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Parking Behavior and Policy

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Editorial

Parking Behavior and Policy

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Parking policies can play a key role within the broader context of managing transport demand. Private vehicles can spend over 90% of their time parked with considerable consequences for land use and economic activities in urban areas. Drivers cruising for parking have important impacts on traffic congestion, air pollution, and accidents; studies such as Shoup [1] indicate that about a 30% of circulating traffic in cities is looking for somewhere to park. However, research in the field of user behaviour when choosing parking has been limited and management policies have often been developed on an ad hoc basis, ignoring theoretical models or available empirical evidence.

In recent decades, a lot of researches into user behavior have been developed in parking choice. In the international literature, important studies are shown that have become a reference for parking management and behavior. Hensher and King [2] reported an important contribution to this research line with the study of the behavior of users of the CBD in Sydney in view of a change in the parking policy (introduction of rates and maximum duration of parking). Additionally, Hess and Polak [3] developed a model in which parking alternatives included the study of illegal parking, to show how it varied if the characteristics of the other types of parking changed. As stated by Shoup, we can no longer continue with the belief that street parking should be free as all urban land areas have a cost for the citizen [4].

These papers generated an important research base on which, during the last years, numerous researches have been developed. Some examples of the latest research carried out in this field are Ibeas et al. [5], where they studied the users' behavior when building an underground parking garage in Santoña (Spain), or Ahmadi Azari et al. [6], who studied how the different parking pricing policies influenced the choice of parking in Montreal, Canada.

This special issue publishes quality papers which can contribute to the understanding of user choice when parking and to the development of parking management policies to help in achieving more sustainable mobility in urban areas.

The special issue is focused on the behaviour of users when choosing the type and location of a parking spot with special emphasis on the evaluation of different parking policies. It is about improving our theoretical knowledge of user choice processes when parking, as well as about the different policies that can significantly influence these decisions.

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Research Article

Parking Management Efficiency Analysis through Various Charge Schemes for Day-Long Commuting considering Elastic Travel Demand

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In this paper, we investigate the travel pattern of the day-long commuting in a bisection bottleneck network and the efficiency of pricing schemes with elastic travel demand. We extend the Vickrey model to morning and evening commutes and allow commuters to arrive at workplace late and depart from workplace early. The parking searching time is considered in the morning commute. Next, we derive the independent morning and evening commuting travel patterns without road toll and parking fee. Then, we propose three pricing regimes: duration dependent parking fees; optimal time-varying road tolls; optimal time-varying road tolls with duration dependent parking fees. We compare the efficiency of the four schemes with elastic demand. Theoretical analysis and the numerical examples show that optimal time-varying road toll is the most efficient pricing scheme. Charging a duration dependent fee neither improves nor deteriorates the scheme of time-varying road toll, if the toll rates are appropriately set. The regime of duration dependent parking fee only is less efficient than the regime of independent morning and evening commuting travel patterns without road toll and parking fee. In the regime of duration dependent parking fee, the social surplus decreases with the increase of duration dependent parking fee rate.

1. Introduction

With the development of metropolis and process of urbanization, traffic demand is increasing steadily. Expanding road network is not efficient, due to the limitation of budget and urban land. Sometimes network expansion is very complicated due to the involvement of various sectors [1]. Parking management provides a new method for urban traffic management. In morning commuting, parking supply cannot meet the traffic demand especially in downtown area and people have to spend much cost for acquiring parking spot. Many scholars have investigated the parking management in morning commuting. Arnott et al. [2] proposed a model that considers spatial distribution of parking in morning commuting and compared the efficiency of road toll and parking fees regimes. Bifulco [3] presented a stochastic user equilibrium assignment model to evaluate parking policies Verhoef et al. [4] studied the parking policies as a substitute to road pricing. Zhang et al. [5] used parking permits to improve the traffic efficiency by eliminating the competition for inadequate parking spots. Qian et al. [6] studied the economics of parking provision for the morning commuting. However, there are few researches in integral analysis of parking searching time for parking space and bottleneck dynamic. In this paper, we analyze how the parking searching time and parking fees affect the commuter's behavior and examine the efficiency of road toll and parking fee to improve the social surplus with elastic demand.

The basic model used in our paper is originated by Vickrey [7]; in the morning, commuters need go to workplace in central business district through a bottleneck with limited service capacity. In the equilibrium, no one can reduce individual travel cost by changing the departure time. Later, many scholars made a lot of research based the bottleneck model.

Daganzo [8] assumed commuters have different working start time and proved uniqueness of the time-dependent equilibrium distribution of arrivals at a single bottleneck. Arnott et al. [9] extended the bottleneck model from fixed demand to elastic demand. Zhang et al. [10] investigated how travelers behave and react on bottlenecks with time-varying capacities, examined the user equilibrium and system optimal traffic patterns, and derived pricing regimes that lead to the system optimum pattern. Recently, many scholars started to measure traffic flows of downtown area. Geroliminis and Daganzo [11] demonstrated the existence of the macroscopic fundamental diagram (MFD), correlating the rate of ending trips with the number of vehicles in an urban area. Arnott [12] assumed that the outflow and the travel time from the downtown area depend on the vehicle accumulation at bottleneck and developed a bathtub model of downtown traffic congestion on the basis of MFD. Fosgerau [13] proposed a similar bathtub model considering the heterogeneity in trip length of population. Geroliminis [14] integrated the traffic dynamic of cruising for parking with a spatially aggregated model of urban hypercongestion, the macroscopic fundamental diagram. Following the study of Geroliminis [14], Liu and Geroliminis [15] explored how the interactions between cruising for parking and congestion reshape the morning commuting considering travelers' scheduling cost and time of departure choice. Ji et al. [16] considered the parking behavior of mixed autonomous and traditional vehicles in a bottleneck and investigated the effect of fare rate of autonomous vehicles. Jiang [17] found that automatic driving can substantially reduce the queuing delay at the intersection bottlenecks. In this paper, we use the traditional queuing model and Vickrey model and treat capacity of bottleneck as a constant value.

The past researches mainly focused on the morning commuting; the evening commuting was not often considered. It was generally believed that the traffic pattern in evening commuting is a mirror image of that in morning commuting. de Palma and Lindsey [18] compared the morning and evening commutes and differed them in just one respect that the schedule preference in morning commuting is in terms of arrival time in destination and the preference in evening is in terms of departure time from destination. Daganzo [19] established the system optimum of day-long commuting and minimized the general social cost of whole day with two travel modes: car and transit. He assumed that the commuters have different wished arrival time and departure time. Gonzales and Daganzo [20] showed that the user equilibrium for isolated morning and evening commutes are asymmetric for different schedule penalty in morning and evening commutes. Zhang et al. [5], Yang et al. [21], and Wang et al. [22] developed methods of parking permit distribution and trading to improve travel efficiency and reduce traffic emission.

Motivated by Arnott et al. [2], Zhang et al. [23] derived a model integrating morning and evening commutes and developed a time-varying road toll and location-dependent parking fee regime to achieve system optimum. Zhang and van Wee [24] compared efficiency of several parking schemes and solved the optimal parking fee rate by minimizing the social cost or maximizing social surplus when considering parking searching time.

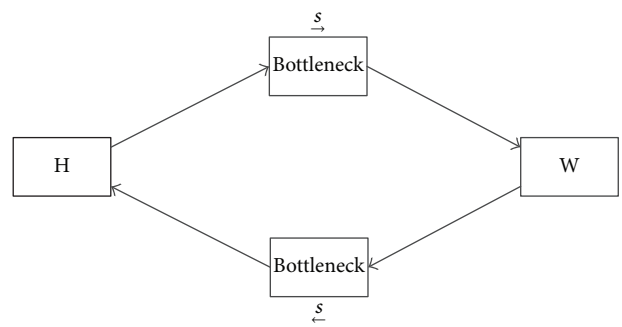

Figure 1: A bidirection bottleneck network in morning and evening commutes.

In this paper, Vickrey's model is developed from a single morning peak to morning and evening peaks. The morning and evening commutes are treated as two independent user equilibrium traffic patterns for the day-long commuting. The analysis of this paper is based on a single bottleneck; it is expected that we can consider day-long parking behavior with network effect with resorting to some approximation methods [25]. Besides, we relax the assumption in the study of Zhang and van Wee [24] by allowing the commuters to arrive at workplace late in morning commuting and leave workplace early in evening commuting. Moreover, traffic demands are often stochastic [26] and dynamic [25]; therefore it is very difficult to precisely predict the travel demands. Travel demands are often influenced by some social and economic factors and affected by travel costs. In the paper, we extend the analysis to considering elastic demands.

Figure 1 shows the network of day-long commuting. In Figure 1, home is represented by "H" and workplace is represented by "W." Let N denote the number of commuters who travel from home to workplace in the morning and return from workplace to home in the evening. The service capacity of bottleneck in home-to-work direction is $\underset{\rightarrow}{s}$ and that in work-to-home direction is $\underset{\leftarrow}{s}$. We assume the parking lot is near to workplace and ignore the commuters' walking time between parking spots and workplace. However, searching time of parking spots is considered in morning commuting. We assume that there is no information provided for auto drivers in the parking lot and the parking searching time increases as the number of occupied parking spots increases with a fixed rate π. Here, π is the increasing searching time rate of unit parking spot. Then the searching time for parking spots in morning commuting with n occupied parking spots is πn. So the first commuter has no parking searching time and the last commuter's parking searching time is πN. When commuters leave from workplace in evening commuting, their searching time for parking spots is zero because they have known where their cars are parked in the morning.

In morning and evening commutes, the commuters have an identical desired arrival time to workplace $\underset{\longrightarrow}{t^*}$ and a departing time from workplace $\underset{\longleftarrow}{t^*}$. In the morning, if

commuters cannot arrive at workplace on time, there are schedule delay costs for them. Let β_1 be the cost of unit early arrival time and γ_1 be the cost of unit late arrival time. In the evening, the commuters also have schedule delay costs for early departing or late departing from workplace. The cost of unit early departing time is β_2 and the cost of unit late departing time is γ_2. The cost of unit travel time is α for both morning and evening commutes. Following previous related studies [18, 27], it is assumed that $\gamma_1 > \alpha > \beta_1$ and $\beta_2 > \alpha > \gamma_2$. For simplifying the model in this paper, we assume the morning commuting and evening commuting are symmetric. It means that the cost of unit early arrival time in morning commuting β_1 is equivalent to the cost of unit late departing time in evening commuting γ_2; the cost of unit late arrival time in morning commuting γ_1 is equivalent to the unit early departing time in evening commuting β_2 and the capacity of bottleneck in home-to-work direction is equivalent to that in work-to-home direction, $\underset{\rightarrow}{s} = \underset{\leftarrow}{s}$.

When there is no toll and parking fee, the individual travel time includes queuing time and searching time for parking spots in morning commuting. However, in evening commuting, the travel time only comprises queuing time. As commuter has known the parking spot, searching time is zero in evening commuting. Besides, we ignore the walking time from parking lot to working place. The free flow travel time spent in home to bottleneck is assumed to be zero in morning, and that in the reverse direction is also zero. It means that commuter arrives to the bottleneck as soon as he leaves home in morning commuting and commuter arrives to bottleneck as soon as he leaves from workplace in evening commuting.

In this paper, we investigate the traffic patterns in morning and evening commutes under various regimes and compare their respective efficiency with elastic demand. The four regimes proposed in this paper are listed as follows:

Regime f: user equilibrium without road toll and parking fee;

Regime u: duration dependent parking fees;

Regime r: optimal time-varying road tolls;

Regime o: optimal time-varying road tolls with duration dependent parking fees.

We present the notations used in this paper to describe traffic pattern of four regimes in Notations.

2. User Equilibrium without Road Toll and Parking Fee (Regime f)

2.1. User Equilibrium in Evening Commuting. In evening commuting, commuters do not need to search parking spots; the individual travel cost C_e^f is a function of the departing time from workplace $\underset{\leftarrow}{t}^f$. In user equilibrium, the individual travel cost cannot further decrease by changing departing time from workplace. So, we first give the individual travel cost of a commuter departing workplace early:

$$C_e^f\left(\underset{\leftarrow}{t}^f\right) = \alpha\frac{D\left(\underset{\leftarrow}{t}^f\right)}{\underset{\leftarrow}{s}} + \beta_2\left(\underset{\leftarrow}{t}^* - \underset{\leftarrow}{t}^f\right) \quad \underset{\leftarrow}{t}_0^f \le \underset{\leftarrow}{t}^f \le \underset{\leftarrow}{t}^*, \quad (1)$$

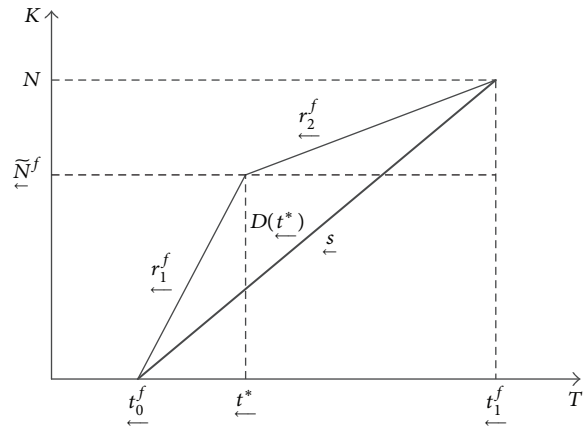

Figure 2: User equilibrium in evening commuting of regime f.

where $\underset{\leftarrow}{t}_0^f$ is the time at which the first commuter leaves from workplace and $D(\underset{\leftarrow}{t}^f)$ is the queue length. The first term of right hand of (1) is the cost of waiting time at bottleneck and the second term is the schedule delay cost.

