Modeling and optimization of multimodal urban networks with limited parking and dynamic pricing

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ABSTRACT

Cruising-for-parking is a critical mobility issue in urban cities. The cost and accessibility of parking significantly influence people's travel behavior (such as mode choice) and facility choice (on-street or garage parking). Car-users may have to cruise for on-street parking space before reaching destinations and cause delays eventually to everyone, even users with destinations outside limited parking areas. It is therefore important to understand the impact of parking limitation on mobility and identify efficient parking policies. However, most existing studies on parking either fall short in reproducing the dynamic spatiotemporal features of traffic congestion in general and the cruising-for-parking phenomenon, or require detailed input data that are costly and difficult to collect. In this paper, we propose an aggregated dynamic model for multimodal mobility with the consideration of parking, and utilize the model to evaluate management policies, such as parking pricing. The proposed approach is based on the recent development of the low-scattered Macroscopic Fundamental Diagram (MFD), where the MFD can capture congestion dynamics at network-level for single-mode and bi-modal (car and bus) systems. A parsimonious parking model is integrated into the MFD-based multimodal modeling framework, where the dynamics of vehicle and bus flows are considered with a change in the aggregated behavior (e.g. mode choice and parking facility choice) caused by parking cruising and congestion. Pricing strategies of parking are then developed with the objective of reducing congestion, as well as the total travel cost. An example on a bi-modal city investigates the traffic performance under various types of parking policies and pricing schemes of different parking facilities, e.g. on-street parking and garage parking.

INTRODUCTION

Cruising-for-parking can significantly influence mobility in congested urban networks. The cost and accessibility of parking significantly impact people's travel behavior, such as mode choice and facility choice (on-street or garage parking). Furthermore, parking affects traffic performance. Car-users may have to cruise for on-street parking space before reaching destinations and cause delays eventually to everyone, even users with destinations outside limited parking areas. Therefore, it is crucial to understand the impact of parking on mobility and identify traffic management policies to avoid the negative externalities.

Consider a system where travelling by car and searching for an on-street parking is the only available mode of transport (see for example Arnott and Rorwse (2009), Arnott and Inci (2010), Geroliminis (2014)). In this case under high demand the system has a stable equilibrium, which is close to gridlock. Parking will always be full and whenever there is a free spot, this will be occupied immediately by the cruising vehicles as very well stated in Arnott and Inci (2010) and also showed in Geroliminis (2014). If passengers have efficient alternative choices (e.g. change of departure time, utilizing a parking garage, switch to public transport) and some of these choices might be properly priced, then the system might end up in non-gridlock states. This paper investigates the traffic dynamics of a system with limited on-street parking, unlimited but priced garage parking and a public transport alternative. It develops a feedback-based pricing scheme that does not require prediction of the state of the system and shows that hyper-congestion and cruising can be avoided. It also investigates how close such a traffic management strategy can get to the system optimum pricing with perfect information of the future conditions of the system. While detailed micro- or agent-based simulations could provide a scenario analysis of such a system, we follow a "dynamic aggregated approach" consistent with the physics of traffic congestion that can contribute to develop some strong physical intuition for such a challenging problem. Time of departure is not considered, as it will make the solution approach too hard for analytical derivations.

Extensive studies have been dedicated to address how parking and parking policies influence people's mode choice and travel delay. Representative works can be found in Arnott and Rorwse (1999), Anderson and de Palma (2004) (2007), Arnott (2006), Forsgerau and de Palma (2013), Qian et al. (2013) and elsewhere. Most of these works are based on the classical bottleneck-model, which was developed by Vickrey (1969), and make important extensions of the model by considering parking constraints to reveal behavioral changes under parking limitation and parking-related policies. However, few studies discuss the dynamic influence of parking on traffic flow. In case of insufficient parking capacity, for instance, cruise-for-parking flows should be treated differently than the normal running flows. Existing analysis on this subject include for instance, Arnott and Rorwse (2009) and Arnott et al. (2013), which took the impact of cruising into account when analyzing parking pricing policies; Martens et al. (2010) examined spatial effect on searching for parking; while Horni et al. (2013) incorporated parking choice and searching-for-parking in an agent-based model with simplistic traffic modeling. However, these studies assumed static traffic states and did not deal with the dynamics of traffic (e.g. how traffic density changes over time) that can be significantly different in the presence of parking limitations. The treatment of the physics of cruising-for-parking and how cruising can lead to congestion remain challenging research subjects.

Recent studies indeed moved toward this direction. For example, Gallo et al. (2011) incorporated parking costs in their traffic assignment model; van Ommeren et al. (2012) carried out an empirical study on the diverse features of cruising time in the Netherlands; while Guo and Gao (2012) developed a model to estimate travel time including the delay from searching for on-street parking space. The issue is that the utilized approach may either require data that are difficult to collect (e.g. detailed information of origin-destination and parking availability at destination) or become computationally expensive in large-scale applications (e.g. microscopic traffic or agent-based models). Several works analyzed delay caused by on-street curb parking at intersection level, see for example Yousif and Purnawan (2004) and Cao et al. (2014). Nevertheless, these models cannot be readily applied on large-scale networks. Latest findings on the low-scattered Macroscopic Fundamental Diagram (MFD) provide a promising tool for modeling the complex dynamics of transport system at network-level. Geroliminis (2014) proposes a macroscopic parking model, which is built into an MFD framework to capture the influence of parking on congestion. This work shows that the MFD-based model not only reflects the dynamics of parking flows in an urban network, but also requires data that can be practically obtained. Moreover, this work reveals that if cruising-for-parking is intense, demand which is lower than the network capacity can create significant congestion due to higher trip lengths. It proposes simple types of traffic management that alleviate the phenomenon, and shows that perimeter control (restricting the inflow 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 inner zone; otherwise applying congestion and parking pricing are more efficient. What is still missing though is a modelling approach, which can be integrated in multi-modal multi-region systems. Furthermore, the impact of parking limitation and parking management strategies on multimodal mobility deserves further research effort. Although mode choice was indeed studied by taking into account the influence of parking availability and cost, see for example in Li et al. (2007), Zhou et al. (2008) and Liu et al. (2009), the utilized approaches again fall short in the dynamic treatment of cruising and congestion.

This work aims to fill in the aforementioned research gaps. The objective is to develop an aggregated macroscopic approach for modeling multimodal system with parking limitation. This approach shall enable the development and optimization of parking pricing strategies for improving multimodal mobility. A recent study by the authors presents a macroscopic approach to model the dynamics of a bi-modal (cars and buses) transport system (Zheng and Geroliminis, 2013) without any parking treatment. The work shows that effective management strategies such as allocation of dedicated-bus-lanes and area-based pricing can be developed by utilizing a low-scattered bi-modal MFD. A parking module will be integrated into this bi-modal modeling framework to capture the dynamic of cruising-for-parking and estimate cruising delay. The bi-modal traffic model that is utilized to reproduce the movement of traffic flows will be extended by specific treatment on the car flow families: moving, cruising-for-parking and parked.

