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Cruising-for-parking in congested cities with an MFD representation

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ABSTRACT

It has been recently proposed and tested that traffic in large urban regions (neighbourhoods) can be modelled dynamically at an aggregate level, if the neighbourhoods are uniformly congested. By exploiting the insights and the properties of a macroscopic fundamental diagram (MFD), we describe the rush hour dynamically in case of multi-region cities that are not uniformly congested. A cruising-for-parking model is developed that considers the dynamics of different types of vehicles, while travelling towards their destinations or cruising. This model describes the physics of hypercongestion caused by the phenomenon, it shows that cruising-for-parking affects all the users of the system, even those with destinations outside the limited parking region and it provides tools to estimate the direct costs of all users, as these expressed by additional vehicle-hours travelled. Also, it describes the rush hour dynamically while vehicles searching for a spot (properly recognizing that delays are greater when flows are lower, unlike existing economic models).

1. Introduction

Urban transportation systems consist of multiple modes that interact in the same road space including non-motorized vehicles, cars moving towards destinations or cruising for parking, taxis cruising for passengers, delivery trucks and more productive modes, such as buses or trams. As multiple modes compete for limited urban space, conflicts and interactions are developed resulting in hypercongestion. However, there is no significant body of work dedicated on the modelling of traffic dynamics and the influence of each mode on the network performance. Most of the existing works fall short either in the scale of application or the treatment of hypercongestion dynamics (small scale and/or static models). Developing and understanding the dynamics of multimodal networks is challenging. This work attempts to integrate the traffic dynamics of cruising for on-street parking with a spatially aggregated model of urban hypercongestion, the macroscopic fundamental diagram (MFD).

Geroliminis and Daganzo (2008) was the first paper to the best of our knowledge to empirically measure a macroscopic relationship between space-mean traffic variables such as flow, density and speed at the level of a downtown neighborhood with dynamic features. This observed empirical relationship, known as MFD demonstrated remarkable stability over the day and between days, which has provided the stimulus for further development of models of urban traffic congestion. While this relationship is not a universal law, the next subsection describes the regularity conditions of network topology and demand, which can possibly ensure small scatter in the MFD. In transportation science there are strong debates between micro-level and aggregated-level models to describe urban traffic congestion.[1] The MFD approach can be a useful tool to be integrated in large-scale traffic management and control. Economists could find this hopefully interesting in light of the long-standing discussion/debate within economics on the relationship between microeconomics and macroeconomics.[2] In the economic literature MFD is usually addressed as a bathtub model, based on the seminal paper of Arnott (2013).

Road traffic networks and management systems constitute a system of systems (SoS) with complex behaviours of various modes of transport competing for the same space. This space should be appropriately modelled, monitored and controlled. The historical organisation of metropolitan areas has led road systems to be operated by a patchwork of different systems without proper communication in exchange data and control actions. Most importantly, they are often competing with one another to avoid congestions on their respective networks. Traffic systems, being inherently a distributed and interconnected process, should be managed as a whole to improve their global operational efficiency while avoiding conflicting decisions. A commonly used fully decentralized control design for traffic management is not appropriate for heterogeneously loaded networks with multiple modes of transport, short links and spillbacks, resulting in the saturation of neighbourhood networks (Haddad et al., 2013). From an economic point of view, a similar critique has been provided by Lucas (1976), who mentions that policy changes are likely to result in changes in empirical macroscopic relationships (see footnote 2).

[1] Note that in traffic engineering, hypercongestion is not a widely used term. Congestion describes the conditions where flow decreases as the density of vehicles (expressed in veh/km) increases. In this paper congestion and hypercongestion have identical meaning.

[2] Based on a discussion with Prof. Richard Arnott.

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1.1. Economics of transportation and cruising-for-parking from a traffic perspective

The general equilibrium models of transport economics and urban land use typically assume an uncongested regime or point-queuing. This assumption does not account for the temporal and spatial evolution of congestion and is not consistent with the physics of traffic. Even recent, conceptually sophisticated models of this type, such as the Regional Economy, Land Use and Transportation (RELU–TRAN) model (Anas and Liu, 2007), do not consider the intra-day traffic dynamics. Moreover, such models involve increased calibration costs for network modelling and require origin–destination trip matrices and traffic assignment procedures to produce a user equilibrium pattern of link travel times. These models involve strong assumptions about the route choice behaviour of travellers, high computational efforts and mathematical properties that are difficult to analyse in large networks and integrate in traffic management. In addition, existing traffic models in urban economics pose severe theoretical and empirical limitations in realistic applications. This is because they employ link travel cost functions, which cannot accurately specify the intra-day traffic dynamics and relate them to land use and urban-scale network characteristics in a way that is computationally tractable and consistent with the physics of traffic. This failure hinders the ability of economic models to support efficient developments for network traffic management and diminish congestion externalities (Tsekeris and Geroliminis, 2013).

Economists have studied and proposed road pricing as an effective policy to relieve traffic congestion in cities for many years. The intention is to alter travellers' behaviour enough to reduce congestion by charging them for the externalities they create. Despite the vast scientific literature, a small number of cities have actually implemented congestion tolls due to social disagreement and political issues (see for example Stockholm, Oslo, Singapore, and London). As an alternative, on-street parking pricing can be proved to be an efficient policy in alleviating congestion, since parking is priced almost everywhere and its implementation is more straightforward compared with cordon or area-based pricing. Nevertheless, this approach should be consistent with correct physics of traffic congestion and its dynamic features, which is one of the main contributions of this work. Pricing parking can be "imperfect" substitutes compared to first-best pricing schemes, as parking fees are charged at the end of a trip and thus usually cannot be differentiated with respect to trip length and routes travelled (Verhoef et al., 1995). Nevertheless, recent advancements in monitoring vehicles with smart sensors combined with proper models of traffic congestion dynamics that integrate these phenomena could improve the estimation of the real cost that cruising-for-parking causes. This work attempts to shed some light towards this direction.

Cruising for parking creates a mobile queue of cars that are waiting for curb vacancies and is an important source of congestion (Shoup, 2005). For example, during peak hour in the area around Harvard square in Massachusetts, 30% of moving vehicles were searching for parking, with an average searching time of 12 min (Shoup, 2006). Axhausen and Polak (1991) found in experiments in Germany and UK that the average ratio between access time to the destination and search time for parking was roughly 2 to 1. Shoup (2006) identified by collecting data from different sources that average cruising time in large cities varies between 6 and 15 min. Cruising for parking influences not only the drivers involved in the search, but also users of the network with external destinations to the limited parking areas.[3]

[3] Increased congestion due to cruising for non-cruising travellers is described as "parking externality cost" by Arnott (2014).

One of the contributions of our work is to show, with a dynamic model of traffic congestion, that if cruising-for-parking is intense, demand which is lower than the network capacity[4] when cruising is negligible, can create significant congestion due to longer trip lengths. Nevertheless, simple types of traffic management can contribute to alleviate the phenomenon. We show that perimeter control (restricting the inflow of vehicles to specific areas by altering traffic signal settings) can significantly reduce delay if cruising-for parking is not so intense and many trips are not originated from the CBD region; otherwise congestion and parking pricing are better.

A significant part of the literature in the effect of parking in traffic is (i) policy oriented (see Shoup, 2005 for a detailed description); or (ii) analyses the economics of parking (Douglas, 1975; Glazer and Niskanen, 1992; Arnott et al., 1991; Arnott and Rowse, 1999; Calthrop et al., 2000; Anderson and de Palma, 2004). For example, Arnott et al. (1991) and Anderson and de Palma (2004) extended the bottleneck model of Vickrey (1969) to analyse the spatial and temporal equilibrium of curbside parking. They also investigated how parking pricing can change the departure time from the origin to decrease the total cost of congestion. The morning commute problem influenced by parking restrictions has also been studied by Zhang et al. (2011), Qian et al. (2012), Yang et al. (2013) and others. A "Vickrey" approach is introduced, where a bottleneck of constant capacity determines the level of congestion in time and space. Other works of parking pricing and how it can have considerable impacts on commuters' travel behaviour is found in Arnott et al. (1991), Verhoef et al. (1995), Zhang et al. (2008), Fosgerau and de Palma (2013) and others. A more comprehensive literature review on the economics of parking can be found in Fosgerau and de Palma (2013) and Arnott and Inci (2010). Some agent-based detailed simulations in cruising-for-parking have developed further insights about the spatiotemporal distribution of parking availability in congested city centres with dynamic characteristics (Benenson et al., 2008; Levy et al., 2013). Nevertheless, an analytical network-level dynamic model as the one proposed in this paper could be integrated in real-time traffic management framework, which would be computationally difficult for a detailed simulation model.