For a commuter departing workplace late, the individual travel cost is

$$C_e^f\left(\underset{\leftarrow}{t}^f\right) = \alpha\frac{D\left(\underset{\leftarrow}{t}^f\right)}{\underset{\leftarrow}{s}} + \gamma_2\left(\underset{\leftarrow}{t}^f - \underset{\leftarrow}{t}^*\right) \quad \underset{\leftarrow}{t}^* \le \underset{\leftarrow}{t}^f \le \underset{\leftarrow}{t}_1^f. \quad (2)$$

Here $\underset{\leftarrow}{t}_1^f$ is the departing time from workplace of the last commuter. According to user equilibrium condition in evening commuting, $dC_e^f(\underset{\leftarrow}{t}^f)/d\underset{\leftarrow}{t}^f = 0$, we can get

$$\frac{dD\left(\underset{\leftarrow}{t}^f\right)}{d\underset{\leftarrow}{t}^f} = \begin{cases} \dfrac{\underset{\leftarrow}{s}}{\alpha}\beta_2 & \underset{\leftarrow}{t}_0^f \le \underset{\leftarrow}{t}^f \le \underset{\leftarrow}{t}^* \\ -\dfrac{\underset{\leftarrow}{s}}{\alpha}\gamma_2 & \underset{\leftarrow}{t}^* \le \underset{\leftarrow}{t}^f \le \underset{\leftarrow}{t}_1^f. \end{cases} \quad (3)$$

According to (3), we can easily obtain the departure rate from workplace $\underset{\leftarrow}{r}_1^f, \underset{\leftarrow}{r}_2^f, \underset{\leftarrow}{r}_1^f = (\beta_2/\alpha + 1)\underset{\leftarrow}{s}$, $\underset{\leftarrow}{r}_2^f = (1 - \gamma_2/\alpha)\underset{\leftarrow}{s}$. Obviously, in the evening commuting in regime f, the departure rate from workplace of early departing $\underset{\leftarrow}{r}_1^f$ is larger than capacity of bottleneck in work-to-home direction, $\underset{\leftarrow}{r}_1^f > \underset{\leftarrow}{s}$, and the departure rate from workplace of late departing $\underset{\leftarrow}{r}_2^f$ is less than $\underset{\leftarrow}{s}$, $\underset{\leftarrow}{r}_1^f < \underset{\leftarrow}{s}$. Then the capacity of bottleneck is fully used in the evening commuting and the beginning time and ending time of evening peak satisfy the equation as follows:

$$\underset{\leftarrow}{t}_1^f - \underset{\leftarrow}{t}_0^f = \frac{N}{\underset{\leftarrow}{s}}. \quad (4)$$

The user equilibrium depicted in Figure 2 requires that the individual travel cost of the first commuter is equivalent to

that of the last commuter, $C_e^f(t_0^f) = C_e^f(t_1^f)$, so the departure times of the first and last commuter are

$$t_0^f = t^* - \left(\frac{\gamma_2}{\beta_2+\gamma_2}\right)\frac{N}{s},$$
$$t_1^f = t^* + \left(\frac{\beta_2}{\beta_2+\gamma_2}\right)\frac{N}{s}. \tag{5}$$

The individual travel cost in evening commuting of regime f is

$$C_e^f = \frac{\beta_2\gamma_2}{\beta_2+\gamma_2}\frac{N}{s}. \tag{6}$$

The system cost in evening commuting of regime f is

$$\mathrm{SC}_e^f = \frac{\beta_2\gamma_2}{\beta_2+\gamma_2}\frac{N^2}{s}. \tag{7}$$

In Figure 2, the departing rate from workplace of early departing commuters is r_1^f and the departing rate of late departing commuter is r_2^f. The capacity of bottleneck is s. The number of early departing commuters is $\tilde{N}^f$. For the commuter who departs from workplace on time, the queue length at bottleneck is $D(t^*)$ and the waiting time is $D(t^*)/s$.

2.2. User Equilibrium in Morning Commuting. In morning commuting, the travel time includes queuing time and the searching time for parking spot. The individual travel cost is a function with respect to the leaving time from bottleneck t^f. The individual travel cost for the commuter arriving to workplace early is

$$C_m^f(t^f) = \alpha\left[\frac{D(t^f)}{s} + \pi s\left(t^f - t_0^f\right)\right] + \beta_1\left[t^* - t^f - \pi s\left(t^f - t_0^f\right)\right]. \tag{8}$$

Here, the arrival time of the first commuter to parking lot is t_0^f. The queuing time at bottleneck is $D(t^f)/s$ and the searching time for parking spot is $\pi s(t^f - t_0^f)$.

The individual travel cost for the commuter who arrives to the workplace late is

$$C_m^f = \alpha\left[\frac{D(t^f)}{s} + \pi s\left(t^f - t_0^f\right)\right] + \gamma_1\left[t^f + \pi s\left(t^f - t_0^f\right) - t^*\right]. \tag{9}$$

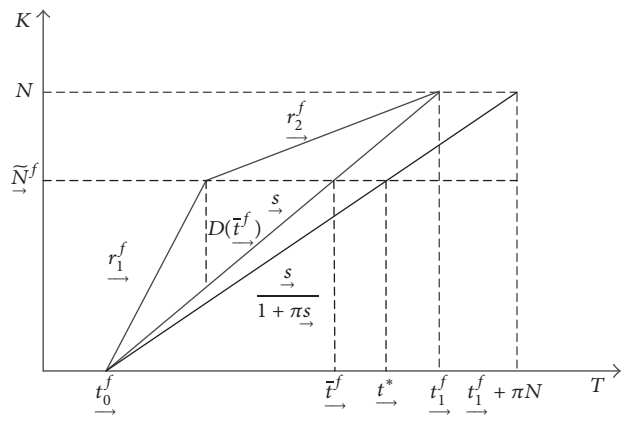

Figure 3: User equilibrium in morning commuting of regime f.

According to the equilibrium condition of morning commuting $dC_m^f(t^f)/dt^f = 0$, we can get

$$\frac{dD(t^f)}{dt^f} = \begin{cases} \frac{s}{\alpha}\left[\beta_1 + (\beta_1-\alpha)\pi s\right] & t_0^f \le t^f \le \bar{t}^f \\ -\frac{s}{\alpha}\left[\gamma_1 + (\gamma_1+\alpha)\pi s\right] & \bar{t}^f < t^f \le t_1^f. \end{cases} \tag{10}$$

Here, we hold the same assumption $\beta_1(1+\pi s) > \alpha\pi s$ to the study of Arnott et al. [2] to ensure a growing queue at the bottleneck. $\bar{t}^f$ is the leaving time from bottleneck of the commuter who arrives at workplace on time. The arrival rate to bottleneck r_1^f and r_2^f can be obtained easily, $r_1^f = \alpha s/(\alpha - [\beta_1 + (\beta_1-\alpha)\pi s])$, $r_2^f = \alpha s/(\alpha + [\gamma_1 + (\gamma_1+\alpha)\pi s])$.

Figure 3 shows user equilibrium in the morning commuting of regime f. The length of rush hour interval is N/s, $t_1^f - t_0^f = N/s$. The equilibrium condition requires the travel cost of the first commuter to be equivalent to that of the last commuter:

$$\beta_1\left(t^* - t_0^f\right) = \gamma_1\left(t_1^f + \pi N - t^*\right) + \alpha\pi N. \tag{11}$$

So we can easily get the leaving times from bottleneck of the first commuter and last commuter:

$$t_0^f = t^* - \frac{\gamma_1 + (\alpha+\gamma_1)\pi s}{\beta_1+\gamma_1}\frac{N}{s},$$
$$t_1^f = t^* + \frac{\beta_1 - (\alpha+\gamma_1)\pi s}{\beta_1+\gamma_1}\frac{N}{s}. \tag{12}$$

The individual travel cost in morning commuting of regime f is

$$C_m^f = \frac{\beta_1\gamma_1 + \beta_1(\alpha+\gamma_1)\pi \underset{\rightarrow}{s}}{\beta_1+\gamma_1}\frac{N}{\underset{\rightarrow}{s}}. \tag{13}$$

The system cost in morning commuting of regime f is

$$\mathrm{SC}_m^f = \frac{\beta_1\gamma_1 + \beta_1\pi \underset{\rightarrow}{s}(\alpha+\gamma_1)}{\beta_1+\gamma_1}\frac{N^2}{\underset{\rightarrow}{s}}. \tag{14}$$

In Figure 3, the arrival rate to bottleneck of early arrival commuters is $\underset{\rightarrow}{r_1^f}$ and the arrival rate to bottleneck of late arrival commuters is $\underset{\rightarrow}{r_2^f}$. The number of early arrival commuters is $\underset{\rightarrow}{\tilde{N}}^f$. The capacity of bottleneck is $\underset{\rightarrow}{s}$ and the arrival rate to the workplace is $\underset{\rightarrow}{s}/(1+\pi\underset{\rightarrow}{s})$. For the commuter who arrives at workplace on time, the queue length is $D(\underset{\rightarrow}{\bar{t}^f})$ and the searching time for parking is $\pi\underset{\rightarrow}{s}(\underset{\rightarrow}{\bar{t}^f} - \underset{\rightarrow}{t_0^f})$. In the user equilibrium, the commuter cannot reduce individual travel cost by changing departing time.

3. Duration Dependent Parking Fees (Regime u)

A continuous duration parking fee usually equals the parking duration time multiplied by charge rate μ [28]. We assume that parking fees are charged based on the parking duration given a uniform parking fee rate μ. Parking costs are assigned to the morning and evening trips, respectively, using an intermediate time point t^Δ, $t^\Delta = (\underset{\leftarrow}{t^*} - \underset{\rightarrow}{t^*})/2$, [5]; t^Δ is denoted as the midday time in this section.

Using the analytic method shown in Appendix A, we can obtain the departure rate from workplace in evening commuting $\underset{\leftarrow}{r_1^u}(\mu)$, $\underset{\leftarrow}{r_2^u}(\mu)$, $\underset{\leftarrow}{r_1^u}(\mu) = \underset{\leftarrow}{s}(1+(\beta_2-\mu)/\alpha)$, $\underset{\leftarrow}{r_2^u}(\mu) = \underset{\leftarrow}{s}(1-(\gamma_2+\mu)/\alpha)$. Here, we require the parking fee rate μ not to exceed β_2, $\mu < \beta_2$, to ensure the growing queue at bottleneck. Then, in regime u, we have $\underset{\leftarrow}{r_1^u}(\mu) > \underset{\leftarrow}{s}$, $\underset{\leftarrow}{r_2^u}(\mu) < \underset{\leftarrow}{s}$.

The first commuter's departure time and the last commuter's departure time are

$$\begin{aligned}\underset{\leftarrow}{t_0^u}(\mu) &= \underset{\leftarrow}{t^*} - \left(\frac{\gamma_2+\mu}{\beta_2+\gamma_2}\right)\frac{N}{\underset{\leftarrow}{s}},\\ \underset{\leftarrow}{t_1^u}(\mu) &= \underset{\leftarrow}{t^*} + \left(\frac{\beta_2-\mu}{\beta_2+\gamma_2}\right)\frac{N}{\underset{\leftarrow}{s}}.\end{aligned} \tag{15}$$

In evening commuting, because commuters in regime u may depart earlier than regime f to reduce their parking fees, the leaving time from workplace is advanced as the commuter's parking fee rate μ increases. From (15), we can find that, in the user equilibrium of regime u, the starting time and ending time of leaving from workplace will be advanced $(\mu/(\beta_2+\gamma_2))(N/\underset{\leftarrow}{s})$ on the basis of that in regime f, $\underset{\leftarrow}{t_0^u}(\mu) - \underset{\leftarrow}{t_0^f} = (\mu/(\beta_2+\gamma_2))(N/\underset{\leftarrow}{s})$.

The individual travel cost in evening commuting of regime u is

$$C_e^u(\mu) = \frac{\beta_2\gamma_2 + (\beta_2-\gamma_2)\mu - \mu^2}{\beta_2+\gamma_2}\frac{N}{\underset{\leftarrow}{s}} + \mu\left(\underset{\leftarrow}{t^*} - t^\Delta\right). \tag{16}$$

The system travel cost in evening commuting of regime u is

$$\begin{aligned}\mathrm{SC}_e^u(\mu) &= \frac{1}{2}\\ &\cdot \frac{\left[2\alpha\beta_2\gamma_2 + \beta_2\gamma_2\mu + (\beta_2-\gamma_2)\left(\mu^2+\alpha\mu\right) - \mu^3\right]}{\alpha(\beta_2+\gamma_2)}\\ &\cdot \frac{N^2}{\underset{\leftarrow}{s}}.\end{aligned} \tag{17}$$

Similarly, the arrival rate of early and late arrival to bottleneck in morning commuting, $\underset{\rightarrow}{r_1^u}(\mu)$ and $\underset{\rightarrow}{r_2^u}(\mu)$ are $\underset{\rightarrow}{r_1^u}(\mu) = \alpha\underset{\rightarrow}{s}/(\alpha-\beta_1-\mu)(1+\pi\underset{\rightarrow}{s})$, $\underset{\rightarrow}{r_2^u}(\mu) = \alpha\underset{\rightarrow}{s}/(\alpha+\gamma_1-\mu)(1+\pi\underset{\rightarrow}{s})$. Obviously, the departure rates from home $\underset{\rightarrow}{r_1^u}(\mu)$, $\underset{\rightarrow}{r_2^u}(\mu)$ increase as the parking fee rate μ increases, and the departure rate in regime u is not less than that in regime f, $\underset{\rightarrow}{r_1^u}(\mu) \geq \underset{\rightarrow}{r_1^f}$, $\underset{\rightarrow}{r_2^u}(\mu) \geq \underset{\rightarrow}{r_2^f}$.

In regime u, if $\mu > \alpha - \beta_1$, the departure rate $\underset{\rightarrow}{r_1^u}(\mu)$ is negative and if $\mu = \alpha - \beta_1$, the departure rate $\underset{\rightarrow}{r_1^u}(\mu)$ is infinity. So we can set $0 \leq \mu < a - \beta_1$ to ensure the existence of equilibrium of morning commuting. Then we have $\underset{\rightarrow}{r_1^u}(\mu) > \underset{\rightarrow}{s}$, $\underset{\rightarrow}{r_2^u}(\mu) < \underset{\rightarrow}{s}$.