The remaining part of the paper is organized as follows. Section II presents the methodology for modeling multimodal traffic system dynamics with parking, building on the work of Geroliminis (2014). Four subsections will be given on the underlying traffic model, parking model, system model and mode choice model, respectively. Two parking pricing strategies are developed in Section III, with the objective to reduce general congestion and the total travel cost. While Section IV discusses the results of a case study, where the rationale of the modeling approach is shown and system performances under different parking pricing strategies are evaluated. Concluding remarks are given in Section IV.

METHODOLOGY

In this section, we present the macroscopic approach for modeling multimodal traffic dynamics with limited parking. For readability, we provide a nomenclature in Table 1 for the main variables and parameters utilized in the paper.

Table 1 List of main variables and parameters

Variables	Description
$P_i^m(t)$	Total distance traveled (production) in region i by mode m at time interval t
$N_i^m(t)$	The accumulation of mode m currently in region i at time t
$G_i^m(N_i^m(t))$	The production MFD for mode m in region i , in function of the accumulation N_i^m at time t
$Q_{i\to j}^{km}(t)$	Demand generated using mode m in region i approaching to the neighbor region j at time t with final destination regions k
$O_{i\to j}^{km}(t)$	Trip completion/transfer flow of mode m from region i approaching to the bounded neighbor regions j with final destination regions k at time t
$O_i^m(t)$	Vehicle outflow of mode m exiting region i at time t
$I_i^m(t)$	Incoming flow of mode m from external regions to region i at time t
$NP_i^m(t)$	Passenger accumulation on mode m currently in region i at time t

$OP_i^m(t)$	Passenger outflow on mode m exiting region i at time t
$N_{x,i}(t)$	Accumulation of car family x in region i at time t ($\boldsymbol{x} = r, s, o, g, os$)
$O_{x,i}(t)$	Outflow flow of car family x in region i at time t
$\omega_{os,i}^c(t) \mid \omega_{g,i}^c(t)$	Fraction of trip-finishing cars for on-street (or garage parking) in region i at time t
$\omega_i^m(t)$	Fraction of passengers travelling with mode m in region i at time t
$O_{r\to s,i}(t) \mid O_{r\to g,i}(t)$	The transfer flow from the running family to searching family or to garage parking in region i at time
$l_{x,i}$	The average trip distance of car family x travelled in region i
$occ_i^m(t)$	The average occupancy of mode m in region i at time t
$N_{os,i}(t)$	The occupied on-street parking spaces at time t of region i
A_i	The total amount of on-street parking spaces of region i
$\varphi_i(t)$	The probably of finding an available on-street parking space at t in i
$L_i(t)$	The average cruising distance before finding an available on-street parking space at time t in region i
$T_{cru,i}(t)$	The average cruising delay at time t in a region i
$p_{os}(t) \mid p_g(t)$	Pricing rates for on-street parking (or garage parking) at time t

Multimodal macroscopic traffic model

Recent findings on the Macroscopic Fundamental Diagram (MFD) significantly advance network level modelling of urban congestion. The idea of macroscopic traffic model for car-only urban networks was initially proposed by Godfrey (1969). The existence of the MFD with dynamic features and from field data was firstly reported in Geroliminis and Daganzo (2008), showing that urban single-mode regions exhibit an MFD relating network production to network density. An interested reader could refer to Mahmassani et al. (2013) and Leclercq et al. (2014) for a review of recent development on MFD-related theories. Latest works extend the MFD from single-mode application to bi-modal, where cars and buses share the same infrastructure (Zheng and Geroliminis (2013), Geroliminis et al. (2014)). The existence of a mixed-traffic MFD and a three-dimensional MFD (3D-MFD) are investigated in these works via micro-simulation studies. Remarkably, the MFDs relate the accumulation of cars and buses to passenger flows representing congestion dynamics under different mode compositions.

We utilize in this work both the single-mode and the multimodal MFD (cars and buses) as the traffic model, relating the total distance travelled in region i of mode m (m can be any vehicular mode that either utilizing dedicated road space or sharing space with other modes) at time t, the production $P_i^m(t)$, to vehicle accumulation $N_i^m(t)$. Mathematically, it is written as follows, for single-mode traffic (e.g. dedicated lanes separating cars and buses) and mixed traffic:

$$P_i^m(t) = G_i^m\left(N_i^m(t)\right) \tag{1}$$

G_i^m is the MFD function which can be obtained via analytical approximations (Geroliminis and Boyaci (2012), Leclercq and Geroliminis (2013)). Based on well-established traffic flow concepts, it is straightforward to estimate trip completion rate, the outflow of a network $O_i^m(t)$, and the average speed $v_i^m(t)$ from the production by: $O_i^m(t) = P_i^m(t)/l_i^m$ where l_i^m is the average trip distance, and $v_i^m(t) = P_i^m(t)/N_i^m(t)$.

Parking model

Consider a network that has two typical parking facilities: on-street parking and garage parking. The on-street parking has total parking space A_i and the occupied parking space at time t is $N_{os,i}(t)$. The available parking space thus is $A_i - N_{os,i}(t) \geq 0$, while the garage parking is assumed to have infinite capacity without cruising delay. To reflect the impact of parking limitation on traffic, a parking model must be introduced. A bi-modal MFD model with unlimited parking such as the one in Zheng and Geroliminis (2013) considers two families of car movements: (I) cars moving towards internal destination, and (II) towards external destinations. We now extend the treatment to three families: (I) cars running towards internal destination but not yet search for parking $N_{r,i}(t)$, (II) cars reaching destination and searching for on-street parking space and (III) cars moving towards external destination regions $N_{o,i}(t)$. Cars reaching destination and successfully parked are denoted by $N_{os,i}(t)$ and $N_{g,i}(t)$ for on-street parking and garage parking, respectively. The interactions among the different families will be illustrated later. For simplicity, mode index c (for cars) is skipped in these family notations.

For family II, the cruising-for-parking process is considered to be repetitive Bernoulli trials, until an available parking spot is obtained, which is expressed by a geometric distribution (number of trials until the first success). The probability $\varphi_i(t)$ that a parking spot is available when being reached, is in direction proportion to the ratio between the available space $A_i - N_{os,i}(t)$ and the total parking space A_i (in this work we consider only one region with parking difficulties, but this can be easily extended to multiple regions) *

$$\varphi_i(t) = \frac{A_i - N_{os,i}(t)}{A_i} \tag{2}$$

We assume the parking spaces evenly distributed around the destinations, with a spacing s_i. Alternatively one may apply a two-dimension cruising model, provided with detailed data on spatial distribution of parking spaces and the cruising behavior of cars.