The bottleneck model and its extensions describe peak-period traffic congestion as a queue behind a bottleneck with fixed capacity. However, an important problem pertaining to all the above models is ignoring the downward-sloping part of the curve between flow and density, known as hypercongestion. Only a few studies have attempted to abstractly represent the network-wide relationships between traffic variables. In some of them, like that of Small and Chu (2003), which permitted hypercongestion, the dynamic analysis cannot ensure a stable macroscopic relationship that is consistent with the physics of traffic. In several studies (e.g. Lago and Daganzo, 2007; Arnott and DePalma, 2011), the CBD was considered as a single point in space, i.e., without physical dimension. The latter assumption constrains the analysis of control strategies (e.g. metering of network access or pricing) for reducing congestion costs. Recently, there are a few studies to integrate network level congestion with time of departure analysis (see Geroliminis and Levinson, 2009; Arnott, 2013; Fosgerau and Small, 2013).

Some useful research in identifying interactions between cruising for parking and traffic congestion from an economic prospective was made by Arnott and Inci (2006, 2010) and Arnott and Rowse (2009). These works modelled parking in the steady state by considering three different types of vehicles: (i) moving, (ii) cruising and (iii) parked.

[4] Network capacity (capacity of a region of a city, e.g. the CBD, can be defined in the same way) is defined as the maximum number of vehicles that can be served by the network (or a region) per unit time (defined in a way analogous to the capacity of a road). The main difference is that a single road has a unique destination (exiting its downstream end) while a network (or a region) have multiple potential exit points, either internal trips finishing inside the network (or region) or external trips that are crossing the boundary to another network (or region).

Although they provided relations between these three types and the economic impacts of the phenomenon, they fall short in describing (i) the dynamics of parking with realistic physics in disequilibrium conditions (i.e. when the rate of accumulations for moving and cruising vehicles is time-varying) and (ii) how cruising-for-parking can lead to congested traffic conditions. Later Arnott and Inci (2010) provided a description of the dynamics for the types of vehicles listed above and solve unsaturated and saturated conditions. Two of the assumptions that we relax in our analysis are that (i) “in the saturated parking regime, all on-street parking spaces are occupied, and as soon as a parking space is vacated it is taken by a car cruising for parking” and (ii) “in the unsaturated parking regime, there are vacant on-street parking spaces, and cars spend no time cruising for parking”. They also provide a careful stability analysis of different equilibria that it is beyond the scope of our work.

The model presented here fills the following gaps of the existing policy- and economics-oriented models: (i) it describes the physics of overcrowding in a more sophisticated way; (ii) shows that cruising-for-parking affects all the users of the system, even those with destinations outside the “region of limited parking”, (iii) provides tools to estimate the direct costs of all users, as these expressed by additional vehicle-hours travelled, and (iv) investigates the feasibility of different policies (traffic management or pricing) for different demand characteristics. Also, it differs from the existing economic models because (i) it can describe the dynamics of parking phenomenon and most importantly (ii) it contains variables and functions that are readily observable or can estimated with field experiments (e.g. this is not possible for a demand curve that most of the economic models assume). Therefore the laws of behaviour can be verified, and the models are expected to produce more reliable outputs.

1.2. The macroscopic fundamental diagram

The physical tool to advance this research is the macroscopic fundamental diagram (MFD) of urban traffic, which provides for some network regions under specific regularity conditions, a unimodal, low-scatter[5] relationship between network vehicle density (veh/km) and network space-mean flow (veh/h).[6] The MFD offers an analytically tractable and parsimonious approach for modelling congestion that is consistent with the physics of traffic and relevant to economic analysis of policies to reduce congestion. The MFD approach permits the analysis of a set of second-best strategies, which could not be investigated in models that fail to include hypercongestion or are intractable for large-scale urban areas. Such measures include the use of advanced technology for metering of access or perimeter control (Geroliminis et al., 2013; Ramezani et al., 2015; Keyvan-Ekbatani et al., 2015), the reallocation of the existing network capacity and land use among urban zones (Tsekeris and Geroliminis, 2013) and area-based pricing (Zheng et al., 2012).

One of the main caveats of economic models is that they assume the traditional average cost vs. demand curve (introduced by Pigou (Pigou, 1912) and applied in most of the marginal-cost models). But, this curve is not consistent with the physics of traffic, as it does not provide an accurate representation of congestion when traffic conditions are not stationary. Consider a region of a city with a well-defined MFD; then the state of the system is governed by the mass conservation equation. This equation simply explains that traffic systems are dynamic and to estimate the average travel time at time t, the knowledge of the input flow/demand is not sufficient, but boundary conditions are needed, i.e. the state of the system at a prior time t'. Thus, a traffic model that estimates the average travel time based on a specific demand–cost curve ignores not only variations in the demand, but more importantly that this travel time will be different if the initial state of the system is uncongested, near to maximum flow or in the congested regime.

The idea of an MFD with an optimum accumulation belongs to Godfrey (1969) but the verification of its existence with dynamic features is recent (Geroliminis and Daganzo, 2008). This work showed that (I) urban regions approximately exhibit an MFD if they are homogeneously congested across space, (II) there is a linear relation between the regional space-mean flow and its total outflow (rate vehicles reach their destinations) and (III) the shape of the MFD is a property of the network infrastructure, the traffic management and control strategy and the spatial distribution of congestion and not very sensitive to origin–destination matrices. Property (I) is important as details in individual links are not critical to describe the dynamics of congestion in cities. It can also be utilized to introduce elegant traffic management strategies to improve mobility in homogeneous city centres, like in Daganzo (2007), Keyvan-Ekbatani et al. (2012), Aboudolas and Geroliminis (2013), and Haddad et al. (2013). The main logic of the strategies is that they try to decrease the inflow in regions with points in the decreasing part of an MFD. Property (II) is important for monitoring purposes as flow can be easily observed with different types of sensors while outflow cannot. In simple terms, property (II) means that the trip length for vehicles travelling a specific region of a city is time-invariant. Note that the total trip length for a trip might change because it passes through multiple regions. This assumption while valid and empirically observed for some networks, it cannot describe situations where the length of the trip might differ because of some endogenous reasons, e.g. when vehicles have to travel longer due to an accident or when vehicles are cruising-for-parking. We show later how this assumption can be relaxed to integrate the dynamics of cruising. Property (III) is important for control purposes as real-time traffic management schemes can be developed without a detailed knowledge of origin–destination matrices, which are difficult to estimate in a time-dependent manner. The assumption of homogeneity is reasonable for some regions, since drivers naturally flock to underused parts of a network, entrances and exits might not disturb the distribution of speed and then city traffic could be treated macroscopically as a dynamic (queueing) system with accumulation n as a single state variable.

Despite these recent findings for the observation of MFDs with low scatter, these curves should not be a universal law. In particular, networks with an uneven and inconsistent distribution of congestion may exhibit traffic states that are too scattered to line along an MFD. Recent findings from empirical data (Geroliminis and Sun, 2011) have identified the spatial distribution of vehicle density as one of the important features that affect the scatter and the shape of an MFD. They observed that the average network flow is consistently higher when link density variance is low for the same network density, but higher densities can create points below an MFD when they are heterogeneously distributed. These findings are of great importance because the concept of an MFD can be applied for heterogeneously loaded cities with multiple centres of congestion, if these cities can be partitioned in a small number of homogeneous clusters (let us call these clusters regions or reservoirs). Recent work created clustering algorithms for heterogeneous transportation networks (Ji and Geroliminis, 2012). The objectives of partitioning are to obtain (i) small variance of link densities within a cluster, which increases the network flow for the same average density and (ii) spatial compactness of each cluster which makes feasible the application of perimeter control strategies.

[5] The traditional Fundamental Diagram (flow-density) of traffic is usually observed for a single location and it contains significant scatter in the congested regime, i.e. for a given value of density there is a large range of flow. At the network level for a given average network density, the network flow has small variance even for different demand profiles.

[6] Space-mean flow for a region of a network is by definition, the total vehicle distance travelled by all vehicles moving in this region divided by the duration of the interval. This interval should be approximately equal to 2–3 periods of a traffic signal cycle (3–5 min). Shorter interval will create strong oscillations while larger interval can smooth significantly flow and lose the notion of dynamics.