The arrival times to parking lot of the first and last commuter are

$$\begin{aligned}\underset{\rightarrow}{t_0^u}(\mu) &= \underset{\rightarrow}{t^*} + \frac{\mu-\gamma_1}{\beta_1+\gamma_1}\frac{N}{\underset{\rightarrow}{s}} + \frac{\mu-\gamma_1}{\beta_1+\gamma_1}\pi N - \frac{\alpha\pi N}{\beta_1+\gamma_1},\\ \underset{\rightarrow}{t_1^u}(\mu) &= \underset{\rightarrow}{t^*} + \frac{\beta_1+\mu}{\beta_1+\gamma_1}\frac{N}{\underset{\rightarrow}{s}} + \frac{\mu-\gamma_1}{\beta_1+\gamma_1}\pi N - \frac{\alpha\pi N}{\beta_1+\gamma_1}.\end{aligned} \tag{18}$$

We can find that, in morning commuting of regime u, commuters can delay their arrival time to workplace to reduce the parking fee. So, commuters will put the arrival time backward till no commuter can reduce individual travel cost. The interval of morning rush hour in regime u will be delayed by $(\mu(1+\pi\underset{\rightarrow}{s})/(\beta_1+\gamma_1))(N/\underset{\rightarrow}{s})$ comparing with that in regime f, $\underset{\rightarrow}{t_0^u}(\mu) - \underset{\rightarrow}{t_0^f} = (\mu(1+\pi\underset{\rightarrow}{s})/(\beta_1+\gamma_1))(N/\underset{\rightarrow}{s})$.

The individual travel cost in morning commuting of regime u is

$$C_m^u(\mu) = \frac{(\beta_1+\mu)(\gamma_1-\mu)}{\beta_1+\gamma_1}\frac{N}{\underset{\rightarrow}{s}}\left(1+\pi\underset{\rightarrow}{s}\right) + \frac{\alpha\pi N}{\beta_1+\gamma_1}(\beta_1+\mu) + \mu\left(t^{\Delta}-\underset{\rightarrow}{t}^*\right). \tag{19}$$

The system cost in morning commuting of regime u is

$$\mathrm{SC}_m^u(\mu) = \frac{\beta_1(\gamma_1-\mu)}{\beta_1+\gamma_1}\frac{N^2}{\underset{\rightarrow}{s}}\left(1+\pi\underset{\rightarrow}{s}\right) + \frac{\alpha\beta_1\pi N^2}{\beta_1+\gamma_1} + \frac{1}{2}\mu\frac{N^2}{\underset{\rightarrow}{s}}\left(1+\pi\underset{\rightarrow}{s}\right). \tag{20}$$

According to (16) and (19), we can find that the midday time t^{Δ} cannot affect the total individual travel cost of day-long commuting and the total system cost. However, the midday time can determine the ratio of morning commuting individual travel cost $C_m^u(\mu)$ (or evening commuting) to the total individual travel cost $C_m^u(\mu)+C_e^u(\mu)$.

4. Optimal Time-Varying Road Tolls (Regime r)

In regime r, the queue delay at bottleneck can be eliminated by time-varying road toll. Then, the system cost is equivalent to the total schedule delay cost and the optimal time rush hour can be obtained by adjusting road toll to minimize the total schedule delay cost.

Using a similar analytic method shown in Appendix B, we can get the toll function $\tau(\underset{\leftarrow}{t}^r)$ with respect to the departing time from workplace $\underset{\leftarrow}{t}^r$ in the evening commuting:

$$\tau\left(\underset{\leftarrow}{t}^r\right) = \begin{cases} \dfrac{\beta_2\gamma_2}{\beta_2+\gamma_2}\dfrac{N}{\underset{\leftarrow}{s}} + \beta_2\left(\underset{\leftarrow}{t}^r-\underset{\leftarrow}{t}^*\right) & \underset{\leftarrow}{t}_0^r \le \underset{\leftarrow}{t}^r \le \underset{\leftarrow}{t}^*, \\ \dfrac{\beta_2\gamma_2}{\beta_2+\gamma_2}\dfrac{N}{\underset{\leftarrow}{s}} - \gamma_2\left(\underset{\leftarrow}{t}^r-\underset{\leftarrow}{t}^*\right) & \underset{\leftarrow}{t}^* < \underset{\leftarrow}{t}^r \le \underset{\leftarrow}{t}_1^r. \end{cases} \tag{21}$$

In the equilibrium shown in Figure 4, the departing times of first and last commuters are

$$\underset{\leftarrow}{t}_0^r = \underset{\leftarrow}{t}^* - \frac{\gamma_2}{\beta_2+\gamma_2}\frac{N}{\underset{\leftarrow}{s}}, \qquad \underset{\leftarrow}{t}_1^r = \underset{\leftarrow}{t}^* + \frac{\beta_2}{\beta_2+\gamma_2}\frac{N}{\underset{\leftarrow}{s}}. \tag{22}$$

In Figure 4, with the existence of time-varying road toll, the queue is eliminated and the departure rates of early and late departing commuter are equivalent to the capacity $\underset{\leftarrow}{s}$.

The individual travel cost in evening commuting of regime r is

$$C_e^r = \frac{\beta_2\gamma_2}{\beta_2+\gamma_2}\frac{N}{\underset{\leftarrow}{s}}. \tag{23}$$

The system cost in evening commuting of regime r is

$$\mathrm{SC}_e^r = \frac{1}{2}\frac{\beta_2\gamma_2}{\beta_2+\gamma_2}\frac{N^2}{\underset{\leftarrow}{s}}. \tag{24}$$

Using a similar method, we can also obtain the optimal toll function in morning commuting which is given as follows:

$$\tau\left(\underset{\rightarrow}{t}^r\right) = \begin{cases} \alpha\pi N + \left[\beta_1\left(1+\pi\underset{\rightarrow}{s}\right) - \alpha\pi\underset{\rightarrow}{s}\right]\left(\underset{\rightarrow}{t}^r - \underset{\rightarrow}{t}_0^r\right) & \underset{\rightarrow}{t}_0^r \le \underset{\rightarrow}{t}^r \le \bar{\underset{\rightarrow}{t}}^r \\ \dfrac{\left(\alpha\pi\underset{\rightarrow}{s}+\gamma_1+\gamma_1\pi\underset{\rightarrow}{s}\right)\left(\beta_1-\gamma_1\pi\underset{\rightarrow}{s}\right)}{\beta_1+\gamma_1}\dfrac{N}{\underset{\rightarrow}{s}} - \left(\alpha\pi\underset{\rightarrow}{s}+\gamma_1+\gamma_1\pi\underset{\rightarrow}{s}\right)\left(\underset{\rightarrow}{t}^r-\underset{\rightarrow}{t}^*\right) & \bar{\underset{\rightarrow}{t}}^r < \underset{\rightarrow}{t}^r \le \underset{\rightarrow}{t}_1^r. \end{cases} \tag{25}$$

In the user equilibrium shown in Figure 5, the arrival times to parking lot of the first and last commuter are

$$\underset{\rightarrow}{t}_0^r = \underset{\rightarrow}{t}^* - \frac{\gamma_1\left(1+\pi\underset{\rightarrow}{s}\right)}{\beta_1+\gamma_1}\frac{N}{\underset{\rightarrow}{s}}, \qquad \underset{\rightarrow}{t}_1^r = \underset{\rightarrow}{t}^* + \frac{\beta_1-\gamma_1\pi\underset{\rightarrow}{s}}{\beta_1+\gamma_1}\frac{N}{\underset{\rightarrow}{s}}. \tag{26}$$

In Figure 5, the queue at bottleneck in morning commuting is also eliminated by time-varying road toll. With the existence of parking searching time, the arrival rate to workplace is $\underset{\rightarrow}{s}/(1+\pi\underset{\rightarrow}{s})$.

The individual travel cost in morning commuting of regime r is

$$C_m^r = \frac{\beta_1\gamma_1\left(1+\pi\underset{\rightarrow}{s}\right)}{\beta_1+\gamma_1}\frac{N}{\underset{\rightarrow}{s}} + \alpha\pi N. \tag{27}$$

The system cost in morning commuting of regime r is

$$\mathrm{SC}_m^r = \frac{1}{2}\alpha\pi N^2 + \frac{1}{2}\frac{\beta_1\gamma_1}{\beta_1+\gamma_1}\frac{N^2}{\underset{\rightarrow}{s}}\left(1+\pi\underset{\rightarrow}{s}\right). \tag{28}$$

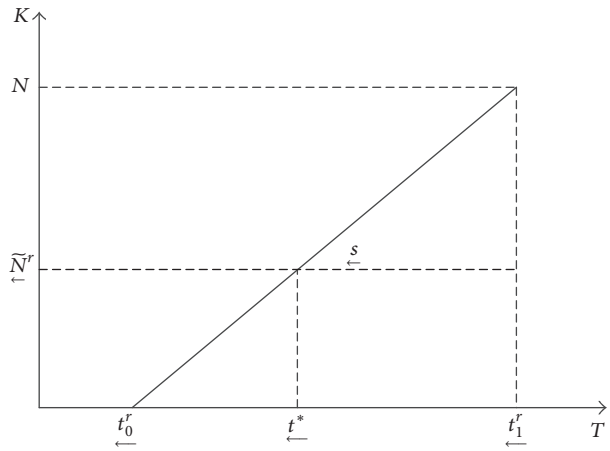

Figure 4: User equilibrium in evening commuting of regime r.

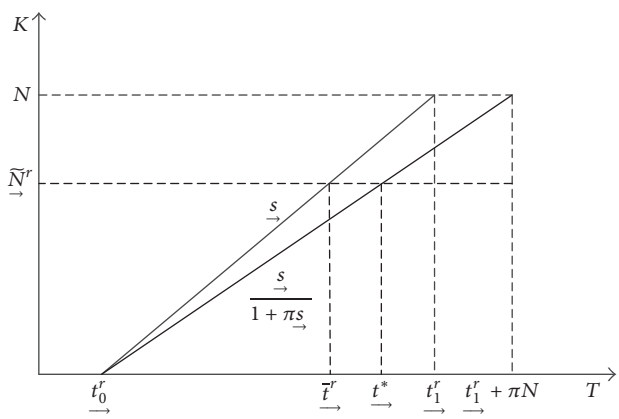

Figure 5: User equilibrium in morning commuting of regime r.

5. Optimal Time-Varying Road Tolls with Duration Dependent Parking Fees (Regime o)

In regime o, commuters need to pay for the road tolls and duration dependent parking fees in day-long commuting. One aim of time-varying road tolls is to eliminate the queue delay at bottleneck and another aim of time-varying road tolls is to minimize the total schedule delay cost and get the optimal starting and ending time of morning and evening commutes.

In Section 3, we have found that commuters are willing to delay the arrival time at workplace in morning commuting and putting forward departing time from workplace in evening commuting reduces duration dependent parking fees in regime u. So, in regime u, the total schedule delay cost is not optimal. Then, in regime o, we can determine the optimal rush hour interval by time-varying road tolls to achieve system optimum. However, the system cost in day-long commuting in regime o cannot be reduced further on the basis of the system cost in regime r, because the queue delay is eliminated by road toll and the two regimes have the same and optimal total schedule delay costs.

Using an analytic method shown in Appendix C, we can obtain the optimal time-varying road toll function in evening commuting which can be given as

$$\tau\left(t^o_{\leftarrow}\right)=\begin{cases}\mu\dfrac{N}{s_{\leftarrow}}+(\beta_2-\mu)\dfrac{\gamma_2}{\beta_2+\gamma_2}\dfrac{N}{s_{\leftarrow}}+(\beta_2-\mu)\left(t^o_{\leftarrow}-t^*_{\leftarrow}\right) & t^o_{0\leftarrow}\le t^o_{\leftarrow}\le t^*_{\leftarrow}\\ (\gamma_2+\mu)\dfrac{\beta_2}{\beta_2+\gamma_2}\dfrac{N}{s_{\leftarrow}}-(\gamma_2+\mu)\left(t^o_{\leftarrow}-t^*_{\leftarrow}\right) & t^*_{\leftarrow}<t^o_{\leftarrow}\le t^o_{1\leftarrow};\end{cases}\tag{29}$$

the optimal starting time and ending time of rush hour in evening commuting are

$$\underset{\leftarrow}{t_0^o} = \underset{\leftarrow}{t^*} - \frac{\gamma_2}{\beta_2+\gamma_2}\frac{N}{\underset{\leftarrow}{s}},$$
$$\underset{\leftarrow}{t_1^o} = \underset{\leftarrow}{t^*} + \frac{\beta_2}{\beta_2+\gamma_2}\frac{N}{\underset{\leftarrow}{s}}. \tag{30}$$

The individual travel cost in evening commuting of regime o is

$$C_e^o = \frac{\beta_2\gamma_2}{\beta_2+\gamma_2}\frac{N}{\underset{\leftarrow}{s}} + \frac{\beta_2\mu}{\beta_2+\gamma_2}\frac{N}{\underset{\leftarrow}{s}} + \mu\left(\underset{\leftarrow}{t^*} - t^{\Delta}\right). \tag{31}$$

The system cost in evening commuting of regime o is

$$\mathrm{SC}_e^o = \frac{1}{2}\frac{\beta_2\gamma_2}{\beta_2+\gamma_2}\frac{N^2}{\underset{\leftarrow}{s}}. \tag{32}$$

Similarly, the optimal time-varying road toll in morning commuting can be obtained as follows:

$$\tau\left(\underset{\rightarrow}{t^o}\right) = \begin{cases} \alpha\pi N - \mu\left(\dfrac{N}{\underset{\rightarrow}{s}} + \pi N\right) + \left[(\beta_1+\mu)\left(1+\pi\underset{\rightarrow}{s}\right) - \alpha\pi\underset{\rightarrow}{s}\right]\left(\underset{\rightarrow}{t^o} - \underset{\rightarrow}{t_0^o}\right) & \underset{\rightarrow}{t_0^o} \le \underset{\rightarrow}{t^o} \le \underset{\rightarrow}{\bar{t}^o} \\ \left[(\gamma_1-\mu)\left(1+\pi\underset{\rightarrow}{s}\right) + \alpha\pi\underset{\rightarrow}{s}\right]\left(\underset{\rightarrow}{t^*} + \dfrac{\beta_1-\gamma_1\pi\underset{\rightarrow}{s}}{\beta_1+\gamma_1}\dfrac{N}{\underset{\rightarrow}{s}} - \underset{\rightarrow}{t^o}\right) & \underset{\rightarrow}{\bar{t}^o} \le \underset{\rightarrow}{t^o} \le \underset{\rightarrow}{t_1^o}. \end{cases} \tag{33}$$

The optimal beginning time and ending time of rush hour in morning commuting are

$$\underset{\rightarrow}{t_0^o} = \underset{\rightarrow}{t^*} - \frac{\gamma_1\left(1+\pi\underset{\rightarrow}{s}\right)}{\beta_1+\gamma_1}\frac{N}{\underset{\rightarrow}{s}},$$
$$\underset{\rightarrow}{t_1^o} = \underset{\rightarrow}{t^*} + \frac{\beta_1-\gamma_1\pi\underset{\rightarrow}{s}}{\beta_1+\gamma_1}\frac{N}{\underset{\rightarrow}{s}}. \tag{34}$$

The individual travel cost in morning commuting of regime o is

$$C_m^o = \frac{\beta_1\gamma_1\left(1+\pi\underset{\rightarrow}{s}\right)}{\beta_1+\gamma_1}\frac{N}{\underset{\rightarrow}{s}} + \alpha\pi N + \mu\left(t^{\Delta} - \underset{\rightarrow}{t^*}\right) - \frac{\mu\beta_1\left(1+\pi\underset{\rightarrow}{s}\right)}{\beta_1+\gamma_1}\frac{N}{\underset{\rightarrow}{s}}. \tag{35}$$

The system cost in morning commuting of regime o is

$$\mathrm{SC}_m^o = \frac{1}{2}\alpha\pi N^2 + \frac{1}{2}\frac{\beta_1\gamma_1}{\beta_1+\gamma_1}\frac{N^2}{\underset{\rightarrow}{s}}\left(1+\pi\underset{\rightarrow}{s}\right). \tag{36}$$

6. Elastic Travel Demand considering Daily Travel Cost

In this section, we investigate the efficiency of each pricing charge scheme proposed from Sections 2 to 5 in the elastic travel demand. The demand function for travel is given as follows:

$$N = D(P), \quad \frac{dD}{dP} < 0, \tag{37}$$

where N is the number of commuters and P is the private daily travel cost. We assume the demand function $D(P)$ is a strictly decreasing linear function with respect to P. Let $D^{-1}(N)$ be the inverse demand function.