Given the geometric distribution, the mean number of parking spaces passed by cars in family II before finding an available parking space is $1/\varphi_i(t)$. The average cruising distance $L_i(t)$ thus can be obtained by Equation (3), while a similar model with similar formulation exists in Geroliminis (2014):

$$L_i(t) = s_i \cdot \frac{1}{\varphi_i(t)} \tag{3}$$

Given the speed $v_i^c(t)$ from the MFD, the cruising delay $T_{cru,i}(t)$ can be obtained as:

$$T_{cru,i}(t) = \frac{L_i(t)}{v_i^c(t)} = \frac{s_i}{\varphi_i(t) \cdot v_i^c(t)} \tag{4}$$

Regarding the pricing of using the facilities, denote $p_{os}(t)$ and $p_g(t)$ for on-street parking rate and garage parking rate at time t. Cruising inside garages is neglected in this study.

* Alternatively one may apply a two-dimension cruising model, provided with detailed data on spatial distribution of parking spaces and the cruising behavior of cars.

Similar aggregated models treating parking limitation can be found in Geroliminis (2014), where a parking model built into an MFD modeling framework was proposed and perimeter flow control strategy was developed to reduce both parking cost and total cost for travelers, for single-mode systems; and in Arnott and Inci (2010), where equilibrium conditions under parking constraint (space, duration) are derived for a single-region single-mode and single-parking-facility system under steady-states.

System dynamics with MFD representation and parking

To apply our model, a large-scale city network shall be firstly clustered into regions. The criteria for clustering are: (i) homogeneous distribution of congestion within each region to obtain a low scatter MFD (see Ji and Geroliminis (2012) for more details) and (ii) similar type of mode usage. Given the regional accumulation $N_i^m(t)$, the regional MFD G_i^m estimates production $P_i^m(t)$ and outflow $O_i^m(t)$ of vehicles, and of persons $OP_i^m(t) = O_i^m(t) \cdot occ_i^m(t)$ provided the average passenger occupancy of mode m, $occ_i^m(t)$. Given the traffic demand of mode choice m, $Q_i^m(t)$, the dynamics of each partitioned region i of this bi-modal system can be described by the change of $N_i^m(t)$ for vehicle flow, and the change of $NP_i^m(t)$ for person flow. A discrete version of the dynamics can be found as follows:

$$N_i^m(t+1) = N_i^m(t) + \frac{Q_i^m(t)}{occ_i^m(t)} + I_i^m(t) - O_i^m(t) \tag{5}$$

$$NP_i^m(t+1) = NP_i^m(t) + Q_i^m(t) + IP_i^m(t) - OP_i^m(t) \tag{6}$$

In the equations, demand $Q_i^m(t)$=$\sum_{k\neq i}\sum_j Q_{i\to j}^{km}(t)$, where $Q_{i\to j}^{km}$ is the demand generated in region i approaching to the neighbor regions j with final destinations k. The regional outflow $O_i^m(t) = \sum_{k\neq i}\sum_j O_{i\to j}^{km}(t)$, is constrained by the receiving capacity of the approaching regions j and the boundary capacity between i and j. Variable I_i^m denotes the total incoming vehicle flow from the neighbor regions, $I_i^m(t) = \sum_k \sum_{j\neq i} O_{j\to i}^{km}(t)$, while $IP_i^m(t)$ is the incoming flow in person units. Note that (i) for route choice between an origin-destination pair, a regional route choice model can be applied to determine the sequence of the passing regions (Yildirimoglu and Geroliminis, 2014), and (ii) for details on the distributions of flows over the different regional ODs, for example $N_{i\to j}^{km}$ over N_i^m, readers can refer to Zheng and Geroliminis (2013).

To estimate the cruising time for cars, it is indispensable to decompose $N_i^c(t)$ in Equation (5) into the three movement families that were introduced in the previous subsection: $N_i^c(t) = N_{r,i}(t) + N_{s,i}(t) + N_{o,i}(t)$. Buses are assumed to have one family of vehicles with external destinations and no generated "demand", as buses operate usually circular routes across the regions with small time-varying service frequencies. Equations (5) and (6) without the demand terms Q are sufficient for describing the dynamics of buses. Figure 1 displays flow movements of buses and cars with parking choices in region i, with all state variables included.

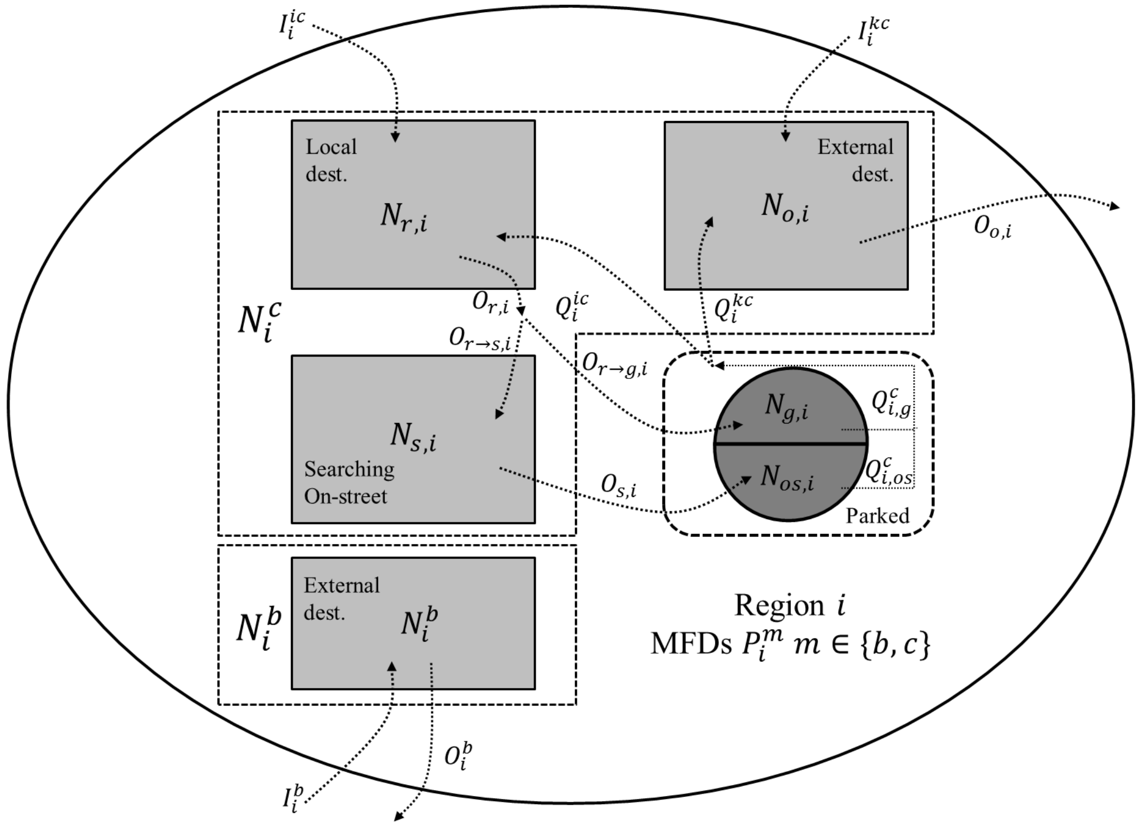

Figure 1 Flow movements in region network $\boldsymbol{i}$ with parking choices

Assume $occ_i^c(t) = 1$ and constant, the flow conservation of the families I, II, III, and the two families of the parked cars can be written as follows and illustrated by Figure 1:

$$N_{r,i}(t+1) = N_{r,i}(t) + Q_{\boldsymbol{i}}^{ic}(t) + I_{\boldsymbol{i}}^{\boldsymbol{ic}}(t) - O_{r,i}(t) \tag{7a}$$

$$N_{s,i}(t+1) = N_{s,i}(t) + O_{r\to s,i}(t) - O_{s,i}(t) \tag{7b}$$

$$N_{o,i}(t+1) = N_{o,i}(t) + Q_{\boldsymbol{i}}^{kc}(t) + I_{\boldsymbol{i}}^{\boldsymbol{kc}}(t) - O_{o,i}(t) \tag{7c}$$

$$N_{os,i}(t+1) = N_{os,i}(t) - Q_{i,os}^c(t) + O_{s,i}(t) \tag{7d}$$

$$N_{g,i}(t+1) = N_{g,i}(t) - Q_{i,g}^c(t) + O_{r\to g,i}(t) \tag{7e}$$

In Equation(7a), $Q_i^{ic}(t)$ is the internal demand from region i to i; I_i^{ic} is the total incoming flow from external regions to region i and ending their trips in region i, where $I_i^{ic} = \sum_{j\neq i} O_{j\to i}^{ic}(t)$. In Equation (7b), $O_{r\to s,i}(t)$ is the transfer flow from running (family I) to searching-for-parking (family II), $O_{r\to s,i}(t) = O_{r,i}(t)\cdot \omega_{os,i}^c(t)$ and $\omega_{os,i}^c(t)$ denotes the percentage of trip-finishing cars that pursuing on-street parking. The term $Q_{\boldsymbol{i}}^{kc}(t) = \sum_{k\neq i}\sum_{j\neq i} Q_{i\to j}^{km}(t)$ in Equation (7c) denotes the total demand generated in region i with external destinations k; $I_{\boldsymbol{i}}^{\boldsymbol{kc}}(t) = \sum_{k\neq i}\sum_{j\neq i} O_{j\to i}^{km}(t)$ is the total through transfer flow; while the last term $O_{o,i}(t) = \sum_{k\neq i}\sum_{j\neq i} O_{i\to j}^{km}(t)$ is the total outflow exiting region i. Equations (7d) and (7e) describe the dynamics of the parking flows, where $Q_{i,os}^c(t)$ and $Q_{i,g}^c(t)$ are the demand generated from on-street parking and garage parking, $Q_{i,os}^c(t) + Q_{i,g}^c(t) = Q_i^{ic}(t) + Q_i^{kc}(t)$.

The family-specific outflow $O_{x,i}(t), x \in \{m, g, s, o\}$ can be obtained by Little's formula:

$$O_{x,i}(t) = \frac{N_{x,i}(t)}{N_i^c(t)} \cdot \frac{P_i^c(t)}{l_{x,i}} \tag{8}$$

Where $N_i^c(t) = \sum_x N_{x,i}(t)$, and $P_i^c(t) = P_i^c(N_i^c(t))$ is estimated by (1). $l_{x,i}$ is the average trip distance of family x travelled in region i, where $l_{m,i} = l_{g,i} = l_{o,i} = l_c$ and l_c is network specific and given. $l_{s,i} = L_i(t)$ is estimated by Equation (3).

Aggregated mode choice

To determine the mode split of the newly-generated demand (between car and bus) a Nested-Logit model is applied based on the latest known trip disutility (costs) $C_i^{c,n}(t)$ for travelling with cars with parking facility choice $n = \{\text{on street vs. garage}\}$, and $C_i^b(t)$ for traveling with buses. For cars, trip disutility includes travel time, cruising delay and the costs of parking. While for buses, trip cost consists of travel time, accessing time and the discomfort of on-board overcrowding (see detail in Zheng and Geroliminis (2014)). In our case, the nest is required by the parking facility choice n. Denote $\omega_{g,i}^c(t)$, $\omega_{os,i}^c(t)$,the percentage of mode choice of cars with garage or on-street parking, and $\omega_i^c(t)$ and $\omega_i^b(t)$, the percentage of mode choice of cars and buses. We assume the travelers choose their mode of transport, either cars or buses, in the beginning of their trips. The estimation of bus share $\omega_i^b(t)$ is given in Equation (9) below

$$\omega_i^b(t) = \frac{\exp\left(\tau_b \cdot C_i^b(t)\right)}{\exp\left(\tau_c \cdot C_i^b(t)\right) + \exp\left(\tau_c \cdot C_i^c(t)\right)} \tag{9}$$

, where $C_i^c(t) = \frac{1}{\beta} \cdot \ln \sum_n \exp\left(\beta \cdot C_i^{c,n}(t)\right)$. Scale parameters $\beta, \tau_b, \tau_c$are calibrated to avoid oscillation in mode shift. By definition $\omega_i^c(t) = 1 - \omega_i^b(t)$. Given the total demand $Q_i(t)$, $Q_i^m(t)$ can be estimated by $\omega_i^c(t)$ and $\omega_i^b(t)$. Given the car demand generation $Q_i^c(t)$, $Q_{i,os}^c(t)$ and $Q_{i,g}^c(t)$ in Equation 7 can be obtained, as we can assume a fixed ratio that demand generated from the parking facilities (meanwhile releasing the parking space) is given.

Note that we assume the car-users have limited knowledge on the possible availability of the on-street parking by the time they arrive at the destination (when they start searching for parking space). Therefore the final choice on parking facility is determined on-site. The distribution of the arriving flow $O_{r,i}(t)$ between the two parking facilities can be estimated trough a ~~normal~~ Logit model by $\omega_{g,i}^c(t)$ and $\omega_{os,i}^c(t)$, where $\omega_{os,i}^c(t) = \exp\left(\beta \cdot C_i^{c,os}(t)\right) / (\exp\left(\beta \cdot C_i^{c,os}(t)\right) + \exp\left(\beta \cdot C_i^{c,g}(t)\right))$. The production of $O_{r,i}(t) \cdot \omega_{os,i}^c(t)$ thus is the input to the cruising family $N_{s,i}(t)$.

PARKING PRICING STRATEGIES

Studies have demonstrated that the MFD modeling can contribute to develop traffic management strategies, examples including congestion pricing (Zheng et al., 2012), space allocation for bus lanes (Zheng and Geroliminis, 2013), and dynamic traffic signal perimeter control (Haddad et al. (2013), Aboudolas and Geroliminis (2013)). We propose two dynamic pricing schemes (strategy P1 and P2) to determine on-street parking pricing $p_{os}(t)$ and garage pricing $p_g(t)$ such that the congestion of traffic and parking is reduced. Pricing is only applied in the center region which experiences more congestion, i.e. a region index is omitted from the above pricing variables. Note that for the strategies under discussion, we assume to have full authority of both pricings whereas in reality they belong to parties with different operating objectives (and competition might occur). We will address this subject in the final part of the paper.