One can model a city as a single or multi-reservoir system depending on the geometry, the demand patterns and the distribution of congestion among the city. An inconsistent distribution of congestion is typical of large urban areas with multiple congested subcentres. To resolve these issues, this paper develops the dynamics of cities with more complicated structure, by considering the cruising-for-parking phenomenon.

Also, as mentioned above the existing MFD models assume that the average trip length is constant with time and ignores phenomena which change trip length, as when vehicles are cruising for parking. But, it is clear that as the number of vehicles searching for parking increases, and the probability of finding a spot decreases, the average trip length in the area increases and vehicles reach their destinations with smaller rates for the same average speed. Thus, a macroscopic model that ignores this phenomenon will overestimate the output of the system for a given accumulation. We integrate this phenomenon in the general framework of macroscopic modelling of traffic in cities consistent with the physics of overcrowding. While route choice is not analysed in this work, the interested reader could refer to Yildirimoglu and Geroliminis (2014) that describes the effect of route choice under MFD dynamics.

In this paper we first introduce a general model of a dynamic multiple-reservoir city with well-defined MFDs for each reservoir and cruising-for-parking. We show that under certain demand and parking supply conditions this model can lead to heavy congestion when vehicles have to cruise before reaching their destination. This model is consistent with the physics of traffic and its variables are observable quantities. Later, we show through a macroscopic simulation that we can obtain additional insights about the key parameters that matter during congestion. Finally, we investigate when perimeter control strategies and simple pricing strategies can be effective and improve mobility when cruising for parking is present and provide final remarks. An interesting observation about perimeter controls is that they do not require much information about origins and destinations of drivers, which is difficult to be estimated. Most existing papers treat cruising-for-parking under steady-state analysis, whereas this work offers an analysis for dynamic (and possibly not in equilibrium) situations as well.

2. Dynamics of the rush hour with MFD representation and cruising-for-parking

Consider now a city partitioned in N reservoirs as in Fig. 1 (region and reservoir are used alternatively in the paper without a change in the meaning). Denote by $i = 1, \ldots, N$ a reservoir in the system, n_i its accumulation and n_{ij} the number of vehicles in i with final destination reservoir j, at a given time. Let P_i, $V_i = P_i/n_i$ and $O_i = P_i/l_i$ be the network *production*[7] (vehicle kilometres travelled per unit time), average space-mean speed and output at a specific time, where l_i is the average trip length for reservoir i. The space-mean speed definition was introduced by Edie (1963) and the last equality is the famous Little's formula for steady-state queuing systems (Little, 1961). Output O_i is the sum of the exit flows $O_{ij} (\forall j \neq i)$ from origin i with final destination j, plus the internal output O_{ii} (internal trip completion rates at i).

We assume that for each reservoir i: (i) there exists a Macroscopic Fundamental Diagram (MFD), $P_i(n_i)$, between accumulation n_i (as expressed by the number of vehicles in the network at the time of observation) and production P_i, which describes the performance of the system in an aggregated way and (ii) equations $O_i(n_i) = P_i(n_i)/l_i$ and $V_i(n_i) = P_i(n_i)/n_i$ hold. The dynamics of an N-reservoir region with time-independent trip lengths for each region i, l_i have been analysed in various traffic oriented publications (e.g. Geroliminis et al., 2013). These models cannot properly integrate cruising-for-parking, which directly influences trip length.

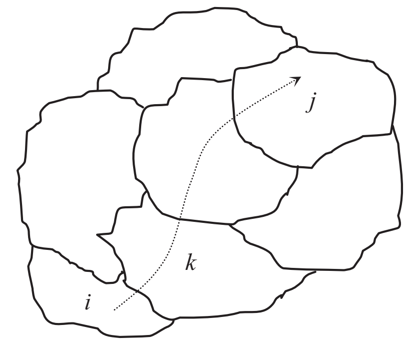

Fig. 1. A multi-reservoir system.

Let us now analyse the effect of cruising-for-parking in the output $O_i(n_i)$ and the dynamics of the rush hour. Consider now a multi-reservoir city, with infinite parking availability for all the reservoirs, except one (reservoir R), where vehicles may have to cruise for parking because of limited on-street parking (this assumption can be easily relaxed by combining dynamic systems with constant trip length as referred above, with the derivations of the current section). We focus the analysis on on-street cruising for parking in R. Its accumulation n is the sum of three families of vehicles: (i) vehicles searching-for-parking n_s (family $\boldsymbol{s}$); (ii) vehicles moving towards their destination internal to the reservoir, but not yet searching for parking, n_m (family $\boldsymbol{m}$), and (iii) vehicles moving with external destinations, n_o (family $\boldsymbol{o}$)

$$n = n_s + n_m + n_o \tag{1}$$

Denote by n_p the vehicles parked on street (family π) and by N_p the total number of parking spots. Also, let $p = (N_p - n_p)/N_p$ be the percentage of available parking spots, and d_1 be the average distance travelled between two adjacent spots (from N_p). We assume that p and d_1 do not vary drastically in the dimension of space. When a vehicle reaches its destination, it is assumed that it does Bernoulli trials with probability of success p, until finding an available spot.[8] The number of trials until the 1st success follows a geometric distribution with mean $1/p$. In each trial a vehicle travels, on average, distance d_1 and the average distance travelled while searching for parking is $l_s = d_1/p$. To model the effect of parking, the reservoir R is divided in three sub-reservoirs:

- A moving reservoir R_{mo} with $n_m + n_o$ vehicles.
- A searching reservoir R_s, where vehicles transfer from R_{mo}, when they arrive close to their destination.
- A parking reservoir R_p, where vehicles transfer from R_s when they find a parking spot. Also, trips generated in R_p, transfer from R_p to R_{mo} and lead to their destinations. Fig. 2 shows this partitioning and movements between different families.

The output for families m, s, o, is estimated using Little's formula in R

$$O_x(n_x, n) = \frac{n_x}{n} \cdot \frac{P(n)}{l_x}, \quad x \in \{m, s, o\} \tag{2}$$

[7] Network production can be estimated as $\sum_j q_j L_j$, where q_j is the flow (in veh/t.u) in one link j of the reservoir (or region) under consideration and L_j is the length of the link j. The duration of estimation should be 1–3 times of the duration of one cycle of a traffic light. Physically speaking production describes the space-mean flow of the network if divided by the total lane-kilometres of road in the network, $\sum_j L_j$.

[8] Similar families of vehicles were assumed by Arnott and Inci (2010) but the following dynamic features were not considered as an MFD depending on the trip length has not been integrated by this time.

The logic of Eq. (2) is the follows: $P(n)$ represents the travel production in the specific region. It is assumed that vehicles have on average the same space mean speed which is a function only of total accumulation n. Thus, the fraction of production for a specific family x is n_x/n of the total production of the region. Then, the output is estimated by dividing by the average trip length of the specific family x. Output from family $\boldsymbol{m}$ is input to family $\boldsymbol{s}$, output from s is input to π, output from π is input to m and o. Output from reservoir i is the sum of outputs from s and o. Fig. 2 shows well the interactions between different sub-regions and families. In the case of $x=s$ (searching), Eq. (2) becomes

$$O_s = \frac{n_s}{n} \cdot \frac{p}{d_1} \cdot P(n) \tag{3}$$

The average cruising time is $l_s/V(n) = d_1/(p \cdot V(n))$. The state of reservoir $R(n_m, n_s, n_o, n_p)$ is described in the dynamic case as follows (time t is omitted from the equations):

$$\frac{dn_m}{dt} = q_{R' \to R} + q_{R \to R} - O_m(n_m, n), \tag{4a}$$

$$\frac{dn_s}{dt} = O_m(n_m, n) - O_s(n_s, n), \tag{4b}$$

$$\frac{dn_o}{dt} = q_{R' \to R'} + q_{R \to R'} - O_o(n_o, n), \tag{4c}$$

$$\frac{dn_p}{dt} = O_s(n_s, n) - q_{R \to R} - q_{R \to R'}, \tag{4d}$$

where $q_{R \to R}$ and $q_{R \to R'}$ are the rate trips starting from R_p with internal (inside R) or external destinations (outside R), respectively; $q_{R' \to R}$ and $q_{R' \to R'}$ are the flows entering from outside with internal or external destinations.[9]

When conditions change slowly with time ($dn_s/dt \cong 0$), note that Eqs. (4b) and (3) yield

$$\frac{n_s}{n_m} = \frac{1}{p} \cdot \frac{d_1}{l_m} \tag{5}$$

This suggests that by measuring p and estimating d_1 and l_m, i.e. the two lengths of the RHS of Eq. (5), we approximate the fraction of vehicles searching for parking. As expected, small values of p lead to a high number of vehicles searching for parking, and as a result the average distance travelled per trip completion in R, l, increases. A similar derivation for equilibrium conditions is described in Arnott and Inci (2010). Note that such a steady-state equation is valid for values of p not very close to zero. The reason is that the dynamics of accumulations (are expressed by Eqs. (4a)–(4d)) are not slow when vehicles are searching for parking. Actually, as we show in the next section, the value of n_s is much higher in the onset of congestion than the value derived by Eq. (5).

