Theoretical insights into parking search to guide parking-related policies and smart-parking solutions

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In many metropolises, parking plays a central role in mode choice. Thus, transport authorities have increasingly used parking restrictions as a lever to enforce changes in mobility. At the same time, the cruising traffic in search of parking contributes to congestion and pollution in city centres. Recently, we introduced a generic modelling framework, valid for any street network and for a wide range of drivers' behaviours, which clarifies the determinants of parking search and quantitatively captures their effect on the search time. It is solved theoretically by leveraging the powerful machinery of graph theory and statistical physics. In our presentation, we will illustrate how these theoretical insights can shed light on two distinct parking-related policies enacted for example in two cities in the South of France, Lyon and Montpellier: (i) restricting the parking supply and (ii) providing a smart-parking solution to guide users towards probably-vacant parking spaces near their destination. In particular, we will outline how the recent theory can be exploited to find optimal routes in a smart-parking solution and to gauge the potential efficiency of such solutions depending on the context.

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1 Introduction

For transport authorities and for individual drivers alike, parking is a central issue in many large metropolitan areas (Shoup, 2018). Motorists may spend several dozens of hours every year searching for parking, according to INRIX survey data (Cookson & Pishue, 2017), while cars cruising for on-street parking may represent more than 10% of the total traffic in many large cities (e.g., 15% in central Stuttgart (Hampshire & Shoup, 2018)) and thus significantly contribute to congestion and pollution in city centres. Thus, many start-ups (as well as larger companies) have developed solutions to guide users towards vacant spaces ('smart parking') and/or reserve a parking space. In parallel, parking is increasingly regarded as a lever to enforce transport policies. In particular, over the last ten or twenty years, restrictions on the parking supply have been implemented, or are under active consideration, in various cities across Europe, including Amsterdam, Copenhagen, Lyon, Munich, Paris, Stockholm, and Zurich (Kodransky & Hermann, 2010). Despite the abundant literature devoted to parking (which we can hardly touch on here, because of the page limit (Dowling *et al.*, 2019)), existing models were either too coarse in terms of spatial resolution (failing to describe the street network) or too restrictive about drivers' behaviours to give (intelligible) quantitative insight into the effect of these smart solutions or policies. Recently, we introduced an agent-based modelling framework that overcomes these limitations (Dutta *et al.*, 2023). We now purport to expose how one can address the concrete aforementioned problems in this new light; our methods will be illustrated using two examples set in cities in the South of France: Lyon, where the on-street parking supply is being reduced year after year, and Montpellier, where a smart, parking-sensitive navigation application is being developed and our methods pave the way for an optimisation of the suggested routes.

2 Methods

Modelling framework. We begin with a recap of the proposed modelling framework. It takes as input a network of streets, with parking spots located along them. Car drivers are grouped into distinct categories $\alpha = 1, 2, \ldots$ depending on their destination, trip purpose, etc. At an intersection, they turn into an outgoing street with a probability given by a category-dependent turn-choice matrix $\underline{\underline{T}}^{(\alpha)}$, giving the probability that an α-car moves along an edge of the graph in one arbitrary time step, *if* it does not park in the meantime. When driving by a spot i, drivers park there with probability $p_i^{(\alpha)}$ if it is vacant. Parked cars pull out at a rate $D^{(\alpha)}$, which is the reciprocal of the average parking duration.

The on-site parking probability $p_i^{(\alpha)}$ may depend on a variety of explanatory variables (rate, distance to destination, etc.); here, these are subsumed into two generic variables: (i) an attractiveness $A_i^{(\alpha)}$ reflecting how attractive a spot i is perceived to be *intrinsically*, (ii) the driver's perception of how easy it currently is to park, $\beta^{(\alpha)} \in [0, \infty)$, viz., $p_i^{(\alpha)}(t) = f(A_i^{(\alpha)}, \beta^{(\alpha)}(t)) \in [0, 1]$. At very low occupancy, when parking seems extremely easy, the driver will refuse to park anywhere but in their preferred spot ($\beta \to \infty$). To the opposite, at extremely high occupancy, virtually any admissible spot will be deemed acceptable ($\beta \to 0$).