Strategy P1 develops a generic widely used control loop feedback mechanism. It tries to succeed two set points, related to (i) the maximum production of the network (in terms of vehicle-kilometers travelled per time interval) and (ii) small cruising time for on-street parking. The strategy calculates an error value as the difference between a measured process variable and the desired set point. It attempts to minimize the error by adjusting the prices $p_{os}(t)$ and $p_g(t)$.

Strategy P2 considers that the dynamic evolution of the system is known and solves a single full horizon optimization problem to minimize the total costs experienced by all passengers. While such an approach can be considered to provide close to system optimum conditions, it is considered an ideal scenario, which is also difficult to implement. Nevertheless, it provides an upper limit for comparison purposes with more feasible strategies like P1 or time-independent pricing.

A congestion- and cruising-responsive feedback parking pricing scheme (Strategy P1)

This pricing scheme should aim to reduce both traffic congestion caused by cars and by cruising. Car users will pay a parking fee based on the magnitude of congestion they cause at the moment they enter the network. A feedback-type controller is employed to update the time-dependent prices $p_{os}(t)$ and $p_g(t)$, where the control variables are the total accumulation $N^c(t)$ and the accumulation of cruising family $N_{s,i}(t)$. Equations (10) and (11) describe mathematically the two pricing control mechanisms respectively, where c_1 and c_2 are control gain parameters. The concept is that garage users have to pay for the hyper-congestion due to large accumulations of cars in the network, while on-street users have to pay for the cost of cruising as well. In this way, both types of congestion can be eliminated. Equation (10) states that the garage price for the next time interval $t+1$, $p_g(t+1)$, increases if the accumulation of car users $N^c(t)$ exceeds the critical accumulation of the network N^{cr} (where the maximum network production is reached and network production decreases if $N^c(t)>N^{cr}$). N^{cr} is derived from the MFD. Equation (11) indicates that the on-street price $p_{os}(t+1)$ charges the same amount for the reduction of network production, and an additional amount for causing cruising delay which is proportional to the difference between $N_s(t)$ and a pre-defined threshold N^{sT}. Having c_1 parameter in both (10) and (11) simply means that all car users have to pay for congestion independently of the parking choice. Parameter N^{sT} can be interpreted as the tolerated amount of cruising vehicles, a policy factor influencing the service level of on-street parking. We will show in a later graph how N^{sT} is chosen. Strategy P1 does not require any prediction and is based only on quantities that can be estimated with existing sensing techniques.

$$p_g(t+1) = p_g(t) + c_1(N^c(t) - N^{cr}) \tag{10}$$

$$p_{os}(t+1) = p_{os}(t) + c_1(N^c(t) - N^{cr}) + c_2(N_s(t) - N^{sT}) \tag{11}$$

A system optimum parking pricing scheme (Strategy P2)

Strategy P2 aims at achieving a system optimum. The goal of this pricing scheme is to minimize the TPC that serves the total demand by optimizing the parking pricings in the center region controlled by a central operator with a full knowledge of the system, while such a strategy is difficult to be implemented due to prediction limitations and day to day variations of demand. Mathematically it can be described as the following:

$$\min_{p_{os}(t),p_g(t)} Z = \sum_{t,i,m} TPC_i^m(t) = \sum_{t,i,m} NP_i^m(t) \cdot T \,, \tag{12}$$

where T is the duration of the time interval t. Problem (12) is subject to the system dynamics introduced in the previous section. We also add a constraint that $p_{os}(t) < p_g(t)$. The reason is the following. Since on-street parking requires cruising time, if $p_g(t)$ was not larger than $p_{os}(t)$, the cost of garage parking would be less and the optimization will consequently rule out the option of on-street parking. Pricing without this constraint will be evaluated as a future work. The optimization problem (12) is highly non-linear. We solve this problem by sequential quadratic programming. We apply this algorithm for multiple initial values (around 1000) to avoid convergence to local minima, which might be the case for a non-smooth objective function.

CASE STUDY AND ANALYSIS

The proposed approach is tested in an idealized two-region bi-modal network. Mixed traffic of buses and cars occurs in the outside region (periphery), while an optimum fraction of road space in the center region (center) is pre-determined and dedicated to bus usage only, similar to case study of Zheng and Geroliminis (2013). We simulate an urban road traffic system for 4-hours (80 time units), a typical morning period. Demand has a symmetric trapezoidal shape with time and the length of peak period is equal to 1hr. A 70% fraction of the demand generated in the periphery will travel to the city center and 30% fraction of the demand generated in the center will travel to the periphery of the city. A mixed bi-modal MFD for the periphery and two single-mode MFDs for the center are utilized and estimated with Leclercq and Geroliminis (2013) and Leclercq et al. (2014). Two modes of transport are considered available in the system, car and bus. We assume that a fraction 10% of the users are captive bus users and do not have access to cars. The average distance between on-street parking spaces $s = 20m$. The duration of on-street parking is 1hr. A sensitivity analysis on parking duration will be reported as future work.

In the first sub-section, we show the resultant dynamics of the two-region bi-modal system under parking limitation and pricing, illustrating the mechanism of the modeling approach. Then we give performance comparison of four parking pricing policies: a base scenario with free on-street parking, a flat parking-rate scenario for both garage and on-street, Strategy P1 and Strategy P2. A discussion is followed in the final sub-section to address indications on parking policy from the results. The base scenario applies a time-constant parking garage fee p_g which creates crowding for the cruising traffic. The flat parking rate scenario estimates constant values of p_{os} and p_g by minimizing objective function (12).

System dynamics with parking pricing

Figure 2 displays the system dynamics for the center region (the region index is skipped in the text), under an optimal fixed-pricing scheme where the pricings are obtained through optimization, minimizing the total cost of the users. The optimal prices are $p_{os} = 0.4\$/hr$ and $p_g = 1.6\$/hr$. In Figure 2(a) and (d), it can be observed that mode share of buses increases during peak-hour as traveling with cars experience higher travel costs than buses. From the outflow-accumulation MFD in Figure 2(b) (with the critical accumulation $N^{cr} = 5200$veh and a decreasing branch up to $N^c(t) = 9000$veh for car network), we can clearly confirm the car network experiences congestion. Judging from the time series of cruising delay in Figure 2(c), limitation of parking contributes to the high travel cost of cars as well. Nevertheless, even if demand is high, on-street parking is not fully occupied because travelers have alternatives of lower total cost (e.g. public transport or garage with fee). Note that such a pricing scheme cannot fully avoid neither congestion nor cruising. The travel cost of buses remains nearly the same since buses are operated on the dedicated lanes with scheduled frequencies, although a slight increase can be found in Figure 2(d) during the peak-hour, which is a reflection of speed reduction due to the longer dwelling time for boarding more passengers. Congested states can be observed in the MFD in Figure 2(b), where different values of outflow occur for the same accumulation. The reduction of outflow can be explained by the reduction of on-street parking availabilities. As cars have to cruise longer distance to compete for a parking space, the outflow drops accordingly (outflow is production over trip length).