Why do we look for l? The cost of cruising-for-parking, in terms of additional vehicle kilometres travelled, can be substantial. If, for example, 20% of vehicles search for parking, distance travelled per trip completion is 25% higher, which results to 20% smaller outputs, even for the same average speed. But the effect is even worse, as average speed V is a decreasing function with accumulation and smaller outputs cause higher accumulations. Especially, when the system enters the congested regime of the Macroscopic Fundamental Diagram, production decreases with accumulation and system can reach gridlock. This feature can be described properly in a dynamic environment. Nevertheless, deriving some approximate analytical formulations can create further intuition for key variables of the model. Quantitatively, we can estimate l using Little's formula for the total output O, i.e. the sum of O_s and O_o

[9] This model neglects trips starting from R and not from R_p (e.g. trips from garages). This assumption can be easily relaxed.

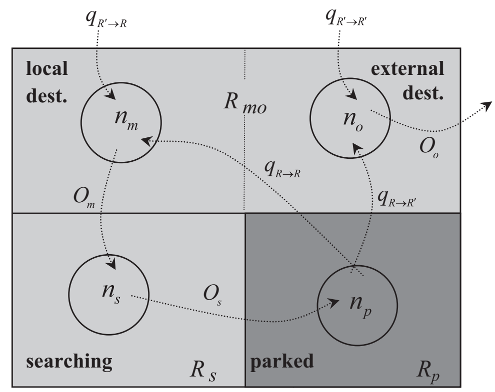

Fig. 2. Different movements to model cruising-for-parking phenomenon.

$$O = O_s + O_o \Leftrightarrow \frac{n \cdot V}{l} = \frac{n_s \cdot V}{l_s} + \frac{n_o \cdot V}{l_o} \Leftrightarrow \frac{1}{l} = \frac{n_s}{n} \cdot \frac{p}{d_1} + \frac{n_o}{n} \cdot \frac{1}{l_o} \tag{6a}$$

Now, if conditions change slowly with time, by using Eq. (5) and assuming $l_o = l_m$, we get

$$\frac{1}{l} = \left(1 - \frac{n_s}{n}\right) \cdot \frac{1}{l_m} \tag{6b}$$

We now estimate the total delay, d_p, caused by the cruising-for-parking effect by comparing the actual vehicle hours of travel with those when $N_p \to \infty$. This delay is not only experienced by vehicles cruising for parking, but also by all moving vehicles, because of decreased speeds. The delay d_p during a time period $[0, T]$ can be estimated using the queueing diagram of Fig. 3, where $n(t)$ is the actual accumulation in i, at time t and $n^*(t)$ the accumulation when $N_p \to \infty$. This graph merely explains that (i) the difference in accumulation with and without cruising, at time t, is the difference between their cumulative outputs $\sigma(t)$ and $\sigma^*(t)$, at time t, and (ii) delay d_p is the shaded area between the cumulative outputs.

While $n(t)$ can be estimated for real networks, the state of the system for when $N_p \to \infty$ is unknown. Nevertheless, $n^*(t)$ can be approximated as

$$n^*(t) \approx n(t) - \int_0^t \left(\frac{P(n^*(\tau))}{l_m} - \frac{P(n(\tau))}{l(\tau)} \right) d\tau \tag{7}$$

where $l(t)$ is given by Eq. (6b). The term inside the integral is the decrease in output, at time t, due to cruising-for-parking phenomenon. Next subsection presents a simulation and gives additional insights to the causes and the results of the phenomenon.

3. A macroscopic simulation of cruising-for-parking

To illustrate numerically the model described in the previous section and investigate if it produces logical results, we now present a cruising-for-parking macro-simulation for different supplies of on-street parking spots based on the model developed in the previous section. The simulated network is a macroscopic representation of the geometric and traffic characteristics of the San Francisco micro-simulated site (Geroliminis and Daganzo, 2007). This test site is a 6 square kilometres area of Downtown San Francisco (Financial District and South of Market Area), including about 100 intersections and 500 links of various link lengths. The number of lanes for through traffic varies from 2 to 5 lanes and the free-flow speed is 50 km/h. Traffic signals are all multiphase fixed-time operating on a common cycle length. In this microsimulation, all the internal trips were completed in garage parking areas and cruising was absent. In reference Geroliminis and Daganzo (2007) traffic was simulated for many periods (∼10)

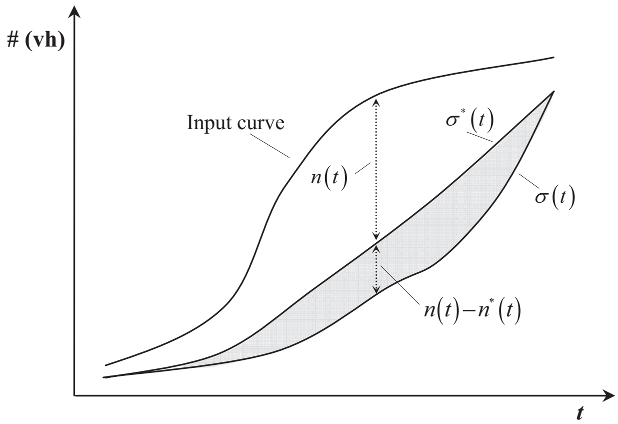

Fig. 3. A queuing diagram for reservoir R.

Table 1
Description of main parameters of the simulation.

Parameter	Value	Description
L	56.25	Total street length (km)
f_{11}	0.1	$f_{ij}=$ fraction of demand generated
f_{12}	0.2	From i with destination j
f_{21}	0.4	$i,j=1$ (internal) or 2 (external)
f_{22}	0.3	
l_m	1.743	Average trip length without cruising (km)
N_p	$[4750,\infty)$	Total number of on-street parking spots
n^p	1500	Vehicles parked at $t=0$
l_1	$2L/N_p$	Average distance traveled between two adjacent spots

of 4 h with time- and space-dependent demand. It was shown that this network has a well-defined MFD, $P(n)$, with the same shape reproduced by vastly different origin–destination patterns and with less scatter than for individual links.

In the macro-simulation of the current paper, a network with two regions is considered and the demand is expressed by variable f_{ij}, the fraction of demand generated from region i with destination j. Index 1 represents the internal region with limited on-street parking as expressed by variable N_p, while index 2 represents the suburbs of the city (external zone) with unlimited parking availability and no cruising. Table 1 summarizes the values of the most important parameters used in this simulation. Variables f_{ij} are time independent.

Time-series of total demand rates were calculated for a run of the micro-simulation that did not create severe congestion in the system without cruising-for-parking (no states observed in the congested regime). Also, averages for the fraction of demand rates with internal or external destinations were calculated across the whole run, so that variables f_{ij} can be estimated from the detailed origin–destination profile. On-street parking spots were assumed to be evenly distributed in both sides of all streets, without restricting the lanes used for traffic movements.

Traffic was simulated for a period of 4.5 h (10,000 time units of 1.62 s each) for $N_p\in[4750,\infty)$ using a discrete version of the dynamic Eqs. (4a)–(4d). All the trips generated from the internal region start from the parking sub-reservoir R_p. Also, in the end of the simulation, traffic demand decreases so that the system returns in a state of low traffic where cruising-for-parking is negligible. Thus, the total input and output of vehicles is the same for all runs and the results are comparable. The MFD, expressed as travel production P vs. accumulation n, has a 3rd degree polynomial shape consistent with the micro-simulated data of San Francisco for each of the two regions simulated, $P(n)=1.52\times10^{-7}n^3-2.88\times10^{-3}n^2+14.11n$ (units of $P(n)$ is veh-meters per time unit and units of n is vehicles). The total demand of trips (i.e. when trips are generated) follows a trapezoidal form starting at zero and having a maximum value of 375 veh/min between time units 3000 and 4500. The demand decreases linearly after 4500 t.u. and reaches zero at time 8500 t.u.

