0.97</td>
<td>0.99</td>
</tr>
<tr>
<td>10</td>
<td>Grange Blanche</td>
<td>Free</td>
<td>0.78</td>
<td>0.95</td>
<td>0.83</td>
</tr>
</tbody>
</table>

Fig. 1. Survey results: average on-street parking search time in function of the measured occupancy ratio.

The same goes if the congestion ratio is considered instead of the occupancy ratio. Another observation is the high variability of the search time for one occupancy ratio value, especially when the latest is higher than 85 % and even if only one district is considered.
4. Model validation with survey results

4.1. Model validation with all survey results

Survey results have then been confronted to the four explicative models indicated in table 2. Table 3 gives the values of parameters $\alpha$ and $\beta$ and the coefficient of determination $R^2$ of the model.

<table>
<thead>
<tr>
<th>Model</th>
<th>$\alpha$ (seconds)</th>
<th>$\beta$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Axhausen</td>
<td>26.1</td>
<td>-</td>
<td>0.39</td>
</tr>
<tr>
<td>Axhausen-congestion</td>
<td>120.3</td>
<td>1.31</td>
<td>0.29</td>
</tr>
<tr>
<td>Exponential</td>
<td>0.307</td>
<td>-7.407</td>
<td>0.40</td>
</tr>
<tr>
<td>Exponential-congestion</td>
<td>0.433</td>
<td>-6.615</td>
<td>0.45</td>
</tr>
</tbody>
</table>

These first results allow for several comments. The value of alpha for the Axhausen model indicates the time needed to find a vacant space for low occupancy ratios. Despite the asymptote for $T_{\text{OCC}} = 100\%$, the model appears to give better results for higher occupancy ratio values. Figure 4 illustrates the result of the regression for the Axhausen model.

The Axhausen-congestion model does not seem valid at all because of the very low value of the coefficient of determination ($R^2=0.29$). Moreover, the very high value of alpha (about 2 minutes) which is supposed to represent the search time in a empty district has no link with reality. This result is not surprising since the formulation is rather theoretical. The exponential model gets a low $R^2$ value, and seems not appropriate for high occupancy ratio values ($T_{\text{OCC}} > 0.92$). Figure 5 illustrates the results of the regression for the exponential model. The exponential-congestion model appears therefore as the most appropriate model, since the value of alpha is consistent with low congestion ratios and since the $R^2$ coefficient is the highest of all. Figure 6 illustrates the result of the regression for the exponential-congestion model.
For Axhausen and Axhausen-congestion formulations, because of the poor results, another test has been done with the inclusion of an additive constant to equations (1’) and (4). This modification gives better $R^2$ value for the Axhausen-congestion model only ($R^2=0.41$), but the new formulation also results in negative search times for $T_{cong} < 67\%$, which is not satisfactory. Henceforth, in the following, the Axhausen and the Axhausen-congestion models are not considered anymore. For the exponential and the exponential-congestion models, the normal Q-Q plot (Figure 7) shows that the points are lining up the $y = x$ line thus indicating that the residuals of the model may be normally distributed. Moreover, this plot reveals that average measures 11, 13 and 15 are not well estimated by the model. In Cook’s distance graph (Figure 6), the same goes for average measure 20 (Figure 8).
The survey database indicates that the average measure 15 results from 14 individual measurements, but the location of the spaces that have been found vacant tends to say that the driver in charge of this part of the survey knows where to find a vacant space from the district entrance: for the last 10 measurements, there are only two different vacant space locations and these locations are quite close from the district entrance. Therefore, the measure has been put aside from the database. The average measure 20 is the one with the lowest occupancy and congestion ratios. However, some individual search time measurements are quite incompatible with the fact that almost one space out of two is vacant. For this reason, the average measure 20 is also put aside from the database. The average measures 11 and 13 are kept in, despite some potential aberrations in a few individual measurements. Without those two measures, the coefficient of determination is a little higher, e.g. $R^2=0.51$ for the exponential-congestion model, as indicated in table 4.

Figure 9 gives a graphical view of the distribution of the residual and the density of the normal distribution. In order to test the normal distribution of the residual, the Shapiro-Wilk test is applied, with a significance level of 0.05. The result gives a p-value of 0.0504, just above the significance level: the hypothesis of the normal distribution...
of the residuals cannot be rejected. If average measures 11 and 13 were put aside from the database, then the p-value would be quite higher (0.099).