Theoretical insight. It is noteworthy that this framework is quite versatile and can be applied to virtually any context; it actually encompasses several existing models (Benenson *et al.*, 2008). On top of its versatility, one of its major assets is that it can be solved not only by means of direct numerical simulations, but also more theoretically, using methods from Statistical Physics and Graph Theory. For that purpose, the street network is handled as a graph, considering that every street position associated with a parking spot as well as every intersection are nodes of this graph. The instantaneous number of cars of category α, α-cars, passing by each node, averaged over random realisations, is then represented by a vector $\underline{V}^{(\alpha)}(t)$. The transition matrix $T_{ij}^{(\alpha)}$ is useful to locate cars after an arbitrary number o steps, *if they do not park in the mean-time.* However, to account for cars pulling in, $T_{ij}^{(\alpha)}$ must be substituted by $M_{ij}^{(\alpha)} = (1 - p_i^{(\alpha)}\, \hat{n}_i) \cdot T_{ij}^{(\alpha)}$, where $\hat{n}_i = 1 - n_i$ is zero (one) if the spot is vacant (occupied).

The average 'driving, searching, and parking' time $\mathrm{T}_s^{(\alpha,j)}$ of an α-car parking at spot j (in arbitrary time steps) can then be derived (Dutta *et al.*, 2023),

$$\mathrm{T}_s^{(\alpha)} = V_i^{(\alpha)}(0) \cdot \left[\underline{\underline{M}}^{(\alpha)} \cdot \left(\underline{\underline{\mathbb{I}}} - \underline{\underline{M}}^{(\alpha)}\right)^{-2}\right]_{ij} \cdot p_j^{(\alpha)}\, \hat{n}_j. \tag{1}$$

To get the mean occupancy $\underline{n}$, we resort to a mean-field approximation in the stationary regime; a conservation equation yields the desired mean-field stationary occupancy $\langle n_j \rangle$, as detailed in Dutta *et al.* (2023). This leads to self-consistent analytical expressions (which can easily be solved with a fixed-point algorithm) that fully characterise the mean occupation of parking spaces and the parking search times, in the stationary regime

3 First example: impact of parking restrictions

Context. Lyon belongs to the second urban area in France, with a municipal population around 500,000 people, and it had more than 80k on-street parking spaces in 2019 (our reference year), excluding garages and private parking. Curbside parking was either free or charged at one of two rates, depending on the zone; residential offers were available. Besides, the city has efficient transit services in the centre, with 4 metro lines, plus many tramway and bus lines. Difficulties to park in the city centre of Lyon have consistently been reported in the past (Belloche, 2015).

Application of the model. Next, we apply the foregoing generic framework to our example of on-street parking in Lyon in the morning peak hour (7am to 10am). Origin-Destination matrices were constructed based on population and employment data and parking occupancy data were measured locally; further details about the specification of the model are provided in (Dutta *et al.*, 2023). The average total travel times (including parking search) simulated numerically are shown in Fig. 1, distinguished between destinations. Remarkably, the theoretical reasoning exposed above (Eq. 1) allows us to quantitatively reproduce most of the numerical results. From the total travel time, the parking search time can be deduced by subtracting the travel time for *vanishing* parking demand from the travel time with the *actual* parking demand. We observe that these search times are also satisfactorily predicted by the analytical formulae.