Fig. 4 presents the results of the simulations for different values of N_p. There is no cruising effect for $N_p>10,000$. Fig. 4a and b shows time-series of accumulation and fraction of available parking spots. Note that for values of N_p smaller than 6000 the network becomes severely congested with states in the congested regime of the MFD, while for $N_p>7500$ remains uncongested. Note as well that, during the same time periods, the fraction of available parking spots is close to zero ($<5\%$) for small N_p, as shown in Fig. 4(c). This indicates that there are cases where cruising-for-parking can lead uncongested systems without very high traffic demand, to severely congested states. Thus, ignoring this phenomenon when developing real-time (or offline) traffic management or policy strategies can lead to significant underestimation of congestion.

Fig. 4c and d shows time-series of the number of vehicles cruising-for-parking and of cumulative output, i.e. total trip completion rate, expressed as an oblique plot for different values of N_p. Oblique plots have extensively utilized in traffic engineering analysis. Instead of plotting the cumulative output across time ($\sum_t O$), a constant value is subtracted at every time period, $q_0=1000$ veh/t.u. Thus, the plot shows $\sum_t O-q_0(t-t_0)$, where t_0 is the beginning of the simulation. This simple transformation is for illustration purposes to highlight differences between curves in the same figure, as otherwise differences are not visible due to high values of cumulative variables over time (see Cassidy and Bertini, 1999 for more explanation). Note that when p is close to zero, the fraction of vehicles cruising-for-parking is significant ($\sim30\%$ for $N_p=5000$), which is a value observed in many cities around the world, e.g. in Massachusetts, even 20 years ago (Shoup, 2005). The area under the graph of Fig. 4b is the total delay for vehicles cruising for parking (family $\boldsymbol{s}$), d_s.[10]

The total delay d_p due to limited parking for a value of N_p is the area (see Fig. 4d) between the graphs (i) for the given N_p and (ii) for $N_p\to\infty$ (for $N_p>10,000$ the delay is zero, so a value of $N_p=10,000$ was used for comparison). There are cases where d_p is 2 or 3 times higher than d_s, which is something neglected in most of the existing studies.

An interesting observation is that the effect of cruising-for-parking can be substantial for vehicles moving in the network towards their destination and not searching for a spot. Fig. 5a shows d_p, d_s and d_p-d_s for the whole period of the simulation for different values of N_p. The estimated d_p-d_s shows the additional delay due to cruising phenomenon for vehicles that are not cruising for parking, i.e. vehicles moving towards their destination (internal or external). Note that the effect for non-cruising vehicles, as this expressed by d_p-d_s, i.e. the total delay for all vehicles excluding the time cruising-for parking, becomes more intense than the time of cruising for parking (family $\boldsymbol{s}$) as N_p decreases. This observation highlights the importance of proper modelling of dynamics of congestion when cruising is intense. The elasticity of their ratio is about -3% per 100 parking spots for $Np\in[5500,7000]$.

Fig. 5b shows the total delay for vehicles with inner (including cruising) and outer (cruising is zero for these vehicles) destinations. Note that as the number of total spots decreases, the effect for vehicles with outer destinations becomes significant. Also, the marginal cost of an additional user with external destination is smaller than that of a user who will cruise for parking; and that an

[10] A study on West Portal Avenue on the city of San Francisco, conducted by San Francisco State University and included in Shoup (2005), found that average cruising time to find a curb space was 3.2 min. This cruising time is the same as in the simulation for $N_p=6000$. But, this delay is not the only cost caused by limited availability in parking.

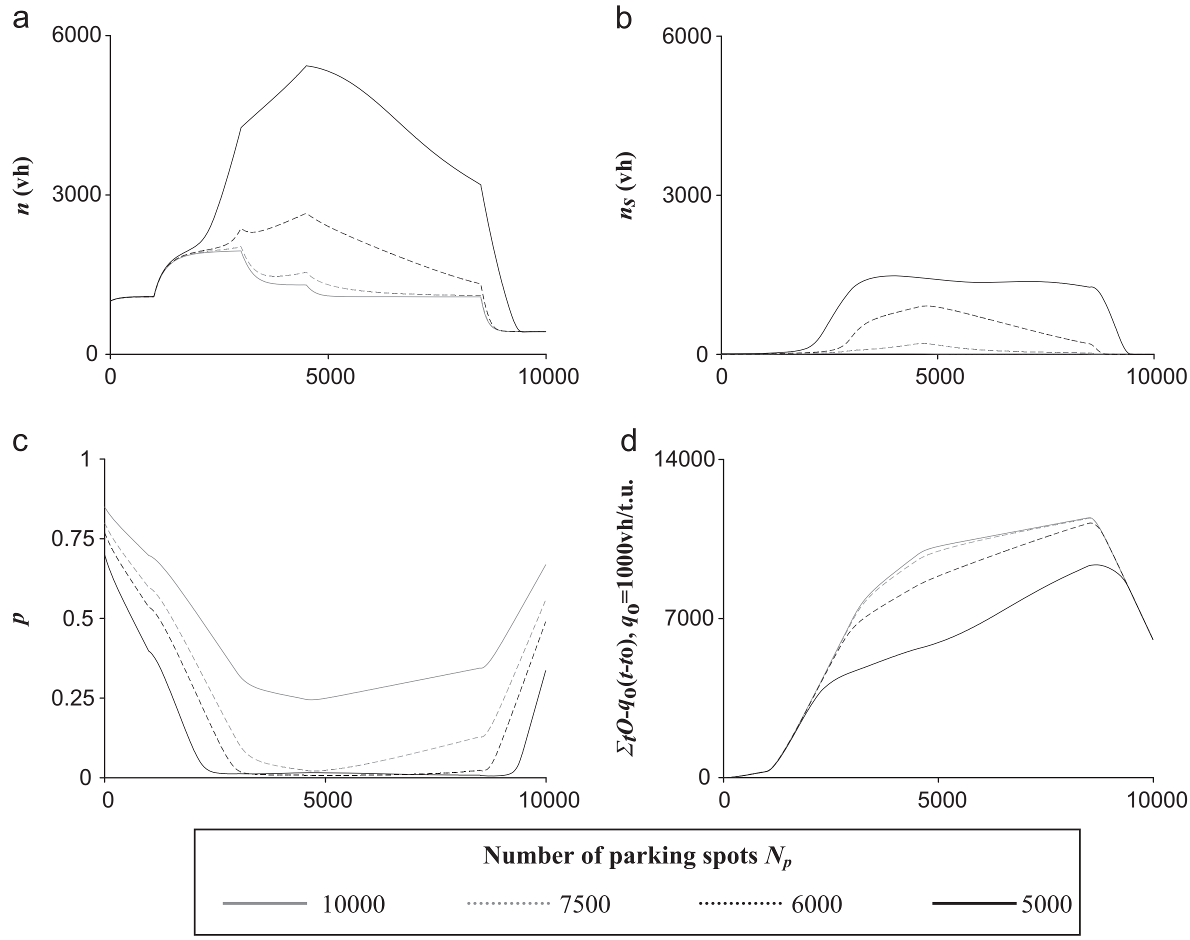

Fig. 4. A simulation of searching-for-parking; time series of (a) accumulation, (b) vehicles searching for parking, (c) % of available parking spots, and (d) cumulative output as an oblique plot.

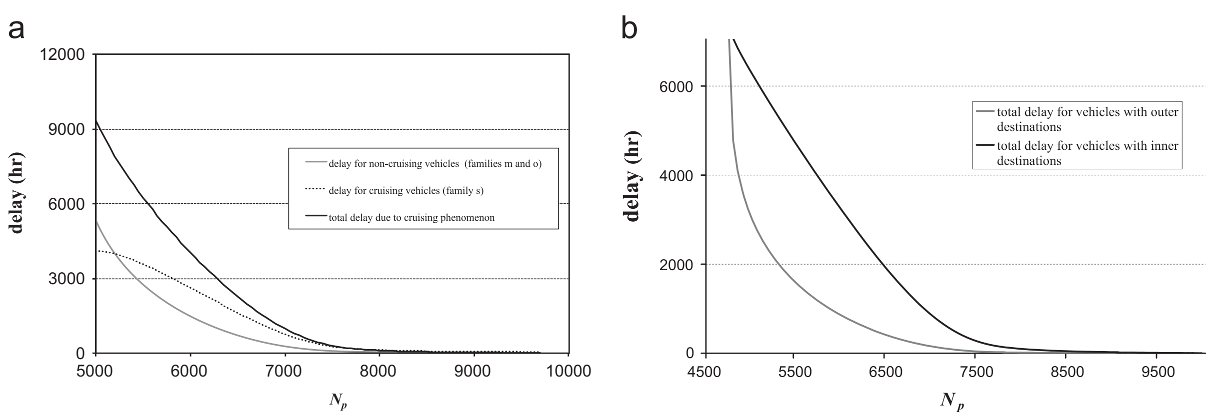

Fig. 5. (a) Delays d_p, d_s and d_p-d_s for different values of N_p. (b) Total delay for vehicles with inner and outer destinations for different values of N_p.

additional user with internal destination causes more delays in the non-cruising vehicles than the cruising ones. This suggests that a pricing scheme (e.g. pricing on-street parking) to increase mobility in cities should consider all different types of costs for the users of the system.