A commuter's surplus with travel demand N is

$$\mathrm{CS}(N) = \int_0^N D^{-1}(x)\,dx - \mathrm{ATC}(N)\,N, \tag{38}$$

where the first term is the total gross benefit and the second term is the total travel cost. The total travel cost is

$$\mathrm{ATC}(N)\,N = \mathrm{SC}(N) + R(N), \tag{39}$$

where the first term is the total social cost and the second term is the total revenue. Then, we can obtain the social surplus $\mathrm{SS}(N)$ which is the sum of the commuter's surplus, the total revenue, and total externality

$$\mathrm{SS}(N) = \int_0^N D^{-1}(x)\,dx - \mathrm{SC}(N), \tag{40}$$

where $\mathrm{SS}(N)$ is the function of travel demand N.

Maximizing the social surplus leads to the following optimality condition:

$$D^{-1}(N) = \mathrm{MSC}(N), \tag{41}$$

where $\mathrm{MSC}(N)$ represents the marginal social cost.

Now we can apply our elastic demand case to evaluate four different parking pricing regimes proposed from Sections 2 to 5. We first formulate the linear daily individual travel cost, $\mathrm{ATC}^k(N) = I^k + K^k N$ for regime k, $k = f, u, r, o$. $I^f = I^r = 0$, $I^u = I^o = \mu(\underset{\leftarrow}{t^*} - \underset{\rightarrow}{t^*})$. The formulas of parameter K^k in four regimes are given in Appendix D.

In market equilibrium, the implemented demand N_e^k can be obtained by solving the two equations representing demand function $N = D(P)$ and cost function $P = I^k + K^k N$, respectively. And the total social cost is proportional to the

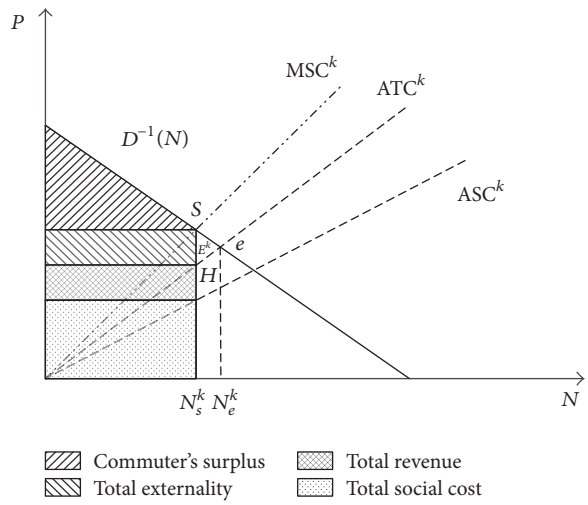

Figure 6: Demand and supply function of day-long commuting.

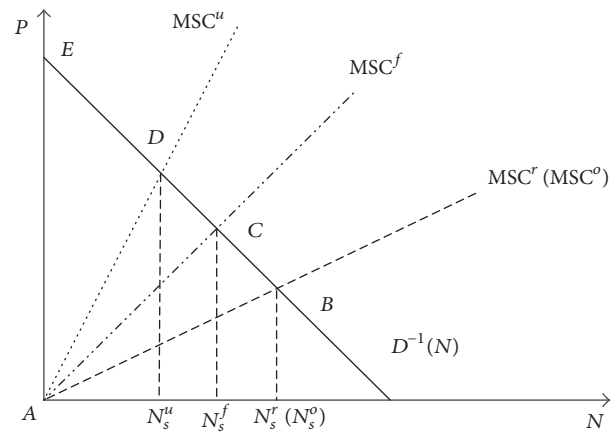

Figure 7: Comparisons of optimal travel demand and total social surplus in four regimes.

square of the demand, $\mathrm{SC}^k(N) = L^k N^2$. The average social cost $\mathrm{ASC}^k(N)$ is $L^k N$, $\mathrm{ASC}^k(N) = L^k N$.

The marginal social cost becomes $\mathrm{MSC}^k(N) = 2L^k N$ and the optimal demand N_s^k can be obtained by solving the demand function $N = D(P)$ and cost function $P = 2L^k N$. If the equilibrium demand N_e^k is not less than the optimal demand N_s^k, $N_e^k \geq N_s^k$, to derive the travel demand N_e^k to N_s^k, the commuter must be charged to internalize the externality E^k which is the difference between marginal social cost and individual travel cost in pricing regime k. The externality E^k is

$$\begin{aligned} E^k &= \mathrm{MSC}^k\left(N_s^k\right) - \mathrm{ATC}\left(N_s^k\right) \\ &= \left(2L^k - K^k\right) N_s^k - I^k, \end{aligned} \tag{42}$$

where N_s^k is the optimal demand level in regime k.

If the equilibrium demand N_e^k is less than the optimal demand N_s^k, $N_e^k < N_s^k$, to achieve system optimum, the commuter should be subsidized the negative externality E^k.

Next, we could compare the number of optimal travel demand N_s^k in four regimes by determining the sequence of parameter L^k at first. The process of comparing parameter L^k is given in Appendix D.

In Figure 6, $D^{-1}(N)$ is the reverse demand function. MSC^k represents marginal social cost and ATC^k is the daily individual travel cost function. ASC^k is the average social cost. When there is no constant toll, the equilibrium appears at point e. Maximizing the social surplus can determine the optimal demand N_s^k shown at the point s. SH represents the externality for each commuter; it can be charged by a constant road toll or parking fee to induce system optimum. At the optimal demand level, we present the constitution of commuter's surplus, total externality, total revenue, and total social cost. Here, total revenue is comprised of time-varying road toll and duration dependent parking fees. In regime f, because of no road toll and parking fee, curve ASC and curve ATC are overlapped and the total revenue is zero.

In the case of elastic demand, we denote $N_s^o, N_s^r, N_s^f, N_s^u$ as the optimal travel demand in regimes o, r, f, u. Let $\mathrm{SS}^o(N_s^o)$, $\mathrm{SS}^r(N_s^r)$, $\mathrm{SS}^f(N_s^f)$, $\mathrm{SS}^u(N_s^u)$ be the social surplus in regimes o, r, f, u. For the same demand function, we can easily find that $N_s^o = N_s^r > N_s^f \geq N_s^u$. In Figure 7, $\mathrm{SS}^o(N_s^o)$ and $\mathrm{SS}^r(N_s^r)$ are area ABE, $\mathrm{SS}^f(N_s^f)$ is area ACE, and $\mathrm{SS}^u(N_s^u)$ is area ADE, so we can easily obtain that $\mathrm{SS}^o(N_s^o) = \mathrm{SS}^r(N_s^r) > \mathrm{SS}^f(N_s^f) \geq \mathrm{SS}^u(N_s^u)$. When the parking fee rate μ is zero, $\mu = 0$, the social surplus of regime u $\mathrm{SS}^u(N_s^u)$ is equivalent to that of regime f $\mathrm{SS}^f(N_s^f)$. If we set a positive parking fee rate μ, $\mu > 0$, the social efficiency of regime u is less than that of regime f, $\mathrm{SS}^u(N_s^u) < \mathrm{SS}^f(N_s^f)$. We find that the best pricing regimes are regimes o and r, followed by regime f; and the worst regime is regime u.

7. Numerical Examples

In the network shown in Figure 1, the service rate of each bottleneck is assumed to be $\underset{\rightarrow}{s} = \underset{\leftarrow}{s} = 500$ veh/h and the total number of commuters $N = 1000$; they go to workplace from home in the morning and go back to home in the evening. We assume each commuter drives his/her car to workplace in the morning and returns home in the evening. The desired arrival time to workplace in the morning $\underset{\longrightarrow}{t^*} = 9{:}00$ and the desired departing time from workplace $\underset{\longleftarrow}{t^*} = 17{:}00$. The unit cost of travel time is $\alpha = 10$ \$/h, the cost of unit early arrival time in the morning is $\beta_1 = 5$ \$/h, and the cost of unit late arrival time in the morning is $\gamma_1 = 20$ \$/h.

In evening commuting, the cost of unit early departing time is $\beta_2 = 20$ \$/h and the cost of unit late departing time is $\gamma_2 = 5$ \$/h. And the searching time of unit parking spot π is 0.72 s/spot. In regime o, the parking fee rate μ is 0.5 \$/h and, in regime u, we set parking fee rate from 1 \$/h to 4 \$/h. The demand function is specified as $N(P) = 2000 - 20P$, where P is the daily private travel cost.

Table 1: Main computing results of various regimes in day-long commuting with elastic demand.

Regime	r	o	f	u						
				1	1.5	2	2.5	3	3.5	4
Equilibrium demand	1453	1384	1488	1321	1244	1171	1101	1034	970	908
Optimal demand	1453	1453	1185	1139	1116	1093	1072	1050	1029	1009
Externality	0	−4.84	20.38	12.72	9.10	5.57	2.15	−1.17	−4.42	−7.60
Individual travel cost	27.33	32.17	20.38	30.35	35.12	39.76	44.27	48.67	52.95	57.14
Social surplus (10^3)	72.674	72.674	59.242	56.927	55.789	54.671	53.576	52.507	51.468	50.460
Marginal social cost	27.33	27.33	40.76	43.07	44.21	45.33	46.42	47.49	48.53	49.54
Social cost (10^3)	19.859	19.859	24.146	24.520	24.665	24.782	24.872	24.937	24.978	24.998
Revenue (10^3)	19.859	26.897	0	10.036	14.523	18.690	22.564	26.170	29.531	32.669

Table 2: Main computing results in regime k ($k = f, r, o, u$) in morning commuting under optimal demand.

Regime k ($k = f, r, o, u$)	r	o	f	u with the following parking fee rate						
				1	1.5	2	2.5	3	3.5	4
$\underrightarrow{r_1^k}$	500	500	909	1136	1299	1515	1818	2273	3030	4545
$\underrightarrow{r_2^k}$	500	500	152	157	159	162	165	168	172	175
$\underrightarrow{\tilde{N}}^k$	1163	1163	991	907	866	827	789	752	717	683
$\vec{\delta}^k$	0.80	0.80	0.84	0.8	0.78	0.76	0.74	0.72	0.70	0.68
$\underrightarrow{t_0^k}$	6:26	6:26	6:49	7:00	7:05	7:10	7:15	7:21	7:25	7:30
$\underrightarrow{t_1^k}$	9:21	9:21	9:11	9:17	9:20	9:22	9:24	9:27	9:29	9:31

Table 1 gives the main computing results. We can find the regimes r and o have the highest social surplus. In regime r, the externality is zero and it means that the time-vary road toll can automatically lead to the system optimum. In regime o, the equilibrium demand is less than the optimal demand and the externality is negative; the decision maker needs to subsidize commuters to achieve system optimum. In regime u, when parking fee rate μ is less than 2.822 \$/h, the externality is charged to balance the optimal demand and supply. Otherwise, when parking fee rate is greater than 2.822 \$/h, the commuters should be subsidized to achieve system optimum due to the negative externality. Besides, we also find that the social surplus decreases as the parking fee rate increases in regime u and the parking fee has a negative social effect. It means regime u has the highest social surplus when the parking fee rate is zero.

In Table 2, $\underrightarrow{r_1^k}$ is the departing rate of early arrival commuter to workplace and $\underrightarrow{r_2^k}$ is the departing rate of late arrival commuter to workplace in regime k, $k = \{r, o, f, u\}$. The number of early arrival commuters in regime k in morning commuting is $\underrightarrow{\tilde{N}}^k$. $\underrightarrow{t_0^k}$ is the departure time of the first commuters and $\underrightarrow{t_1^k}$ is the departure time of the last commuter in regime k.

In morning commuting, the departure rates from home of early arrival and late arrival of regimes r and o are equivalent to the capacity of bottleneck due to the time-varying road toll. In regimes r and o, the optimal starting time is 6:26 and the optimal ending time is 9:21. In regime u, as the duration dependent parking fee rate μ increases, the departure rates from home $\underrightarrow{r_1^u}$ and $\underrightarrow{r_2^u}$ increase and the commuters push back their starting and ending time of the morning commuting, $\underrightarrow{t_0^u}$ and $\underrightarrow{t_1^u}$ to reduce the duration dependent parking fee. Figure 8 shows the ratio of early departing commuters of four schemes. When the parking fee rate μ increases from 0 \$/h to 4 \$/h, the ratio of the number of early departing commuters

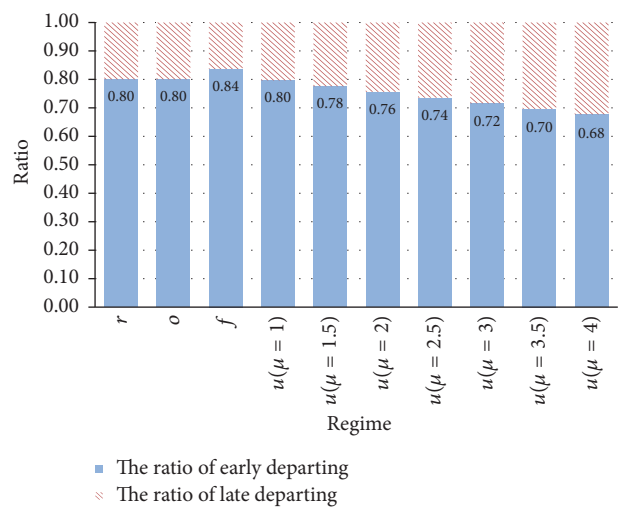

Figure 8: The ratio of early and late departing commuters to total demand of four pricing regimes in the morning commuting.