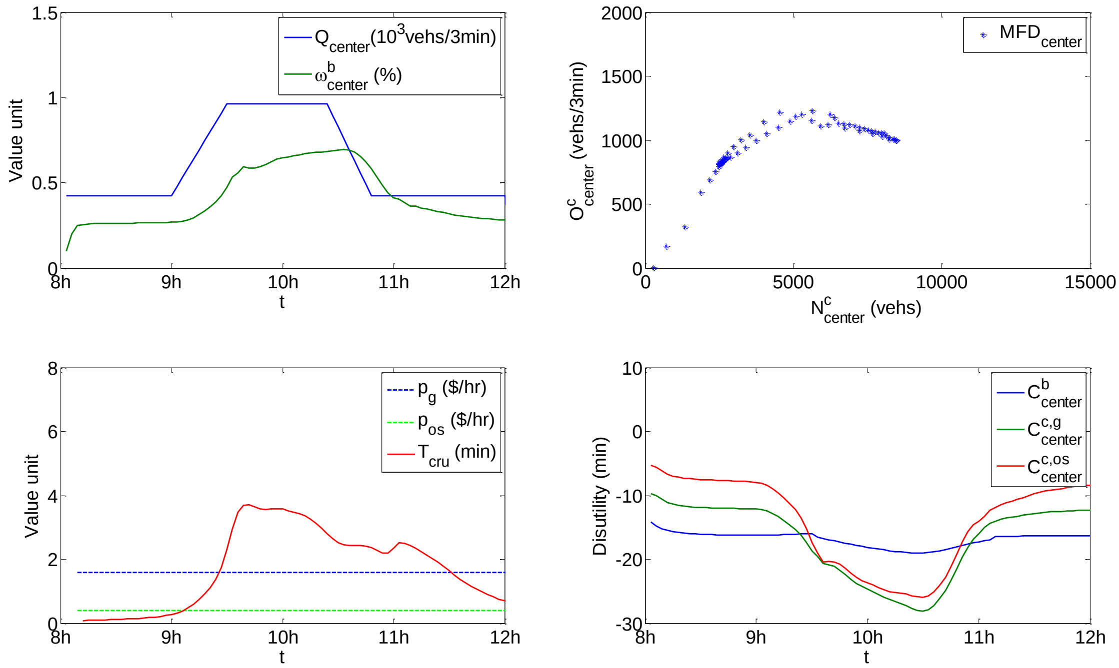

Figure 2 System dynamics and traffic performance under the optimal constant parking pricing scheme for the center region: (a-top left) mode share of bus ω^b_{center} and total travel demand over time, (b-top right) the MFD of the center region car network with congestion observed, (c-down left) the prices of p_{os} and p_g, and cruising-for-parking time, and (d-down right) the cost of traveling with each mode over time.

Figure 3 illustrates the resultant system performance under the feedback-type time-dependent pricing Strategy P1. Prices are updated every 15min (5 interval units). In Figure 3(c), the time-dependent pricing rates $p_{os}(t)$ and $p_g(t)$ are plotted where higher pricing rates are found for the peak hour. Figure 3(a) plots the cruising condition of the basic scenario. For the applied Strategy P1, the objective is to control the cruising delay under 3min therefore we choose a value of 900veh for N^{sT} (note that T_{cru} may be monitored directly from existing data collection technology and used to control the pricing for cruising, nevertheless the same principle applies). Then shown in Figure 3(d), the accumulations $N^c(t)$ and $N_s(t)$ fluctuate closely around the critical values N^{cr} and N^{sT}, though there are a few cases where congestion exceeds the desired states. This shows consistency with the expected system dynamics by feedback controllers.

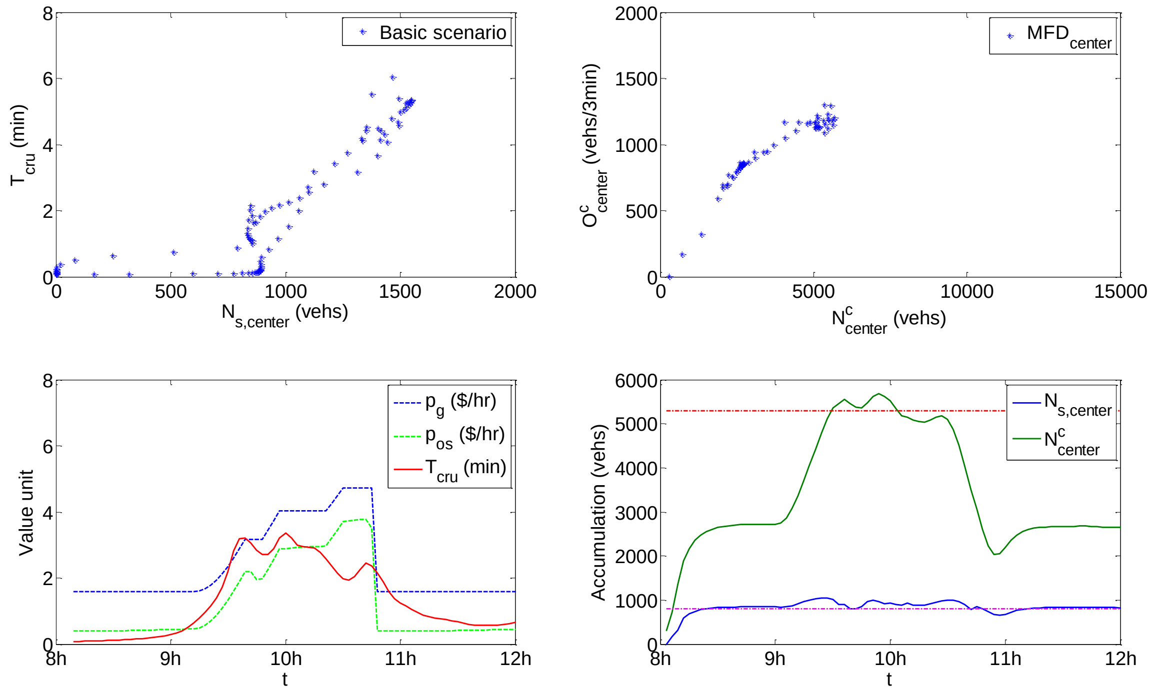

Figure 3 (a-top left) relationship between cruising delay T_{cru} and cruising vehicles $N_{s,center}$ in the basic scenario; System performance by Strategy P1: (b-top right) the MFD of the center region car network, (c-down left) the prices of p_{os} and p_g, and T_{cru}, and (d-down right) the evolution of accumulations with the desired states in dotted lines: upper red for critical accumulation N^{cr} and magenta for the cruising threshold N^{sT}

Now let us examine the performance under Strategy P2. The same graphs of Figure 2 are reproduced and displayed in Figure 4. Comparing to Strategy P1, the cruising delay and accumulation further decrease. Higher maximum outflow can be observed from the MFD. With a careful investigation on the resultant mode shares of bus, we conclude that the improvement of performance under Strategy P2 is due to its capability of triggering an earlier mode shift from cars to buses during the on-set of the peak-hour. Remarkably, such small change (roughly a mode share difference of 2% during 20min) in the mode share creates significantly different traffic performances. Furthermore, it should be highlighted that less total pricing is charged on the users in strategy P2.