Previous research (e.g. Arnott and Inci, 2006, 2010) derived elegant equations under steady-state equilibrium conditions. We now test under the dynamic environment of Eqs. (4a)–(4d) how accurate a steady-state equation described in (5) is valid. Fig. 6 presents the ratio $(n_s p)/(n_m d_1)$, which is considered constant if $dn_s/dt=0$ for the simulations with time-dependent demand for $Np=5000$, 6000 and 7500 (horizontal axis is parking availability). It is clear that for small values of parking availability ($p<15\%$), this ratio significantly deviates both in the onset and offset of congestion (dn_s/dt being positive or negative). Note that the value of $(n_s p)/(n_m d_1)$ for $p>15\%$ is the reciprocal of the average trip length for zero cruising (see also Eqs. (5) and (6b)). Thus, a dynamic pricing scheme should consider the dynamics presented in our work if the objective is to correctly penalize the users that are responsible for congestion. Previous policy oriented studies (e.g. Shoup, 2006) conjectured that an on-street parking availability should be around 10%, a range where p experiences strong dynamic features as shown in Fig. 6.

Most of the existing studies evaluate the effect of the cruising-for-parking phenomenon by the average time cruising for parking. One

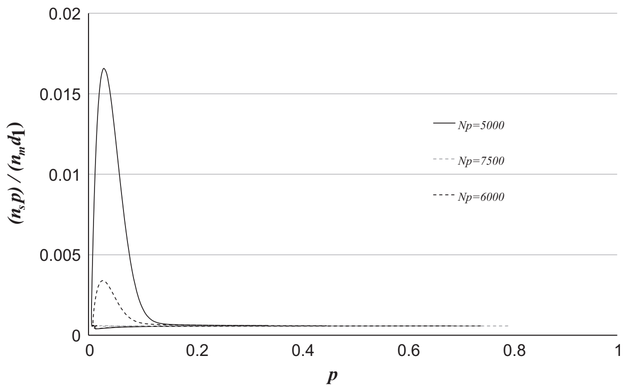

Fig. 6. Investigating the validity of steady-state (5) under dynamic conditions.

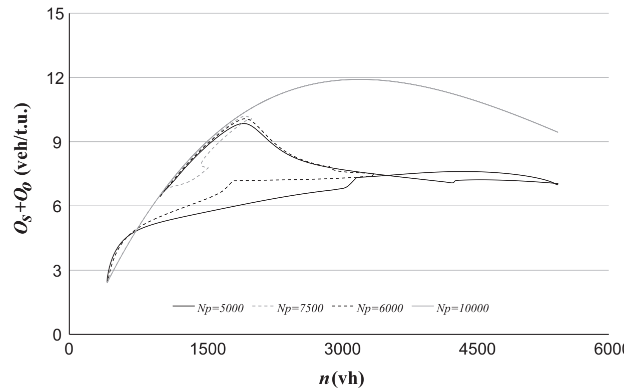

Fig. 7. Output vs. accumulation for different values of total parking spots N_p.

should expect that for a given demand, average cruising time will increase as parking limitations become intense, i.e. N_p decreases. But, this is not necessarily true, especially when traffic is congested. A "surprising" observation is that (i) d_s becomes concave for values of $N_p < 5500$, and (ii) d_s is about constant for values of N_p close to 5000, as Fig. 5a shows. Thus, cruising delay d_s is bounded but total delay is not. The reason for this is that the system reaches quickly the congested regime of the MFD and the output O_m, which is the input to R_s (sub-reservoir of cruising vehicles), becomes very small; at the same time, average speed is very low, too (<10 km/h). Thus, vehicles do not reach their internal destination because they are "stuck" in congestion and the number of vehicles cruising-for-parking is small. Results for values of $N_p < 5000$ are presented in Fig. 5b and it is clear that delays increase exponentially because the system reaches gridlock conditions very fast. A simple model without these dynamics features and proper modelling of hypercongestion would not be able to identify these disequilibrium conditions.

4. Perimeter control to reduce cruising-for-parking

Previous research (see the introduction section) showed that perimeter control can be beneficial for single and multi-neighbourhood cities. A main characteristic of these strategies is that they treat equally all the users that are metered, independently of their destination. A fair question to ask is if perimeter control can improve mobility when "metered" users have different characteristics and contribute differently to congestion levels, e.g. when the cruising-for-parking phenomenon is intense. In that case, people with destinations inside the inner reservoir inconvenience the system more than users driving through the inner reservoir, with outer destinations. Perimeter control restricts the inter-transfers between successive regions (e.g. by changing the traffic signal settings) with an objective to keep accumulations at desired levels and maximize the output of the system. The desired levels are close to the critical value of the MFD. Fig. 7 shows how the total output of the cruising-for-parking region varies with the total accumulation for simulations with different values of N_p. Output describes the rate that vehicles reach their destination and is the sum of O_s and O_o, without considering the output from the moving reservoir to the cruising reservoir (as this is not a real trip ending). The upper envelope shows the shape of the MFD if trip length is constant and vehicles find a parking spot immediately when they arrive at the destination (cruising is negligible for values $N_p \geq 10,000$ i.e. it is the 3rd degree polynomial function introduced before divided by the average trip length without cruising). Note that due to cruising phenomenon and significant increase in the trip length, maximum output cannot reach the value without cruising. Another interesting observation is that the output decreases for values of accumulation larger than 1800 veh/h, which is much smaller than the value that maximizes the output with high parking availability. Note that the total production as expressed by the vehicle-kilometres travelled per unit time does not depend on the value of trip length and it is the same in all scenarios for time periods with equal accumulations, i.e. production is maximized for accumulation close to 3200 veh.[11]

To get a better understanding, we now test how traffic conditions are influenced by perimeter control while vehicles are cruising-for-parking. For comparison purposes, we simulate the same network settings used to analyse the cruising-for-parking phenomenon. For different values of the total number of parking spots N_p we run the simulation with exactly the same traffic and demand characteristics. The only difference is that we apply two different types of perimeter control policies: (Strategy I) a simple bang-bang "single-reservoir strategy" similar to Daganzo (2007), where when accumulation enters in the congested regime of the production MFD (the one without cruising for parking), we meter the inputs from the periphery with desired accumulation $n=3200$ veh.[12] Strategy II is stricter and input flows are restricted either when accumulation is in the congested regime of the output MFD (critical value close to 1800 veh) or when accumulation is close to the critical value, but parking availability is limited ($p < 0.15$). The second strategy aims to moderate the cruising-for-parking phenomenon. We also estimate the additional vehicle hours of delay experienced by the metered vehicles, for both strategies. For simplicity, we assume that the outer region is completely uncongested and the only delay because of the perimeter control is the one while waiting for entering the inner region. Fig. 7 summarizes the results.

Fig. 8a shows the total delay due to cruising-for-parking, d_{tot}, (including the delay of the metered vehicles) and the delay while searching for a spot, d_s, for the two different strategies. We see that in all the cases the stricter "strategy II" moderates some of the searching time, but the penalty experienced by metered vehicles is much higher, i.e. strategy II is always worse than strategy I. The reason is that while the perimeter control meters the input from the outer region, it cannot restrict the generation of trips from the inner region. Thus, the parking sub-reservoir still saturates quickly due to high demand of trips starting from the inner region and perimeter control makes the overall situation worse. Note that such a strategy succeeds to keep accumulation at the desired level of 1800 veh, but is unable

[11] Thus, even if the system is able to "produce" a specific value of veh-km/u.t. (with small variations), the number of vehicles that reach destinations is significantly influenced by trip length, which is directly related to cruising-for-parking.