Table 3: Main computing results in regime k ($k = f, r, o, u$) in evening commuting under optimal demand.

Regime k ($k = f, r, o, u$)	r	o	f	u with the following parking fee rate μ						
				1	1.5	2	2.5	3	3.5	4
$\overleftarrow{r_1^k}$	500	500	1500	1450	1425	1400	1375	1350	1325	1300
$\overleftarrow{r_2^k}$	500	500	250	200	175	150	125	100	75	50
$\overleftarrow{\tilde{N}}^k$	291	291	711	792	827	857	884	907	927	945
$\overleftarrow{\delta}^k$	0.20	0.20	0.60	0.70	0.74	0.78	0.82	0.86	0.90	0.94
$\overleftarrow{t_0^k}$	16:25	16:25	16:32	16:27	16:25	16:23	16:21	16:20	16:18	16:16
$\overleftarrow{t_1^k}$	19:20	19:20	18:53	18:44	18:39	18:34	18:30	18:26	18:22	18:18

to total demand $\overrightarrow{\delta}^k$ decreases from 0.84 to 0.68. It means that more commuters depart late from home as the parking fee rate increases in the morning commuting of regime u.

Table 3 lists the main numerical results in regime k, $k = \{r, o, f, u\}$ in the evening commuting. Here, $\overleftarrow{r_1^k}$ is the departing rate of early departing commuters from workplace and $\overleftarrow{r_2^k}$ is the departing rate of late departing commuters from workplace. The number of early departing commuters in evening commuting is $\overleftarrow{\tilde{N}}^k$. $\overleftarrow{t_0^k}$ is the departure time of the first commuter and $\overleftarrow{t_1^k}$ is the departure time of the last commuter.

In the evening commuting of regimes r and o, the queues are eliminated by the road toll, so the departure rates from workplace of early departing commuters and late departing commuters $\overleftarrow{r_1^k}$, $\overleftarrow{r_2^k}$, $k = r, o$, are same to the capacity of bottleneck $\overleftarrow{s}$. In regimes r and o, the optimal starting time of rush time $\overleftarrow{t_0^r}$, $\overleftarrow{t_0^o}$ is 16:25 and the optimal ending time $\overleftarrow{t_1^r}$, $\overleftarrow{t_1^o}$ is 19:20. In regime u, as the duration dependent parking fee rate μ increases, the departure rates from workplace $\overleftarrow{r_1^u}$, $\overleftarrow{r_2^u}$ are reduced, and the commuters put forward their starting and ending time of the evening commuting $\overleftarrow{t_0^u}$, $\overleftarrow{t_1^u}$ to reduce the duration dependent parking fee. Figure 9 shows the ratio of early departing commuters of four schemes in the evening commuting. When the parking fee rate μ increases from 0 \$/h to 4 \$/h, the ratio of the number of early departing commuters to total demand $\overleftarrow{\delta}^k$ also increases from 0.6 to 0.94. It means that more commuters depart from workplace early with the growth of parking fee rate in the evening commuting of regime u.

Figures 10 and 11 show the road toll curves of evening and morning commutes in regimes r and o. The two pricing schemes have the same and optimal starting time and ending time in evening and morning commutes. In the evening commuting, the optimal starting and ending times of rush time of regimes r and o are 16:25 and 19:20. The road tolls of first commuter and last commuter are zero in regime r.

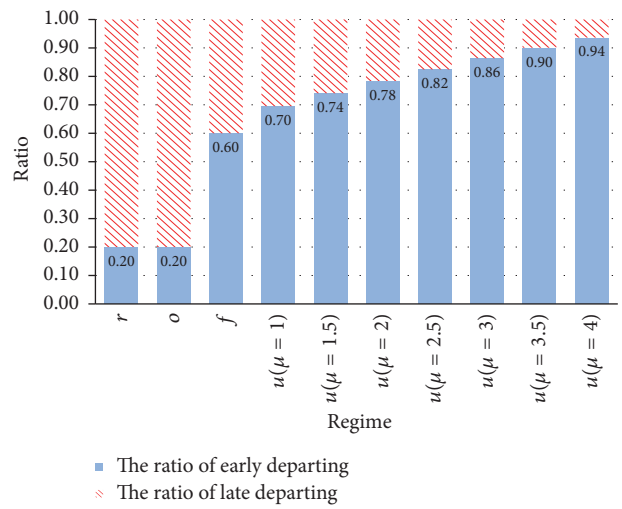

Figure 9: The ratio of early and late departing commuters to total demand of four pricing regimes in the evening commuting.

The road toll of first commuter in regime o is 1.45\$ and the road toll of last commuter is zero. The commuter who departs from workplace at 17:00 should pay for the maximum road toll 12.79\$ in regime o and the maximum road toll 11.62\$ in regime r.

In the morning commuting, the optimal starting and ending times of rush time are 6:26 and 9:21. In regime r, the road toll of first commuter is 2.91\$ and the road toll of last commuter is zero. In regime o, the road toll of first commuter is 1.31\$ and the road toll of last commuter is zero. The commuter who arrives at workplace on time should pay for the maximum road toll 13.05\$ in regime o and the maximum road toll 13.37\$ in regime r.

8. Conclusions

In this paper, we extend the bottleneck model from a single morning commuting to a day-long commuting. The morning commuting and evening commuting are treated as two independent user equilibriums. On the basis of previous study of Zhang et al. [23], we relax the assumption by allowing commuters to arrive later than the desired arrival time in

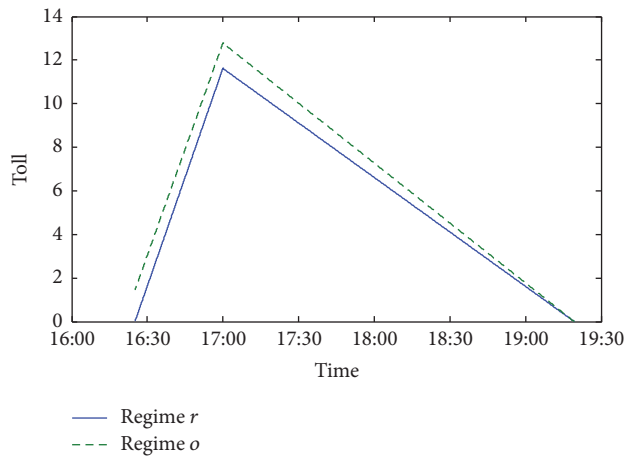

Figure 10: Time-varying road toll of evening commuting in regimes r and o.

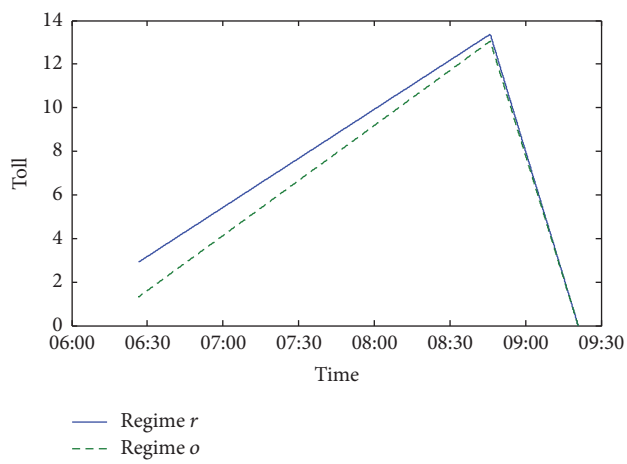

Figure 11: Time-varying road toll of morning commuting in regimes r and o.

morning commuting and depart earlier than the desired time in evening commuting. Besides, we assume that the morning and evening commutes are symmetric.

We investigated the day-long commuting of four regimes (regimes f, u, r, o) and derived the traffic pattern of each regime. In user equilibrium of regime f and u, no one can reduce the individual travel cost by changing the departure time. In regimes r and o, the queues at the bottleneck of morning and evening commutes are eliminated by road toll. We first determine the optimal starting and ending time of rush hour by minimizing the total schedule delay cost. Then, we utilize road toll to achieve system optimum.

Next, we analyze efficiency of four schemes with elastic demand and find that the regimes r and o have the highest social surplus, followed by regime f and the regime u has the lowest social surplus. In regime u, the duration parking fee may drive commuters to narrow their work duration for reducing the parking fee and the duration parking fee cannot increase social surplus. Furthermore, as the parking fee rate increases, the social surplus decreases. In regimes r and o, the optimal travel demands are equivalent and the two pricing schemes have the highest social surplus. However, in regime o, the duration dependent parking fee should be subsidized to commuters to balance the optimal travel demand and supply as a result of negative externality.

These findings also have several implications for traffic management; first, the duration dependent parking fee may reduce the average parking time per car to relieve the pressure of parking demand, but it will reduce the social surplus under optimal travel demand. Second, the time-varying road toll can eliminate the queue delay and minimize schedule delay cost by optimizing the arrival and departure time interval in morning and evening commutes in regime r and o. Third, if the time-varying road toll is carried out, it is inefficient to charge duration dependent parking fee; the duration dependent parking fee cannot increase the social surplus in basis of time-varying road toll except for refunding a part of revenue as a subsidy to commuters.

The current paper considers the morning commuting and evening commuting are symmetric. However, the symmetry between morning and evening commutes is easily broken when commuters are heterogeneous [20]. If the commutes have different desired working starting and ending times, then the traffic pattern could be FIFO (first in first out) in day-long commuting and the morning and evening commutes may not be independent. So if we relax this assumption, the single morning or evening commuting is not an independent user equilibrium anymore, and the problem may be more complicated and worth investigating in the future.

Appendix

A. User Equilibrium in Duration Dependent Parking Fees

In regime u, the individual travel cost of the commuter who leaves workplace early in evening commuting is

$$C_e^u\left(\overleftarrow{t}^u, \mu\right) = \alpha \frac{D\left(\overleftarrow{t}^u\right)}{\overleftarrow{s}} + \beta_2\left(\overleftarrow{t}^* - \overleftarrow{t}^u\right) + \mu\left(\overleftarrow{t}^u - t^\Delta\right). \tag{A.1}$$

The individual travel cost of the commuter who leaves workplace late is

$$C_e^u\left(\overleftarrow{t}^u, \mu\right) = \alpha \frac{D\left(\overleftarrow{t}^u\right)}{\overleftarrow{s}} + \gamma_2\left(\overleftarrow{t}^u - \overleftarrow{t}^*\right) + \mu\left(\overleftarrow{t}^u - t^\Delta\right). \tag{A.2}$$

According to the equilibrium condition $\partial C_e^u / \partial \overleftarrow{t}^u = 0$, we can get

$$\frac{dD\left(\overleftarrow{t}^u\right)}{d\overleftarrow{t}^u} = \begin{cases} \dfrac{\overleftarrow{s}}{\alpha}\left(\beta_2 - \mu\right) & \overleftarrow{t}_0^u \le \overleftarrow{t}^u \le \overleftarrow{t}^* \\ -\dfrac{\overleftarrow{s}}{\alpha}\left(\gamma_2 + \mu\right) & \overleftarrow{t}^* < \overleftarrow{t}^u \le \overleftarrow{t}_1^u. \end{cases} \tag{A.3}$$

From (A.3), the departure rate from workplace $\overleftarrow{r_1^u}(\mu)$, $\overleftarrow{r_2^u}(\mu)$ could be solved, $\overleftarrow{r_1^u}(\mu) = \overleftarrow{s}(1+(\beta_2-\mu)/\alpha)$, $\overleftarrow{r_2^u}(\mu) = \overleftarrow{s}(1-(\gamma_2+\mu)/\alpha)$. Here, we require the parking fee rate μ not to exceed β_2, $\mu < \beta_2$, to ensure the growing queue at bottleneck. Then, in regime u, we have $\overleftarrow{r_1^u}(\mu) > \overleftarrow{s}$, $\overleftarrow{r_2^u}(\mu) < \overleftarrow{s}$.

The equilibrium requires the travel costs of the first and last commuter to be equivalent, $C_e^u(\overleftarrow{t_0^u}, \mu) = C_e^u(\overleftarrow{t_1^u}, \mu)$, which is presented in the equation as follows:

$$\beta_2\left(\overleftarrow{t^*} - \overleftarrow{t_0^u}\right) + \mu\left(\overleftarrow{t_0^u} - t^\Delta\right) = \gamma_2\left(\overleftarrow{t_1^u} - \overleftarrow{t^*}\right) + \mu\left(\overleftarrow{t_1^u} - t^\Delta\right). \tag{A.4}$$

And the length of evening commuting is $N/\overleftarrow{s}$, so the first commuter's departure time and the last commuter's departure times are

$$\begin{aligned}\overleftarrow{t_0^u}(\mu) &= \overleftarrow{t^*} - \left(\frac{\gamma_2+\mu}{\beta_2+\gamma_2}\right)\frac{N}{\overleftarrow{s}},\\ \overleftarrow{t_1^u}(\mu) &= \overleftarrow{t^*} + \left(\frac{\beta_2-\mu}{\beta_2+\gamma_2}\right)\frac{N}{\overleftarrow{s}}.\end{aligned} \tag{A.5}$$

For morning commuting in regime u, when $\overrightarrow{t_0^u} \le \overrightarrow{t^u} \le \overrightarrow{\bar{t}^u}$, the individual travel cost for the commuter who arrives to workplace early is

$$\begin{aligned}C_m^u\left(\overrightarrow{t^u}, \mu\right) = {}& \alpha\left[\frac{D\left(\overrightarrow{t^u}\right)}{\overrightarrow{s}} + \pi\overrightarrow{s}\left(\overrightarrow{t^u} - \overrightarrow{t_0^u}\right)\right]\\ &+ \beta_1\left[\overrightarrow{t^*} - \overrightarrow{t^u} - \pi\overrightarrow{s}\left(\overrightarrow{t^u} - \overrightarrow{t_0^u}\right)\right]\\ &+ \mu\left[t^\Delta - \overrightarrow{t^u} - \pi\overrightarrow{s}\left(\overrightarrow{t^u} - \overrightarrow{t_0^u}\right)\right].\end{aligned} \tag{A.6}$$

On right-hand side of (A.6), the first term is the cost of travel time including queuing time and searching time for parking spots, the second term is the schedule delay cost for early arrival, and the last term is the parking fee.