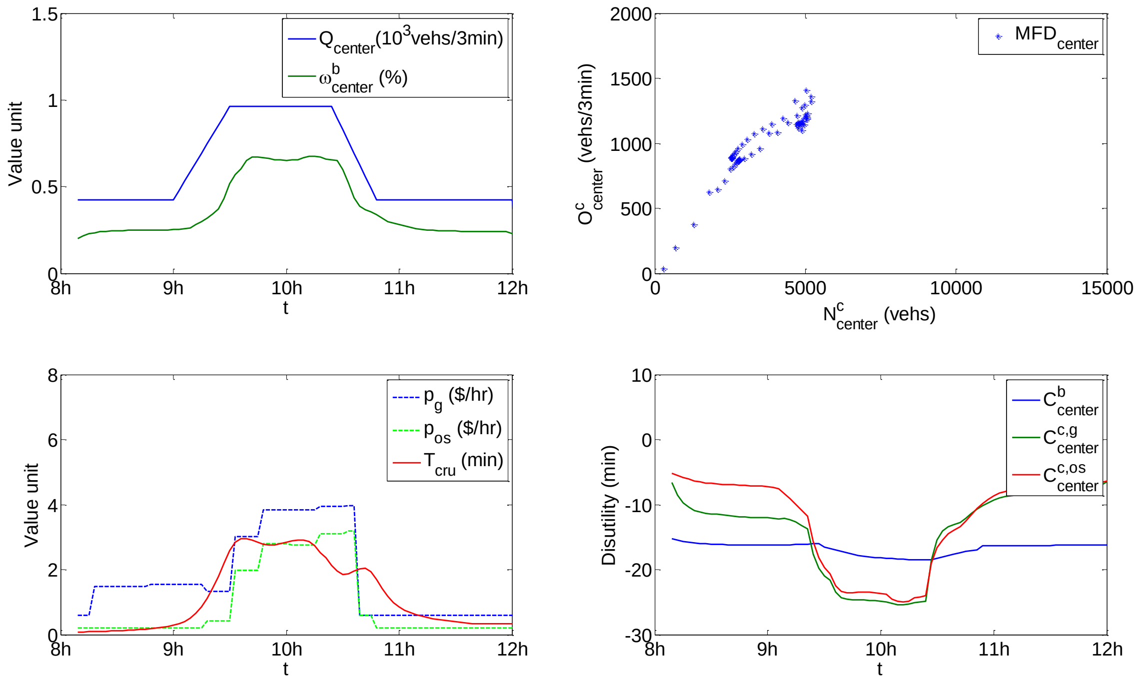

Figure 4 System dynamics and traffic performance under the optimal Strategy P2. The same graphs are reproduced as in Figure 2.

Efficiency evaluation of the pricing schemes

The proposed modeling approach is capable of producing the physics of overcrowding in general traffic and on-street parking, the effect of cruise-for-parking, and the aggregated behavioral change (mode choices) given parking space limitation and cost. The second part of this case study is to test and attain efficient pricing strategies. We compare the resultant system costs among the 4 scenarios by the following performance indicators: the savings in total person hours travelled (PHT) comparing to the base scenario, the total toll paid (TTP, converted to time unit with a mean value-of-time of 16$/hr), the toll efficiency (TF) which is the ratio between the savings in PHT and the corresponding TTP, and the average cruising delay which is the total delay time divided by total amount of on-street parkers. The statistics are listed in Table 2.

Table 2 Comparison of the performances of different pricing schemes

	Saving in PHT (hrs)	Total toll (hrs)	Toll efficiency (ratio: PHT.sav/TTP)	Ave. cruising delay (min)
Base scenario	PHT=45337	660	0	3.7
Constant pricing	1211 (2.7%)	2641	45.8%	1.9
Strategy P1	5944 (13.0%)	7207	82.5%	1.4
Strategy P2	6990 (15.5%)	5857	119.5%	1.2

The base scenario applies a flat rate to garage parking only. In this case, on-street parking is highly desired at first, as parking on-street experiences less cost until the cruising time cost is equivalent to garage pricing rate. However due to the large demand for on-street parking, on-street parking becomes full and results an average 3.7min cruising delay for the later travelers. For the studied network, the average travel time per trip is 6min under free-flow condition and 15min under congestion. A 3.7min cruising time is a relatively considerable amount. Small improvement in PHT can be found when flat-rate tolls are implemented and optimized for both garage and on-street parking. From an efficiency point of view, however, the constant-pricing strategy makes users pay two times more than they gain in the reduction of travel time (in terms of PHT savings), reflected by the toll efficiency value of 45.8%.

Applying Strategy P1, it is observed that the PHT significantly decrease by 13%. To achieve this, however, excessive parking tolls have to be charged. The resultant toll efficiency is around 80% albeit improved over 45% of applying constant pricings. Stimulating results are obtained by the implementation of Strategy P2. The toll efficiency ratio is found nearly at 120%. Moreover, the cruising delay by Strategy P2 outweighs Strategy P1 by 15%. The difference in efficiency between the two pricing strategies P1 and P2 can be explained as the following. Since Strategy P1 is responsive, controllers (10) and (11) do not explicitly consider congestion evolution. While benefiting from the optimization, Strategy P2 is able to predict and adapt traffic conditions and set optimal tolls to trigger an early mode shift. As mentioned-above, a slight mode shift during the on-set of peak-hour could lead to substantial improvement. While strategy P2 is difficult to be implemented in reality as it requires future predictions, a careful analysis of historical data can possibly make this feasible through a model predictive control approach where uncertainty will be treated in the optimization horizon. This is a challenging but interesting future direction.

Parking policy indication

Time-dependent parking-rate represents the current mainstream parking price management in urban areas, though the rates may be determined based on different criteria. For instance, the public-owned parking facilities in the city of San Francisco operate demand-responsive parking pricing which updates the prices at a monthly or shorter basis to reduce cruising time. Strategies P1 attempts to employ such pricing mechanism with a second objective to reduce general congestion. The result shows that the strategy indeed effectively reduces the total PHT and average cruising time. Strategy P2 demonstrates higher efficiency thanks to the opportunities of adapting the changing conditions of both the users and the parking prices. Such opportunities in practice can be offered through online information system.