4.2. Model validation with part of the survey results

Since on-street parking in different districts may follow different laws, the analysis has then been done on different samples of average measures. A multiple correspondence analysis and a hierarchical ascendant classification have first been used to determine samples, but with poor results. Hence, samples have been elaborated depending on the district parking characteristics and of the time of the measure. This sampling does not give better results, except for the 'metered and mixed payment mode' districts sample, and without doubtful average measures 11 and 13 ($n=45$). For this sample, and with the exponential-congestion model, values of alpha and beta are given in table 5. If the coefficient of determination is higher ($R^2=0.69$), the alpha and beta values are quite different from the values found for the all-measure sample.

Table 5. Metered and mixed payment mode sample: values of alpha and beta and of the coefficient of determination for the exponential-congestion model.

<table>
<thead>
<tr>
<th>Model</th>
<th>$\alpha$ (seconds)</th>
<th>$\beta$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exponential-congestion</td>
<td>0.450</td>
<td>-6.433</td>
<td>0.69</td>
</tr>
</tbody>
</table>

Figure 10 illustrates the exponential-congestion model for the 'metered and mixed payment mode' sample.

4.2. Model validation with part of the survey results

Since on-street parking in different districts may follow different laws, the analysis has then been done on different samples of average measures. A multiple correspondence analysis and a hierarchical ascendant classification have first been used to determine samples, but with poor results. Hence, samples have been elaborated depending on the district parking characteristics and of the time of the measure. This sampling does not give better results, except for the 'metered and mixed payment mode' districts sample, and without doubtful average measures 11 and 13 ($n=45$). For this sample, and with the exponential-congestion model, values of alpha and beta are given in table 5. If the coefficient of determination is higher ($R^2=0.69$), the alpha and beta values are quite different from the values found for the all-measure sample.

Table 5. Metered and mixed payment mode sample: values of alpha and beta and of the coefficient of determination for the exponential-congestion model.

<table>
<thead>
<tr>
<th>Model</th>
<th>$\alpha$ (seconds)</th>
<th>$\beta$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exponential-congestion</td>
<td>0.450</td>
<td>-6.433</td>
<td>0.69</td>
</tr>
</tbody>
</table>

Figure 10 illustrates the exponential-congestion model for the 'metered and mixed payment mode' sample.
The Shapiro-Wilk test gives a p-value of 0.30, thus the residuals are likely to be normally distributed. This normal distribution of the residual may suggest that errors come rather from experimental data than from the modeling itself.

5. Conclusions and discussion

To get on-street parking search time, and from models suggested in the literature, the exponential congestion model seems the most relevant. Indeed, the consideration of the congestion ratio rather than the occupation ratio brings out better results. This result is consistent with the need to take on-street parking behavioral aspects into consideration. Moreover, the Axhausen formulation-based models were at first focused on off-street parking search time, and not on-street: this may explain the poor results obtained with those formulations. With the exponential-congestion model, the most interesting results are summed up with equations (6) and (7) below:

- all-survey data \((n=96)\): \(R^2=0.51\)

\[
t = 0.217 e^{-7.364 T_{cong}}
\] (6)

- 'metered and mixed payment mode' district \((n=45)\): \(R^2=0.69\)

\[
t = 0.450 e^{-6.433 T_{cong}}
\] (7)

However, the differences in \(\alpha\) and \(\beta\) values between the all-measure sample and the 'metered and mixed payment mode' sample denote that the model is not yet as general as it should be, and other parameters may interfere in the on-street parking search time formulation. Amongst parameters indicated in the literature review paragraph, the turnover rate is certainly the most promising one. Indeed, residuals that have been obtained with the 'metered and mixed parking mode' sample are likely to be more normally shaped than the all-sample residuals, and the turnover rate is often supposed to be more homogeneous in metered districts – because of the parking duration limit – than in free parking districts where no parking duration limit exists. Unfortunately, the turnover rate has not been recorded in the survey carried out in Lyon. Another survey considering both the congestion ratio and the turnover rate would then be useful to test the hypothesis of the influence of the latest and to explain on-street parking search time.

Acknowledgements

The author thanks the Traffic Engineering Lab (LICIT) of the French Institute of science and technology for transport, development and networks (IFSTTAR) for their advices and their contribution to this paper.

References