When $\overrightarrow{\bar{t}^u} \le \overrightarrow{t^u} \le \overrightarrow{t_1^u}$, the individual travel cost for the commuter who arrives at workplace late is

$$\begin{aligned}C_m^u\left(\overrightarrow{t^u}, \mu\right) = {}& \alpha\left[\frac{D\left(\overrightarrow{t^u}\right)}{\overrightarrow{s}} + \pi\overrightarrow{s}\left(\overrightarrow{t^u} - \overrightarrow{t_0^u}\right)\right]\\ &+ \gamma_1\left[\overrightarrow{t^u} + \pi\overrightarrow{s}\left(\overrightarrow{t^u} - \overrightarrow{t_0^u}\right) - \overrightarrow{t^*}\right]\\ &+ \mu\left[t^\Delta - \overrightarrow{t^u} - \pi\overrightarrow{s}\left(\overrightarrow{t^u} - \overrightarrow{t_0^u}\right)\right].\end{aligned} \tag{A.7}$$

According to the user equilibrium condition $\partial C_m^u/\partial\overrightarrow{t^u} = 0$, we can get

$$\frac{dD\left(\overrightarrow{t^u}\right)}{d\overrightarrow{t^u}} = \begin{cases}\dfrac{\overrightarrow{s}}{\alpha}\left[(\beta_1+\mu)\left(1+\pi\overrightarrow{s}\right) - \alpha\pi\overrightarrow{s}\right] & \overrightarrow{t_0^u} \le \overrightarrow{t^u} \le \overrightarrow{\bar{t}^u}\\ -\dfrac{\overrightarrow{s}}{\alpha}\left[(\gamma_1-\mu)\left(1+\pi\overrightarrow{s}\right) + \alpha\pi\overrightarrow{s}\right] & \overrightarrow{\bar{t}^u} < \overrightarrow{t^u} \le \overrightarrow{t_1^u}.\end{cases} \tag{A.8}$$

As the capacity of bottleneck is $\overrightarrow{s}$ in morning commuting, the length of morning rush hour interval is $N/\overrightarrow{s}$. In equilibrium, the travel costs of the first commuter are equivalent to that of the last commuter:

$$\begin{aligned}&\beta_1\left(\overrightarrow{t^*} - \overrightarrow{t_0^u}\right) + \mu\left(t^\Delta - \overrightarrow{t_0^u}\right)\\ &\quad= \gamma_1\left(\overrightarrow{t_1^u} + \pi N - \overrightarrow{t^*}\right) + \mu\left(t^\Delta - \overrightarrow{t_1^u} - \pi N\right)\\ &\qquad+ \alpha\pi N.\end{aligned} \tag{A.9}$$

The arrival times to parking lot of the first and last commuter can be obtained:

$$\begin{aligned}\overrightarrow{t_0^u}(\mu) &= \overrightarrow{t^*} + \frac{\mu-\gamma_1}{\beta_1+\gamma_1}\frac{N}{\overrightarrow{s}} + \frac{\mu-\gamma_1}{\beta_1+\gamma_1}\pi N - \frac{\alpha\pi N}{\beta_1+\gamma_1},\\ \overrightarrow{t_1^u}(\mu) &= \overrightarrow{t^*} + \frac{\beta_1+\mu}{\beta_1+\gamma_1}\frac{N}{\overrightarrow{s}} + \frac{\mu-\gamma_1}{\beta_1+\gamma_1}\pi N - \frac{\alpha\pi N}{\beta_1+\gamma_1}.\end{aligned} \tag{A.10}$$

B. User Equilibrium in Optimal Time-Varying Road Tolls

For evening commuting in regime r, the queue is eliminated by time-varying road toll. So the individual travel cost of the commuter who departs early from workplace is

$$C_e^r\left(\overleftarrow{t^r}\right) = \tau\left(\overleftarrow{t^r}\right) + \beta_2\left(\overleftarrow{t^*} - \overleftarrow{t^r}\right) \quad \overleftarrow{t_0^r} \le \overleftarrow{t^r} \le \overleftarrow{t^*}. \tag{B.1}$$

Here, $\overleftarrow{t^r}$ is the departing time from workplace and $\overleftarrow{t_0^r}$ is the departing time of the first commuter. On the right-hand side of (B.1), the first term is the road toll to the commuter with departing time $\overleftarrow{t^r}$; the second term is the schedule delay cost for early departing.

The individual travel cost for the commuter who departs late from workplace is

$$C_e^r\left(\overleftarrow{t^r}\right) = \tau\left(\overleftarrow{t^r}\right) + \gamma_2\left(\overleftarrow{t^r} - \overleftarrow{t^*}\right) \quad \overleftarrow{t^*} < \overleftarrow{t^r} \le \overleftarrow{t_1^r}. \tag{B.2}$$

User equilibrium condition $dC_e^r/d\overleftarrow{t^r} = 0$ requires

$$\frac{d\tau\left(\overleftarrow{t^r}\right)}{d\overleftarrow{t^r}} = \begin{cases}\beta_2 & \overleftarrow{t_0^r} \le \overleftarrow{t^r} \le \overleftarrow{t^*}\\ -\gamma_2 & \overleftarrow{t^*} < \overleftarrow{t^r} \le \overleftarrow{t_1^r}.\end{cases} \tag{B.3}$$

The optimal rush hour interval is determined by minimizing the total schedule delay cost. Given the arrival rate $\underleftarrow{s}$, total schedule delay cost is minimized by equating the schedule delay cost of the first and last commuters:

$$\beta_2\left(\underleftarrow{t^*}-\underleftarrow{t_0^r}\right)=\gamma_2\left(\underleftarrow{t_1^r}-\underleftarrow{t^*}\right). \tag{B.4}$$

Combining (B.4) with the condition $\underleftarrow{t_1^r}-\underleftarrow{t_0^r}=N/\underleftarrow{s}$, we obtain

$$\begin{aligned}\underleftarrow{t_0^r}&=t^*-\frac{\gamma_2}{\beta_2+\gamma_2}\frac{N}{\underleftarrow{s}},\\ \underleftarrow{t_1^r}&=t^*+\frac{\beta_2}{\beta_2+\gamma_2}\frac{N}{\underleftarrow{s}}.\end{aligned} \tag{B.5}$$

To keep a lowest no-negative toll level, the last commuter pays no toll, $\tau(\underleftarrow{t_1^r})=0$. In the user equilibrium, the travel cost of the first commuter is equivalent to that of the last commuter:

$$C_e^r\left(\underleftarrow{t_0^r}\right)=C_e^r\left(\underleftarrow{t_1^r}\right). \tag{B.6}$$

Given (B.1)–(B.3) and (B.5)-(B.6) and the user equilibrium condition, we can obtain the optimal time-varying road toll presented as follows:

$$\tau\left(\underleftarrow{t^r}\right)=\begin{cases}\dfrac{\beta_2\gamma_2}{\beta_2+\gamma_2}\dfrac{N}{\underleftarrow{s}}+\beta_2\left(\underleftarrow{t^r}-\underleftarrow{t^*}\right) & \underleftarrow{t_0^r}\le\underleftarrow{t^r}\le\underleftarrow{t^*}\\ \dfrac{\beta_2\gamma_2}{\beta_2+\gamma_2}\dfrac{N}{\underleftarrow{s}}-\gamma_2\left(\underleftarrow{t^r}-\underleftarrow{t^*}\right) & \underleftarrow{t^*}<\underleftarrow{t^r}\le\underleftarrow{t_1^r}.\end{cases} \tag{B.7}$$

For the morning commuting in regime r, as the queue is eliminated by road toll, the travel time only is the searching time for parking spots. So the individual travel cost of commuter who arrive early is

$$\begin{aligned}C_m^r\left(\underrightarrow{t^r}\right)&=\alpha\pi\underrightarrow{s}\left(\underrightarrow{t^r}-\underrightarrow{t_0^r}\right)\\&\quad+\beta_1\left[\underrightarrow{t^*}-\underrightarrow{t^r}-\pi\underrightarrow{s}\left(\underrightarrow{t^r}-\underrightarrow{t_0^r}\right)\right]\\&\quad+\tau\left(\underrightarrow{t^r}\right)\quad\underrightarrow{t_0^r}\le\underrightarrow{t^r}\le\underrightarrow{\bar{t}^r}.\end{aligned} \tag{B.8}$$

Here, $\underrightarrow{t^r}$ is the arrival time to parking lot, $\underrightarrow{t_0^r}$ is the arrival time to parking lot of the first commuter, and $\underrightarrow{\bar{t}^r}$ is arrival time to parking lot of the commuter who arrives at workplace on time. On right-hand side of (B.8), the first term is the cost of searching time for parking spots, the second term is schedule delay cost for early arrival, and the third term is time-varying road toll.

The individual travel cost of the commuter who arrive late is

$$\begin{aligned}C_m^r\left(\underrightarrow{t^r}\right)&=\alpha\pi\underrightarrow{s}\left(\underrightarrow{t^r}-\underrightarrow{t_0^r}\right)\\&\quad+\gamma_1\left[\underrightarrow{t^r}+\pi\underrightarrow{s}\left(\underrightarrow{t^r}-\underrightarrow{t_0^r}\right)-\underrightarrow{t^*}\right]\\&\quad+\tau\left(\underrightarrow{t^r}\right)\quad\underrightarrow{\bar{t}^r}<\underrightarrow{t^r}\le\underrightarrow{t_1^r}.\end{aligned} \tag{B.9}$$

According to the equilibrium condition $dC_m^r/d\underrightarrow{t^r}=0$, we can get

$$\frac{d\tau\left(\underrightarrow{t^r}\right)}{d\underrightarrow{t^r}}=\begin{cases}\beta_1\left(1+\pi\underrightarrow{s}\right)-\alpha\pi\underrightarrow{s} & \underrightarrow{t_0^r}\le\underrightarrow{t^r}<\underrightarrow{\bar{t}^r}\\ -\alpha\pi\underrightarrow{s}-\gamma_1\left(1+\pi\underrightarrow{s}\right) & \underrightarrow{\bar{t}^r}<\underrightarrow{t^r}\le\underrightarrow{t_1^r}.\end{cases} \tag{B.10}$$

The arrival rate to parking lot is given as $\underrightarrow{s}$ by optimal time-varying road toll, so the length of rush hour interval is $N/\underrightarrow{s}$. For the morning commuting, the optimal rush hour interval is determined by minimizing the total schedule delay cost. The beginning and ending time of rush hour are obtained by

$$\beta_1\left(\underrightarrow{t^*}-\underrightarrow{t_0^r}\right)=\gamma_1\left(\underrightarrow{t_1^r}+\pi N-\underrightarrow{t^*}\right). \tag{B.11}$$

According to the length of interval and (B.11), we can get

$$\begin{aligned}\underrightarrow{t_0^r}&=\underrightarrow{t^*}-\frac{\gamma_1\left(1+\pi\underrightarrow{s}\right)}{\beta_1+\gamma_1}\frac{N}{\underrightarrow{s}},\\ \underrightarrow{t_1^r}&=\underrightarrow{t^*}+\frac{\beta_1-\gamma_1\pi\underrightarrow{s}}{\beta_1+\gamma_1}\frac{N}{\underrightarrow{s}},\\ \underrightarrow{\bar{t}^r}&=\underrightarrow{t^*}-\frac{\gamma_1\pi\underrightarrow{s}}{\beta_1+\gamma_1}\frac{N}{\underrightarrow{s}}.\end{aligned} \tag{B.12}$$

To keep a lowest nonnegative toll level, the road toll of last commuter is set to zero, $\tau(\underrightarrow{t_1^r})=0$. In user equilibrium, the travel costs of the first and last commuter are equivalent:

$$C_m^r\left(\underrightarrow{t_0^r}\right)=C_m^r\left(\underrightarrow{t_1^r}\right). \tag{B.13}$$

Combining (B.8)–(B.13), we can obtain the optimal time-varying road toll as follows:

$$\tau\left(\underset{\longrightarrow}{t^r}\right) = \begin{cases} \alpha\pi N + \left[\beta_1\left(1+\pi \underset{\rightarrow}{s}\right) - \alpha\pi \underset{\rightarrow}{s}\right]\left(\underset{\longrightarrow}{t^r} - \underset{\longrightarrow}{t_0^r}\right) & \underset{\longrightarrow}{t_0^r} \le \underset{\longrightarrow}{t^r} \le \underset{\longrightarrow}{\bar{t}^r} \\ \dfrac{\left(\alpha\pi \underset{\rightarrow}{s} + \gamma_1 + \gamma_1\pi \underset{\rightarrow}{s}\right)\left(\beta_1 - \gamma_1\pi \underset{\rightarrow}{s}\right)}{\beta_1+\gamma_1}\dfrac{N}{\underset{\rightarrow}{s}} - \left(\alpha\pi \underset{\rightarrow}{s} + \gamma_1 + \gamma_1\pi \underset{\rightarrow}{s}\right)\left(\underset{\longrightarrow}{t^r} - \underset{\longrightarrow}{t^*}\right) & \underset{\longrightarrow}{\bar{t}^r} < \underset{\longrightarrow}{t^r} \le \underset{\longrightarrow}{t_1^r}. \end{cases} \tag{B.14}$$

C. User Equilibrium in Optimal Road Tolls with Duration Dependent Parking Fees

In evening commuting of regime o, the individual travel cost of the commuter of early departing is

$$C_e^o\left(\underset{\longleftarrow}{t^o}, \mu\right) = \beta_2\left(\underset{\longleftarrow}{t^*} - \underset{\longleftarrow}{t^o}\right) + \tau\left(\underset{\longleftarrow}{t^o}\right) + \mu\left(\underset{\longleftarrow}{t^o} - t^\Delta\right). \tag{C.1}$$

Here, $\underset{\longleftarrow}{t^o}$ is the departing time from workplace. The right-hand side of (C.1) includes three terms; the first term is schedule delay cost, the second term is road toll, and the third term is duration dependent parking fee.