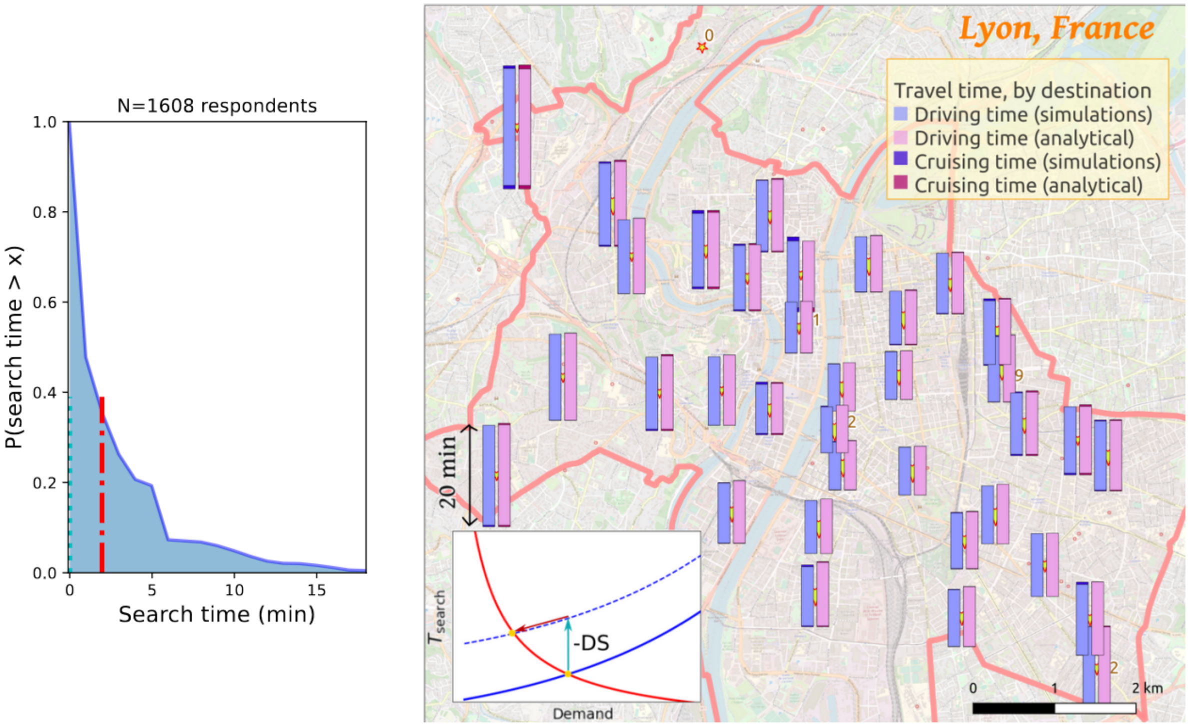

Figure 1 – *On-street parking search times in Lyon, France. (Left) Survival function of search times, as declared by respondents to a 2015 survey by Cerema CEREMA (2015). (Right) Mean travel times (driving and cruising): comparison between simulations (in blue) and theory (in pink) for all destinations, irrespective of the entry point, for a global injection rate of 30 cars/min. (*Inset*) Schematic relation between the search time afforded by the street network and the parking demand, and the effect of a reduction DS in parking supply.*

Impact of Parking Restrictions. Now consider a policy of parking supply reduction (say, from S parking spaces to $S' = S + \Delta S$, with $\Delta S < 0$), in the vein of the policy conducted in Lyon since 2019. After some calculations, the impact of this measure, *ceteris paribus*, on the parking search time $T_{\text{search}}(N, S)$ reads

$$\frac{dT_s}{dS} = \frac{1}{1 + \frac{N}{T_s} \cdot |\epsilon_N| \cdot \frac{\partial T_s}{\partial N}} \cdot \frac{\partial T_s}{\partial S}, \tag{2}$$

where $N = N(T_{\text{search}})$ is the (variable) parking demand. Importantly, we notice that the expected hike of T_s, $\partial T_s / \partial S$, is mitigated by the dip in demand that it induces, via the elasticity ϵ_N of the demand to the search time. If the public transit network is accessible and efficient, we expect a high elasticity $|\epsilon_N|$, hence a modest impact of the parking supply reduction on the search time because of mode shift. The reasoning can be pushed further to estimate the environmental impact of the change.

4 Second example: smart-parking solution

Context. Compared to Lyon, Montpellier is a smaller city, located further south, along the Mediterranean coast, with a municipal population of 280k inhabitants. Quite proactive with respect to the mobility transition, it operated a transition to free public transportation at the end of 2023. In parallel, the main transport provider, *Transports de l'agglomération de Montpellier* (TaM), is developing a smart-parking solution in the form of a GPS navigation application that guides users towards their destinations while taking into account the probability of finding a vacant parking space, in light of the occupation records collected by patrolling cars. Within the frame of a research partnership, we have started transposing the methods presented above and leveraging them in order to improve the routing algorithm.

Method. Technically, this requires writing a generalised cost that balances the (negative) contribution of the driving and cruising (searching) times and the (positive) feature of proximity to the destination. The latter, along with the parking rate, is well captured by the attractiveness variable $A_i^{(\alpha)}$ introduced in Sec. 2, so that the generalised cost reads $T_s^{(\alpha)} - A_i^{(\alpha)}$. Since $T_s^{(\alpha)}$ depends on the occupation field n_i via Eq. 1, one can optimise the suggested route at very low computational cost, as a function of the estimated occupation of parking spaces $\langle n_i \rangle$. From a broader perspective, the framework allows one to gauge the potential efficiency (hence, the interest) of a smart-parking application, which estimates the occupations n_i on the basis of historical and close-to-real-time data, as compared to a driver relying on her past experience to approximate the (un)availability of parking spaces $\langle n_i \rangle$, or to a naïve driver.

Conclusion. In summary, we will use the concrete examples of distinct parking-related strategies currently carried out in two cities in the south of France to illustrate how a recently proposed quantitative model can be exploited to address practical issues about parking and gauge strategies and solutions in an objective way.

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