[12] The physical reasoning of this choice is that veh-kilometres travelled includes all vehicles moving in the region and represents the maximum possible circulating flow. More complex perimeter control strategies with multiple regions and more complex dynamics can be found in Ramezani et al. (2015) and Aboudolas and Geroliminis (2013).

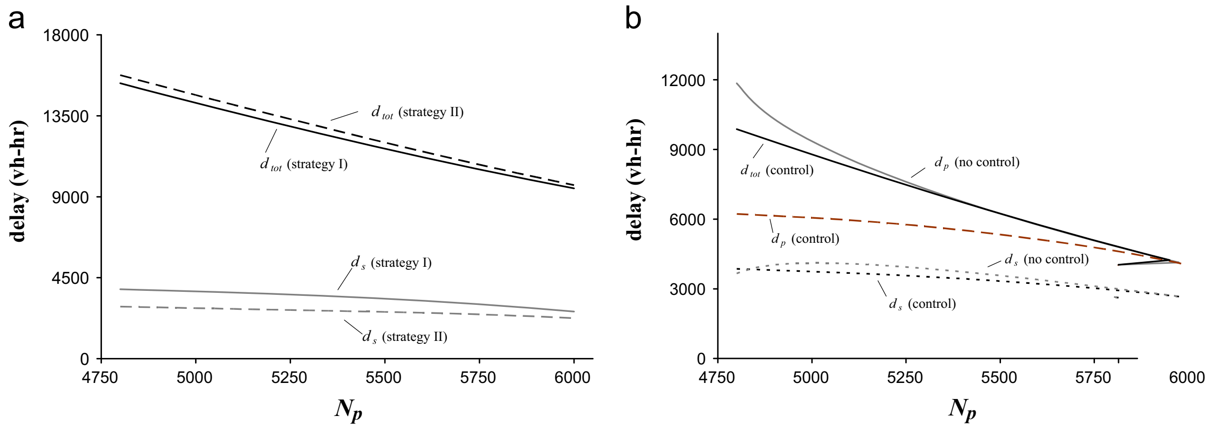

Fig. 8. Simulation results for different values of N_p: (a) d_{tot} and d_s for two different strategies; (b) comparison of control strategy I and no control.

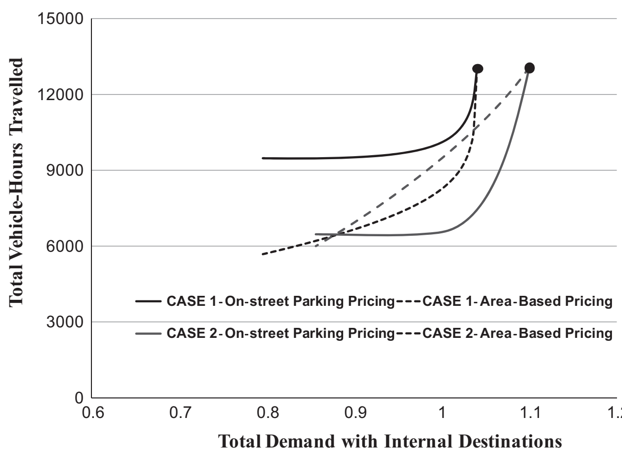

Fig. 9. Area-based pricing vs. on-street parking pricing; CASE 1: $f_{in} = 1.04, f_{ex} = 1.46, N_p = 4500$; CASE2 : $f_{in} = 1.1, f_{ex} = 1.1, N_p = 6000$.

to keep the outflow at the value of 10 veh/t.u. (see Fig. 7) because cruising remains intense, trip lengths increase and output decreases. Let us now compare strategy I with the original case of no control.

Fig. 8b shows different types of delays for control strategy I and the original case for different values of N_p. First note that perimeter control has minor effect in the delay of vehicles cruising-for-parking, d_s. Note also that the delay for all the vehicles of the inner region, d_p, (excluding metered vehicles) decreases significantly (e.g. more than 30% for $N_p < 5200$). But, there is major penalty for the metered vehicles, which is increasing when the original system becomes heavily congested for smaller values of N_p (accumulations in the congested regime). Thus, the overall delay decreases 10–15% and only when the inner region reaches congested states. Note also that in the no control case $d_p = d_{tot}$ because there is no metering for vehicles coming from the outer region. (For the given demand when N_p is high and cruising negligible, the system remains uncongested at all times.)

These results show that perimeter control cannot have a significant positive effect (i) when many trips are originated from the inner region and (ii) when the cruising-for-parking phenomenon is intense. In these cases, it is necessary to decrease the demand of vehicles on the road. Congestion pricing or parking enforcement are alternative methods that can lead to better results, in terms of mobility and accessibility for the system. This is an ongoing research direction.

We also test the feasibility of congestion pricing. Fig. 9 presents some results on how two pricing schemes (area-base pricing vs. on-street parking pricing) can decrease the cruising effect and decrease the total vehicle hours travelled for two different cases. The two cases represent the same city structure of San Francisco network but with different demands for internal f_{in} and external destinations f_{ex}. The black dots represent the two base scenarios without pricing, which produce a similar total delay of 13,000vh-h. In case 1, external destinations are about 50% more than internal destinations and N_p=4500 spots. In case 2, demands for internal and external destinations are equal and N_p=6000 spots. Then we apply the two different pricing schemes with an objective to change the demand profiles.[13] Area-based pricing decreases equally the demand for f_{in} and f_{ex}, while on-street pricing is assumed to just persuade drivers to parking in garages and not cruise, i.e. the demand of trips is the same, but the decrease in f_{in} is equal to the increase of f_{ex}. Note how more efficient is the parking pricing in case 2, which decreases the total delays by 40% (from 13,000 to 9000vh-h) with only 5% shift in the demand from on-street parking to garage parking. In contrary, parking pricing is less efficient in case 1 because external destination demand is high, and area-based pricing is needed for mobility improvements. This is an encouraging result because on-street pricing is much easier to be implemented in terms of operation and implementation costs compared to the area-based pricing. More research is required towards this direction.

5. Final remarks

This paper described the dynamics of the rush hour for multi-neighbourhood cities, where congestion is not evenly distributed across a city. This analysis is an intermediate, but necessary, step in developing perimeter control strategies for cities with multiple centres of congestion, which can increase the mobility of the system, without requiring the knowledge of detailed information about origin–destination tables.

Also, this paper modelled in a parsimonious way the cruising-for-parking phenomenon and showed the multiple effects in all drivers, even those with destinations outside the cruising region. These results can be misinterpreted. We are not advocating increasing parking to meet the demand for travel. This can be a devastating decision because of (i) the tremendous cost to keep pace with increase in travel demand and (ii) the phenomenon of induced demand. For example, according to the Department of Traffic and Parking the city of San Francisco in 2007 had around 450,000 registered vehicles, and this increases by about 35,000

[13] Note that a pricing scheme is not properly developed in this paper. What it is assumed that there exist some pricing scheme that can influence the demand profiles in a desired way. For example Zheng et al. (2012) have tested an MFD-type area pricing scheme in an agent-based simulation for the city of Zurich.

vehicles during each year. But, dwellers or San Francisco in 2007 elections, voted against a proposition, which would prevent all reductions in parking spaces, allow developers to provide more parking spaces in downtown, and set minimum parking requirements for neighbourhoods.

Only if we decide to limit parking (e.g. with pricing), we can limit the demand of individual cars and have positive consequences for more sustainable and less congested cities. In this paper we have developed all the necessary tools to estimate the total costs for a city due to cruising phenomenon, given the total number of parking spots and the aggregated demand. We can then estimate the percentage of demand decrease needed, to eliminate this effect and improve the mobility of the system. In case of high demand for internal destinations, pricing only these types of users (e.g. by pricing curb parking) can help. But, in case of high demand for external (with regard to the cruising region) destinations, toll pricing can be more efficient.

Research underway tries to integrate a multi-region multi-modal framework in the modelling approach where users can choose to travel between public transport or car. They also have to choose if they will cruise for parking or pay a higher garage fee. Interesting insights are expected from such analysis for different types of pricing schemes. Another research priority is to combine the MFD dynamics with a "Vickrey" equilibrium approach, where users can also choose their departure time. Some interesting results towards this direction are derived in Geroliminis and Levinson (2009), Arnott (2013), and Gonzales and Daganzo (2012, 2013) for simple network structures.