Note that in this study, we assume policy-makers operate the two parking facilities and have full control of the pricings p_{os} and p_g. In practice, the authorities belong to different operators, e.g. city policy-makers operate on-street parking while real-estate companies operate garage parking. These operators can be considered that have different objectives, e.g. city tries to minimize the generalized cost of all users, TPC, while garage operator maximizes its profit. Then Problem (12) can be re-formulated as the follows:

$$\min_{p_{os}(t)} TPC = \sum_{t,i,m} \left(PHT_i^m(t) + Tos_i^c(t) + Tg_i^c(t) \right) \tag{13}$$

$$\max_{p_{og}(t)} BG = \sum_{t,i} Tg_i^c(t) \tag{14}$$

where $Tos_i^c(t)$, $Tg_i^c(t)$ is the total toll collected at time t in region i from car users using on-street parking and garage parking, respectively.

It can be seen that direct conflict of interests, represented by the term $Tg_i^c(t)$ in Equations (13) and (14), exists between the two operators. Competition behaviour thus should be expected. Let us provide some preliminary result on the system performance under conditions with the existence of competition, while more detailed investigation will be reported in a later version of the paper.

Assume now that the two operators are cooperative with each other and they compete to maximize the common profit. Then solving Problems (13) and (14) can be considered as a bi-objective optimization problem. We apply standard optimization procedure, to obtain the efficient frontier. Two scale parameters valued (0, 1) are given to the two objective functions respectively, where the sum of the two parameters equals to 1. With the scale parameters, the problem is transformed into a single-objective optimization and different Pareto optimal solutions are produced. Figure 5(a) displays the efficient frontier of this problem. With our system model, the potential combination of management pricing policies can be readily estimated.

Assume a second scenario that the two operators are selfish. The pricing competition is a responsive and negotiate-alike process, where each operator changes the pricing strategy after recognizing the impact of the other party's action. We consider solving such competition by a leader-follower optimization procedure, where the policy-maker as the higher level leads the process and the real-estate companies as the lower level follows. At each competition round, each operator tries to optimize its own objective given the action of the previous one. To avoid oscillatory behavior of the optimization procedure, we add constraints that the actions of the one optimization problem should not worsen the other problem by more than 20% compared to the previous step. Comparing to the existing applications of bi-level optimization in transport-related researches, such as in Yin (2000), the challenges here are two-fold: (i) the two objective functions have direct conflict, and (ii) the existence of equilibrium or a competition efficient frontier where the two parties cannot improve their profit. Result of a simulated competition is displayed in Figure 5(b), which illustrates that a long-term equilibrium can be reached for the pricing strategies between the two operators. On-going work makes further effort in the investigation of convergence towards this direction.

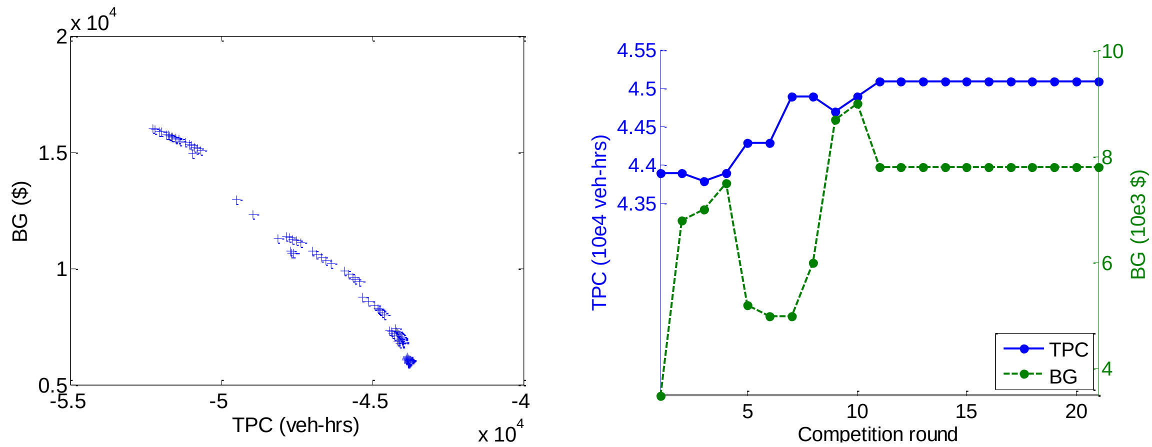

Figure 5 (a) The efficient frontier between maximizing the system performance (minimizing total cost TPC) for the on-street parking operator and maximizing BG the revenue for garage parking operator; (b) The evolution of the costs of TPC and BG over 20 rounds of leader-follower pricing competition

CONCLUSION

In this study, we proposed a macroscopic modeling approach for modeling multi-modal traffic system with parking limitation and cruising-for-parking flow. Parking limitation was integrated in the developed multi-modal system model, where vehicles need to cruise for parking before reaching destination. The time of cruising was estimated by assuming the probability of finding a parking space follows a geometric distribution and depends on the dynamic parking availability. The effect of cruising on the global performance, e.g. the average speed, was also captured, by the MFD dynamics. A case study was carried out in a two-region bi-modal network. Two parking choices were considered: (i) limited on-street parking requiring cruising, and (ii) unlimited garage parking with higher parking fee but no cruising cost. The resultant system behavior under parking limitation and pricing were consistent with the common expectations. We then used the system model to test two network-level parking pricing strategies. Strategy P1 adapted a feedback-type controller for determining the parking price, which was congestion- and parking availability-dependent. Applying this pricing strategy, traffic performance was maintained at desired (controlled) levels. Strategy P2 was obtained through optimization of the total cost (PHT + parking fee). Applying this strategy, pricing efficiency was further improved, as the prices were determined with long-term impact taking into account. Inspired by this result, we investigated the impact of competition on the performance of the pricing strategy, assuming that the authorities of on-street and garage parking belong to different parties who manage prices with different objectives. We presented preliminary results of cooperative-competition via a bi-objective optimization, while a bi-level optimization framework was proposed to simulate a responsive and negotiate-alike parking pricing market. More detailed discussion will be reported in a later version of the paper.

On-going work extends the investigation on the efficiency of parking management under pricing competition. Sensitivity analysis will be carried out on parking duration and parking capacity to reveal their impacts on parking choices, for instance, excessive on-street parking space may lead to cases that fewer travelers go for garage parking even though it is much cheaper. Furthermore, the current treatment of cruising is dimensionless, meaning that the cruising cost is estimated without identifying the detailed routes of cruising. Such consideration aims at the average cost at system level and ignores the cruising possibilities at disaggregated level. Nevertheless large disaggregated heterogeneity is not expected given the spatial correlations in the distribution of congestion and well-defined bi-modal MFD can possibly be found for more complex city structures.

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