For the commuter of late departing, the individual travel cost is

$$C_e^o\left(\underset{\longleftarrow}{t^o}, \mu\right) = \gamma_2\left(\underset{\longleftarrow}{t^o} - \underset{\longleftarrow}{t^*}\right) + \tau\left(\underset{\longleftarrow}{t^o}\right) + \mu\left(\underset{\longleftarrow}{t^o} - t^\Delta\right). \tag{C.2}$$

The equilibrium condition requires $\partial C_e^o / \partial \underset{\longleftarrow}{t^o} = 0$, so the road toll rate can be obtained as follows:

$$\frac{d\tau\left(\underset{\longleftarrow}{t^o}\right)}{d\underset{\longleftarrow}{t^o}} = \begin{cases} \beta_2 - \mu & \underset{\longleftarrow}{t_0^o} \le \underset{\longleftarrow}{t^o} \le \underset{\longleftarrow}{t^*} \\ -\left(\gamma_2 + \mu\right) & \underset{\longleftarrow}{t^*} < \underset{\longleftarrow}{t^o} \le \underset{\longleftarrow}{t_1^o}. \end{cases} \tag{C.3}$$

Using the method in Appendix B, we can also acquire the optimal starting time and ending time of rush hour:

$$\begin{aligned} \underset{\longleftarrow}{t_0^o} &= \underset{\longleftarrow}{t^*} - \frac{\gamma_2}{\beta_2+\gamma_2}\frac{N}{\underset{\leftarrow}{s}}, \\ \underset{\longleftarrow}{t_1^o} &= \underset{\longleftarrow}{t^*} + \frac{\beta_2}{\beta_2+\gamma_2}\frac{N}{\underset{\leftarrow}{s}}. \end{aligned} \tag{C.4}$$

To keep a lowest no-negative toll level, the last commuter pays no toll, $\tau(\underset{\longleftarrow}{t_1^o}) = 0$. In user equilibrium, the travel costs of the first and last commuter are equivalent:

$$C_e^o\left(\underset{\longleftarrow}{t_0^o}, \mu\right) = C_e^o\left(\underset{\longleftarrow}{t_1^o}, \mu\right). \tag{C.5}$$

Given (C.1)–(C.5), the optimal time-varying road toll is obtained as

$$\tau\left(\underset{\longleftarrow}{t^o}\right) = \begin{cases} \mu\dfrac{N}{\underset{\leftarrow}{s}} + \left(\beta_2 - \mu\right)\dfrac{\gamma_2}{\beta_2+\gamma_2}\dfrac{N}{\underset{\leftarrow}{s}} + \left(\beta_2 - \mu\right)\left(\underset{\longleftarrow}{t^o} - \underset{\longleftarrow}{t^*}\right) & \underset{\longleftarrow}{t_0^o} \le \underset{\longleftarrow}{t^o} \le \underset{\longleftarrow}{t^*} \\ \left(\gamma_2 + \mu\right)\dfrac{\beta_2}{\beta_2+\gamma_2}\dfrac{N}{\underset{\leftarrow}{s}} - \left(\gamma_2 + \mu\right)\left(\underset{\longleftarrow}{t^o} - \underset{\longleftarrow}{t^*}\right) & \underset{\longleftarrow}{t^*} < \underset{\longleftarrow}{t^o} \le \underset{\longleftarrow}{t_1^o}. \end{cases} \tag{C.6}$$

For morning commuting of regime o, the individual travel cost of the commuter who arrive early is

$$\begin{aligned} C_m^o\left(\underset{\longrightarrow}{t^o}, \mu\right) = {} & \alpha\pi \underset{\rightarrow}{s}\left(\underset{\longrightarrow}{t^o} - \underset{\longrightarrow}{t_0^o}\right) \\ & + \beta_1\left(\underset{\longrightarrow}{t^*} - \underset{\longrightarrow}{t^o} - \pi \underset{\rightarrow}{s}\left(\underset{\longrightarrow}{t^o} - \underset{\longrightarrow}{t_0^o}\right)\right) \\ & + \tau\left(\underset{\longrightarrow}{t^o}\right) \\ & + \mu\left[t^\Delta - \underset{\longrightarrow}{t^o} - \pi \underset{\rightarrow}{s}\left(\underset{\longrightarrow}{t^o} - \underset{\longrightarrow}{t_0^o}\right)\right]. \end{aligned} \tag{C.7}$$

Here, $\underset{\longrightarrow}{t^o}$ is the departing time from bottleneck which is also the arrival time to parking lot. On the right-hand side of (C.7), the first term is the cost of searching time for parking spots, the second term is schedule delay cost, the third term is the road toll, and the fourth term is duration dependent parking fee.

For commuter who arrives late, the individual travel cost is

$$\begin{aligned} C_m^o\left(\underset{\longrightarrow}{t^o}, \mu\right) = {} & \alpha\pi \underset{\rightarrow}{s}\left(\underset{\longrightarrow}{t^o} - \underset{\longrightarrow}{t_0^o}\right) \\ & + \gamma_1\left(\underset{\longrightarrow}{t^o} + \pi \underset{\rightarrow}{s}\left(\underset{\longrightarrow}{t^o} - \underset{\longrightarrow}{t_0^o}\right) - \underset{\longrightarrow}{t^*}\right) \\ & + \tau\left(\underset{\longrightarrow}{t^o}\right) \\ & + \mu\left[t^\Delta - \underset{\longrightarrow}{t^o} - \pi \underset{\rightarrow}{s}\left(\underset{\longrightarrow}{t^o} - \underset{\longrightarrow}{t_0^o}\right)\right]. \end{aligned} \tag{C.8}$$

According to the equilibrium condition $dC_m^o/d\underset{\longrightarrow}{t^o} = 0$, we can get

$$\frac{d\tau\left(\underset{\longrightarrow}{t^o}\right)}{d\underset{\longrightarrow}{t^o}} = \begin{cases} (\beta_1+\mu)\left(1+\pi\underset{\longrightarrow}{s}\right)-\alpha\pi\underset{\longrightarrow}{s} & \underset{\longrightarrow}{t_0^o} \le \underset{\longrightarrow}{t^o} \le \underset{\longrightarrow}{\bar{t}^o} \\ -(\gamma_1-\mu)\left(1+\pi\underset{\longrightarrow}{s}\right)-\alpha\pi\underset{\longrightarrow}{s} & \underset{\longrightarrow}{\bar{t}^o} \le \underset{\longrightarrow}{t^o} \le \underset{\longrightarrow}{t_1^o}. \end{cases} \tag{C.9}$$

The optimal beginning time and ending time of rush hour and the arrival time to parking lot of the commuter who arrives to the workplace on time are

$$\underset{\longrightarrow}{t_0^o} = \underset{\longrightarrow}{t^*} - \frac{\gamma_1\left(1+\pi\underset{\rightarrow}{s}\right)}{\beta_1+\gamma_1}\frac{N}{\underset{\rightarrow}{s}},$$

$$\underset{\longrightarrow}{t_1^o} = \underset{\longrightarrow}{t^*} + \frac{\beta_1-\gamma_1\pi\underset{\rightarrow}{s}}{\beta_1+\gamma_1}\frac{N}{\underset{\rightarrow}{s}},$$

$$\underset{\longrightarrow}{\bar{t}^o} = \underset{\longrightarrow}{t^*} - \frac{\gamma_1\pi\underset{\rightarrow}{s}}{\beta_1+\gamma_1}\frac{N}{\underset{\rightarrow}{s}}. \tag{C.10}$$

To keep a lowest no-negative toll level, the last commuter pays no toll, $\tau(\underset{\longrightarrow}{t_1^o}) = 0$. In the user equilibrium, we also have

$$C_m^o\left(\underset{\longrightarrow}{t^o},\mu\right) = C_m^o\left(\underset{\longrightarrow}{t^o},\mu\right). \tag{C.11}$$

Given (C.7)–(C.11), we can obtain the optimal time-varying road toll presented as follows:

$$\tau\left(\underset{\longrightarrow}{t^o}\right) = \begin{cases} \alpha\pi N-\mu\left(\dfrac{N}{\underset{\rightarrow}{s}}+\pi N\right)+\left[(\beta_1+\mu)\left(1+\pi\underset{\rightarrow}{s}\right)-\alpha\pi\underset{\rightarrow}{s}\right]\left(\underset{\longrightarrow}{t^o}-\underset{\longrightarrow}{t_0^o}\right) & \underset{\longrightarrow}{t_0^o} \le \underset{\longrightarrow}{t^o} \le \underset{\longrightarrow}{\bar{t}^o} \\ \left[(\gamma_1-\mu)\left(1+\pi\underset{\rightarrow}{s}\right)+\alpha\pi\underset{\rightarrow}{s}\right]\left(\underset{\longrightarrow}{t^*}+\dfrac{\beta_1-\gamma_1\pi\underset{\rightarrow}{s}}{\beta_1+\gamma_1}\dfrac{N}{\underset{\rightarrow}{s}}-\underset{\longrightarrow}{t^o}\right) & \underset{\longrightarrow}{\bar{t}^o} \le \underset{\longrightarrow}{t^o} \le \underset{\longrightarrow}{t_1^o}. \end{cases} \tag{C.12}$$

D. Process of Comparing Parameter L^k

According to the individual travel cost and system cost in morning and evening commutes of four regimes, we can obtain the parameters K^k and L^k which are given as follows:

$$K^f = \frac{\beta_2\gamma_2}{(\beta_2+\gamma_2)\underset{\leftarrow}{s}} + \frac{\beta_1\gamma_1+\beta_1(\alpha+\gamma_1)\pi\underset{\rightarrow}{s}}{(\beta_1+\gamma_1)\underset{\rightarrow}{s}},$$

$$K^u = \frac{\beta_2\gamma_2+(\beta_2-\gamma_2)\mu-\mu^2}{(\beta_2+\gamma_2)\underset{\leftarrow}{s}} + \frac{(\beta_1+\mu)(\gamma_1-\mu)}{\beta_1+\gamma_1}\frac{\left(1+\pi\underset{\rightarrow}{s}\right)}{\underset{\rightarrow}{s}} + \frac{\alpha\pi(\beta_1+\mu)}{\beta_1+\gamma_1},$$

$$K^r = \frac{\beta_2\gamma_2}{(\beta_2+\gamma_2)\underset{\leftarrow}{s}} + \frac{\beta_1\gamma_1\left(1+\pi\underset{\rightarrow}{s}\right)}{(\beta_1+\gamma_1)\underset{\rightarrow}{s}} + \alpha\pi,$$

$$K^o = \frac{\beta_2\gamma_2}{(\beta_2+\gamma_2)\underset{\leftarrow}{s}} + \frac{\beta_2\mu}{(\beta_2+\gamma_2)\underset{\leftarrow}{s}} + \frac{\beta_1\gamma_1\left(1+\pi\underset{\rightarrow}{s}\right)}{(\beta_1+\gamma_1)\underset{\rightarrow}{s}} + \alpha\pi - \frac{\mu\beta_1\left(1+\pi\underset{\rightarrow}{s}\right)}{(\beta_1+\gamma_1)\underset{\rightarrow}{s}},$$

$$L^f = \frac{\beta_2\gamma_2}{(\beta_2+\gamma_2)\underset{\leftarrow}{s}} + \frac{\beta_1\gamma_1+\beta_1\pi\underset{\rightarrow}{s}(\alpha+\gamma_1)}{(\beta_1+\gamma_1)\underset{\rightarrow}{s}},$$

$$L_e^u(\mu) = \frac{\left[2\alpha\beta_2\gamma_2+\beta_2\gamma_2\mu+(\beta_2-\gamma_2)\left(\mu^2+\alpha\mu\right)-\mu^3\right]}{2\alpha(\beta_2+\gamma_2)\underset{\leftarrow}{s}},$$

$$L_m^u(\mu) = \frac{\beta_1(\gamma_1-\mu)}{\beta_1+\gamma_1}\frac{\left(1+\pi\underset{\rightarrow}{s}\right)}{\underset{\rightarrow}{s}} + \frac{\alpha\beta_1\pi}{\beta_1+\gamma_1} + \frac{\mu\left(1+\pi\underset{\rightarrow}{s}\right)}{2\underset{\rightarrow}{s}},$$

$$L^u(\mu) = L_e^u(\mu)+L_m^u(\mu),$$

$$L^r = \frac{1}{2}\frac{\beta_2\gamma_2}{(\beta_2+\gamma_2)\underset{\leftarrow}{s}} + \frac{1}{2}\alpha\pi + \frac{1}{2}\frac{\beta_1\gamma_1}{\beta_1+\gamma_1}\frac{\left(1+\pi\underset{\rightarrow}{s}\right)}{\underset{\rightarrow}{s}},$$

$$L^o = \frac{1}{2}\frac{\beta_2\gamma_2}{(\beta_2+\gamma_2)\underset{\leftarrow}{s}} + \frac{1}{2}\alpha\pi + \frac{1}{2}\frac{\beta_1\gamma_1}{\beta_1+\gamma_1}\frac{\left(1+\pi\underset{\rightarrow}{s}\right)}{\underset{\rightarrow}{s}}. \tag{D.1}$$

Obviously, we can find that $L^r = L^o$. Here, the proof of $L^f > L^r$ is given as follows:

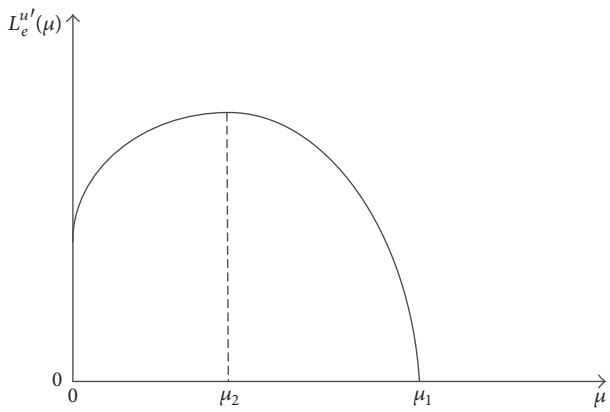

FIGURE 12: The first derivative function of parameter $L_e^u(\mu)$ in evening commuting.