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References

Aboudolas, K., Geroliminis, N., 2013. Perimeter and boundary flow control in multi-reservoir heterogeneous networks. Transp. Res. Part B 55, 265–281.
Anas, A., Liu, Y., 2007. A regional economy land use and transportation model (RELU–TRAN): formulation algorithm design and testing. J. Regional Sci. 47 (3), 415–455.
Anderson, S.P., de Palma, A., 2004. The economics of pricing parking. J. Urban Econ. 55 (1), 1–20.
Arnott, R., 2013. A bathtub model of downtown traffic congestion. J. Urban Econ. 76, 110–121.
Arnott, R., 2014. On the optimal target curbside parking occupancy rate. Econ. Transp. 3 (2), 133–144.
Arnott, R., de Palma, A., Lindsey, R., 1991. A temporal and spatial equilibrium analysis of commuter parking. J. Pub. Econ. 45 (3), 301–335.
Arnott, R., DePalma, E., 2011. The corridor problem: preliminary results on the no-toll equilibrium. Transp. Res. Part B: Methodol. 45 (5), 743–768.
Arnott, R., Inci, E., 2006. An integrated model of downtown parking and traffic congestion. J. Urban Econ. 60 (3), 418–442.
Arnott, R., Inci, E., 2010. The stability of downtown parking and traffic congestion. J. Urban Econ. 68 (3), 260–276.
Arnott, R., Rowse, J., 1999. Modeling parking. J. Urban Econ. 45 (1), 97–124.
Arnott, R., Rowse, J., 2009. Downtown parking in auto city. Reg. Sci. Urban Econ. 39 (1), 1–14.
Axhausen, K.W., Polak, J.W., 1991. Choice of parking: stated preference approach. Transportation 18 (1), 59–81.
Benenson, I., Martens, K., Birfir, S., 2008. PARKAGENT: an agent-based model of parking in the city. Comput. Environ. Urban Syst. 32, 6.
Calthrop, E., Proost, S., van Dender, K., 2000. Parking policies and road pricing. Urban Stud. 37 (1), 63–76.
Cassidy, M.J., Bertini, R.L., 1999. Some traffic features at freeway bottlenecks. Transp. Res. Part B: Methodol. 33 (1), 25–42.
Daganzo, C.F., 2007. Urban gridlock: macroscopic modeling and mitigation approaches. Transp. Res. Part B 41 (1), 49–62.
Douglas, R., 1975. A parking model—the effect of supply on demand. Am. Econ. 19, 85–86.
Edie, L.C., 1963. Discussion of traffic stream measurements and definitions. In: Almond, J. (Ed.), Proceedings of the 2nd International Symposium on the Theory of Traffic Flow. OECD, Paris, pp. 139–154.
Fosgerau, M., de Palma, A., 2013. The dynamics of urban traffic congestion and the price of parking. J. Pub. Econ. 105, 106–115.
Fosgerau, M., Small, K.A., 2013. Hypercongestion in downtown metropolis. J. Urban Econ. 76, 122–134.
Geroliminis, N., Daganzo, C.F., 2007. Macroscopic modeling of traffic in cities. In: Transportation Research Board 86th Annual Meeting. No. 07-0413.
Geroliminis, N., Daganzo, C.F., 2008. Existence of urban-scale macroscopic fundamental diagrams: some experimental findings. Transp. Res. Part B 42 (9), 759–770.
Geroliminis, N., Haddad, J., Ramezani, M., 2013. Optimal perimeter control for two urban regions with macroscopic fundamental diagrams: a model predictive approach. IEEE Trans. Intell. Transp. Syst. 14 (1), 348–359.
Geroliminis, N., Levinson, D.M., 2009. Cordon pricing consistent with the physics of overcrowding, Transportation and Traffic Theory 2009: Golden Jubilee. Springer, Hong Kong, pp. 219–240.
Geroliminis, N., Sun, J., 2011. Properties of a well-defined macroscopic fundamental diagram for urban traffic. Transp. Res. Part B 45, 3.
Glazer, A., Niskanen, E., 1992. Parking fees and congestion. Sci. Urban Econ. 22 (1), 123–132.
Godfrey, J.W., 1969. The mechanism of a road network. Traffic Eng. Control 11 (7), 323–327.
Gonzales, E.J., Daganzo, C.F., 2012. Morning commute with competing modes and distributed demand: user equilibrium, system optimum, and pricing. Transp. Res. Part B: Methodol. 46 (10), 1519–1534.
Gonzales, E.J., Daganzo, C.F., 2013. The evening commute with cars and transit: duality results and user equilibrium for the combined morning and evening peaks. Transp. Res. Part B: Methodol. 57, 286–299.
Haddad, J., Ramezani, M., Geroliminis, N., 2013. Cooperative traffic control of a mixed network with two urban regions and a freeway. Transp. Res. Part B: Methodol. 54, 17–36.
Ji, Y., Geroliminis, N., 2012. On the spatial partitioning of urban transportation networks. Transp. Res. Part B 46 (10), 1639–1656.
Keyvan-Ekbatani, M., Kouvelas, A., Papamichail, I., Papageorgiou, M., 2012. Exploiting the fundamental diagram of urban networks for feedback-based gating. Transp. Res. Part B: Methodol. 46 (10), 1393–1403.
Keyvan-Ekbatani, M., Yildirimoglu, M., Geroliminis, N., Papageorgiou, M., 2015. Multiple concentric gating traffic control in large-scale urban networks. IEEE Trans. Intell. Transp. Syst. PP (99), 1–14 〈http://dx.doi.org/10.1109/TITS.2015.2399303〉.
Lago, A., Daganzo, C.F., 2007. Spillovers, merging traffic and the morning commute. Transp. Res. Part B: Methodol. 41 (6), 670–683.
Levy, N., Martens, K., Benenson, I., 2013. Exploring cruising using agent-based and analytical models of parking. Transportmet. A: Transp. Sci. 9 (9), 773–797.
Little, J.D., 1961. A proof for the queuing formula: $L=\lambda w$. Oper. Res. 9 (3), 383–387.
Lucas, R.E., 1976. Econometric policy evaluation: a critique. In: Carnegie–Rochester Conference Series on Public Policy. vol. 1. Elsevier, pp. 19–46.
Pigou, A.C., 1912. Wealth and Welfare. Macmillan, London.
Qian, Z.S., Xiao, F.E., Zhang, H., 2012. Managing morning commute traffic with parking. Transp. Res. Part B: Methodol. 46 (7), 894–916.
Ramezani, M., Haddad, J., Geroliminis, N., 2015. Dynamics of heterogeneity in urban networks: aggregated traffic modeling and hierarchical control. Transp. Res. Part B: Methodol. 74, 1–19.
Shoup, D. C., 2005. The High Cost of Free Parking, vol. 7. Planners Press, American Planning Association Washington, DC, USA.
Shoup, D.C., 2006. Cruising for parking. Transp. Policy 13 (6), 479–486.
Small, K.A., Chu, X., 2003. Hypercongestion. J. Transp. Econ. Policy, 319–352.
Tsekeris, T., Geroliminis, N., 2013. City size, network structure and traffic congestion. J. Urban Econ. 76, 1–14.
Verhoef, E., Nijkamp, P., Rietveld, P., 1995. The economics of regulatory parking policies: the (im) possibilities of parking policies in traffic regulation. Transp. Res. Part A: Policy Pract. 29, 2.
Vickrey, W.S., 1969. Congestion theory and transport investment. Am. Econ. Rev., 251–260.
Yang, H., Liu, W., Wang, X., Zhang, X., 2013. On the morning commute problem with bottleneck congestion and parking space constraints. Transp. Res. Part B: Methodol. 58, 106–118.
Yildirimoglu, M., Geroliminis, N., 2014. Approximating dynamic equilibrium conditions with macroscopic fundamental diagrams. Transp. Res. Part B: Methodol. 70, 186–200.
Zhang, X., Huang, H.J., Zhang, H., 2008. Integrated daily commuting patterns and optimal road tolls and parking fees in a linear city. Transp. Res. Part B: Methodol. 42 (1), 38–56.
Zhang, X., Yang, H., Huang, H.J., 2011. Improving travel efficiency by parking permits distribution and trading. Transp. Res. Part B: Methodol. 45 (7), 1018–1034.
Zheng, N., Waraich, R.A., Axhausen, K.W., Geroliminis, N., 2012. A dynamic cordon pricing scheme combining the macroscopic fundamental diagram and an agent-based traffic model. Transp. Res. Part A: Policy Pract. 46 (8), 1291–1303.