$$L^f = \frac{\beta_2\gamma_2}{(\beta_2+\gamma_2)\underset{\leftarrow}{s}} + \frac{1}{2}\frac{\beta_1\gamma_1\left(1+\pi\underset{\rightarrow}{s}\right)}{(\beta_1+\gamma_1)\underset{\rightarrow}{s}} + \frac{1}{2}\frac{\beta_1\gamma_1\left(1+\pi\underset{\rightarrow}{s}\right)}{(\beta_1+\gamma_1)\underset{\rightarrow}{s}} + \frac{\beta_1}{(\beta_1+\gamma_1)}\alpha\pi. \tag{D.2}$$

We have assumed $\beta_1(1+\pi\underset{\rightarrow}{s}) > \alpha\pi\underset{\rightarrow}{s}$ in Section 2.2, so we have

$$\begin{aligned} L^f &> \frac{\beta_2\gamma_2}{(\beta_2+\gamma_2)\underset{\leftarrow}{s}} + \frac{1}{2}\frac{\beta_1\gamma_1\left(1+\pi\underset{\rightarrow}{s}\right)}{(\beta_1+\gamma_1)\underset{\rightarrow}{s}} + \frac{1}{2}\frac{\gamma_1}{(\beta_1+\gamma_1)}\alpha\pi + \frac{\beta_1}{(\beta_1+\gamma_1)}\alpha\pi \\ &= \frac{1}{2}\frac{\beta_2\gamma_2}{(\beta_2+\gamma_2)\underset{\leftarrow}{s}} + \frac{1}{2}\frac{\beta_1\gamma_1\left(1+\pi\underset{\rightarrow}{s}\right)}{(\beta_1+\gamma_1)\underset{\rightarrow}{s}} + \frac{1}{2}\alpha\pi + \frac{1}{2}\frac{\beta_2\gamma_2}{(\beta_2+\gamma_2)\underset{\leftarrow}{s}} + \frac{1}{2}\frac{\beta_1}{(\beta_1+\gamma_1)}\alpha\pi \\ &= L^r + \frac{1}{2}\frac{\beta_2\gamma_2}{(\beta_2+\gamma_2)\underset{\leftarrow}{s}} + \frac{1}{2}\frac{\beta_1}{(\beta_1+\gamma_1)}\alpha\pi. \end{aligned} \tag{D.3}$$

And in regime u, $L^u(\mu)$ is a strictly increasing function with respect to parking fee rate μ, $0 \le \mu < \alpha - \beta_1$; here $\alpha - \beta_1 = \alpha - \gamma_2$; it means that $L^u \ge L^f$. This can be proved as follows.

Proof. By solving $L_e^{u\prime}(\mu_1) = 0$, $L_e^{u\prime\prime}(\mu_2) = 0$, we can obtain that $\mu_1 = ((\beta_2-\gamma_2) + \sqrt{(\beta_2-\gamma_2)^2 + 3(\alpha\beta_2+\beta_2\gamma_2-\alpha\gamma_2)})/3$, $\mu_2 = (\beta_2-\gamma_2)/3$. We could easily get $\mu_1 > \mu_2$. □

Figure 12 shows the diagram of the first derivative of parameter L_e^u. For the first derivative of L_e^u, if $0 \le \mu \le \mu_1$, $L_e^{u\prime}(\mu) > 0$ and if $\mu > \mu_1$, $L_e^{u\prime}(\mu) < 0$. For the second derivative of L_e^u, if $0 \le \mu \le \mu_2$, $L_e^{u\prime\prime}(\mu) \ge 0$ and if $\mu > \mu_2$, $L_e^{u\prime\prime}(\mu) < 0$.

Scenario 1. If $a - \gamma_2 \le \mu_1$, $L_e^{u\prime}(\alpha-\gamma_2) \ge 0$. Then $L_e^u(\mu)$ is monotone increase when $0 \le \mu < a - \gamma_2$. For the morning commuting of regime u, $L_m^{u\,\prime} = (1/2)((\gamma_1-\beta_1)/(\beta_1+\gamma_1))((1+\pi\underset{\rightarrow}{s})/\underset{\rightarrow}{s})$. We have that $L_m^u(\mu)$ increases as μ increases. So $L^u(\mu)$ is a monotone increasing function in regime u.

Scenario 2. If $a - \gamma_2 > \mu_1$, then $L_e^{u\prime}(\alpha-\gamma_2) < 0$. We could solve the first derivative of $L^u(\mu)$ with respect to parking fee rate μ when $\mu = a - \gamma_2$:

$$L^{u\prime}(\alpha-\gamma_2) = L_e^{u\prime}(\alpha-\gamma_2) + L_m^{u\,\prime}(\alpha-\gamma_2), \tag{D.4}$$

$$L^{u\prime}(\alpha-\gamma_2) = \frac{1}{2}\frac{\left(-3\alpha^2-\gamma_2^2+3\alpha\beta_2-\beta_2\gamma_2+3\alpha\gamma_2\right)}{\alpha(\beta_2+\gamma_2)\underset{\leftarrow}{s}} + \frac{1}{2}\frac{\gamma_1-\beta_1}{\beta_1+\gamma_1}\frac{\left(1+\pi\underset{\rightarrow}{s}\right)}{\underset{\rightarrow}{s}}, \tag{D.5}$$

$$L^{u\prime}(\alpha-\gamma_2) = \frac{1}{2\alpha(\beta_2+\gamma_2)\underset{\leftarrow}{s}}\left[\left(3\alpha\beta_2-3\alpha^2\right) + (\alpha\beta_2-\beta_2\gamma_2) + \left(2\alpha\gamma_2-\gamma_2^2\right) + a(\beta_2-\gamma_2)\pi\underset{\leftarrow}{s}\right]. \tag{D.6}$$

Obviously, each term on the right hand of (D.6) is positive and the first derivative of L^u with respect to parking fee rate μ when $\mu = \alpha - \gamma_2$ is greater than zero, $L^{u\prime}(\alpha-\gamma_2) > 0$.

When $\mu_2 < \mu < a - \gamma_2$, the second derivative of L^u in evening commuting with respect to parking fee rate is less than zero, $L_e^{u\prime\prime}(\mu) < 0$; then we have $L_e^{u\prime}(\mu) > L_e^{u\prime}(\alpha-\gamma_2)$ and $L_m^{u\,\prime}(\mu) = L_m^{u\,\prime}(\alpha-\gamma_2) = (1/2)((\gamma_1-\beta_1)/(\beta_1+\gamma_1))((1+\pi\underset{\rightarrow}{s})/\underset{\rightarrow}{s}) > 0$; then we have $L^{u\prime}(\mu) > L^{u\prime}(\alpha-\gamma_2) > 0$.

When $0 \le \mu \le \mu_2$, the first derivatives of $L_e^u(\mu)$ and $L_m^u(\mu)$ are larger than zero, $L_e^{u\prime}(\mu) > 0$ and $L_m^{u\,\prime}(\mu) > 0$, so the first derivatives of L^u with respect to parking fee rate are greater than zero, $L^{u\prime}(\mu) > 0$, and $L^u(\mu)$ is a monotone increasing function in regime u.

Notations

$\underset{\leftarrow}{t}^*$: The desired departing time from workplace in the evening commuting

$\underset{\leftarrow}{t}^k$: The departing time from workplace in regime k, $k = \{f, u, r, o\}$

$\underset{\leftarrow}{t}_0^k$: The departing time from workplace of the first commuters in regime k, $k = \{f, u, r, o\}$

$\underset{\leftarrow}{t}_1^k$: The departing time from workplace of the last commuters in regime k, $k = \{f, u, r, o\}$

C_e^k: The individual travel cost in the evening commuting in regime k, $k = \{f, u, r, o\}$

SC_e^k: The system cost in the evening commuting in regime k, $k = \{f, u, r, o\}$

$\underset{\leftarrow}{\tilde{N}}^k$: The number of commuters who depart early from workplace in regime k, $k = \{f, u, r, o\}$

$\underset{\leftarrow}{r}_1^k$: Departure rate from workplace of early departing in regime k, $k = \{f, u, r, o\}$

$\overleftarrow{r_2^k}$: Departure rate from workplace of late departing in regime k, $k = \{f, u, r, o\}$

$\overleftarrow{s}$: The capacity of bottleneck in work-to-home direction

$\overrightarrow{t^*}$: The desired arrival time to workplace in the morning commuting

$\overrightarrow{t^k}$: The leaving time from bottleneck in regime k, $k = \{f, u, r, o\}$

$\overrightarrow{t_0^k}$: The arrival time to parking lot of the first commuter in regime k, $k = \{f, u, r, o\}$

$\overrightarrow{\bar{t}^k}$: The arrival time to parking lot of the commuter who arrives to the workplace on time in regime k, $k = \{f, u, r, o\}$

$\overrightarrow{t_1^k}$: The arrival time to parking lot of the last commuter in regime k, $k = \{f, u, r, o\}$

C_m^k: The individual travel cost in the morning commuting in regime k, $k = \{f, u, r, o\}$.

SC_m^k: The system travel cost in the morning commuting in regime k, $k = \{f, u, r, o\}$

$\overrightarrow{s}$: The capacity of bottleneck in home-to-work direction

$\overrightarrow{\tilde{N}^k}$: The number of commuters who arrive early to workplace in regime k, $k = \{f, u, r, o\}$

$\overrightarrow{r_1^k}$: Departure rate from home of early arrival in regime k, $k = \{f, u, r, o\}$

$\overrightarrow{r_2^k}$: Departure rate from home of late arrival in regime k, $k = \{f, u, r, o\}$.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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Research Article

The Impact of Bottom-Up Parking Information Provision in a Real-Life Context: The Case of Antwerp

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A number of studies have analyzed the possible impacts of bottom-up parking information or parking reservation systems on parking dynamics in abstract simulation environments. In this paper, we take these efforts one step further by investigating the impacts of these systems in a real-life context: the center of the city of Antwerp, Belgium. In our simulation, we assume that all on-street and off-street parking places are equipped with technology able to transmit their occupancy status to so-called smart cars, which can receive information and reserve a parking place. We employ PARKAGENT, an agent-based simulation model, to simulate the behavior of smart and regular cars. We obtain detailed data on parking demand from FEATHERS, an activity-based transport model. The simulation results show that parking information and reservation hardly impact search time but do reduce walking distance for smart cars, leading to a reduction in total parking time, that is, the sum of search time and walking time. Reductions in search time occur only in zones with high occupancy rates, while a drop in walking distance is especially observed in low occupancy areas. Societal benefits of parking information and reservation are limited, because of the low impact on search time and the possible negative health effects of reduced walking distance.

1. Introduction

Technological advances in the past decade have enabled the development of bottom-up parking information and reservation systems that incorporate both on-street and off-street parking [1]. These systems may have benefits for drivers and the wider society alike, suggesting that it may be warranted for cities to invest in such systems [2]. Drivers might benefit in terms of a reduction in parking search time and walking distance to the destination. The society at large may reap indirect benefits, as a decrease in parking search time may reduce traffic congestion and pollution and may enhance traffic safety and the quality of the urban environment [3]. Possibly, too, an enhanced driver experience may add to the relative attractiveness of urban areas suffering from poor parking conditions, such as historic city centers. Clearly, an improvement in the parking experience for drivers may also lead to rebound effects: it may increase the attractiveness of driving, potentially leading to a modal shift in favor of the car. Furthermore, there may be (indirect) negative health effects, due to shorter walking distances and a shift away from other, more active, transport modes to driving [4, 5].

The complexity of these interrelationships underscores that it is by no means certain that an improvement in the parking experience of drivers will also have societal benefits. But before that question can be answered, it is necessary to identify in more detail whether parking information and reservation systems may indeed enhance drivers' parking experience in terms of reduced search times and walking distances. Recent studies show that the benefits of so-called bottom-up information systems are much smaller than expected and depend strongly on the conditions, notably parking occupancy rates and the combination of parking information with a parking reservation system [6, 7]. These findings relate to simulations carried out in an abstract, strongly simplified, spatial environment. The current paper builds on these papers and analyses the impacts of a bottom-up parking information and reservation system on parking

search time and walking distance in the real-life context of the city of Antwerp.

This paper is organized as follows. Following this introduction, Section 2 provides a brief review of the literature on the impact of information provision on (on-street) parking performance. In Section 3 we provide an extensive description of our methodology, including a description of the employed parking model, the data on parking demand and parking supply, the parking choice heuristics, the parking information and reservation system, and the simulation environment. The results of the simulation runs are presented in Section 4. We end with a conclusion and discussion of the possible policy implications (Section 5).

2. Literature Review

The role of information provision has received substantial interest in parking research. Studies have initially focused on the traditional on-route parking guidance systems [8–10]. The information provided via these parking guidance systems is typically provided in a top-down manner: a central organization, typically a local government, collects information on the parking occupancy rate at various off-street parking facilities and provides it to drivers via dynamic information signs along main routes in a city.

The recent advances in communication technology have enabled a bottom-up approach to the provision of parking information. In this case, information collection and provision are not the responsibility of a centralized organization, but information is gathered and disseminated by local units, such as a car or a parking place sensor. Both a car leaving a parking place and a parking sensor can disseminate information on an available parking place. This information is subsequently disseminated to other local units in the direct surrounding, that is, to cars, which in turn pass on the information. Through this sharing process, each car can ultimately have information on parking availability in a substantial larger area than the area which is in direct view of the car driver. Bottom-up information provision can be used to provide information on off-street and on-street parking availability. An important advantage of bottom-up information provision is that drivers can receive tailored information on parking place availability in the vicinity of their specific destination.

Bottom-up parking information provision can furthermore be combined with a reservation option, whereby drivers can reserve a vacant parking place about which they receive information. Such a system can avoid the problem that multiple cars are heading for the same vacant parking space and can thus further reduce or even eliminate competition over parking spaces among informed drivers. However, reservation systems also have two drawbacks: they require enforcement to avoid car drivers (with or without information) from illegally occupying a reserved parking space; and they imply that a parking place will have to be booked for a time slot that is at least slightly longer than the intended parking duration of a driver, thereby de facto reducing the effective parking capacity [11].

A number of authors have studied the possible benefits of bottom-up information provision, with or without a reservation possibility. While the results of these former type of studies differ [12–15], the most recent studies suggest that the benefits of merely bottom-up information provision are limited. Reduction in search time for drivers with information is paralleled by increases in search time for drivers without information, in most circumstances [6, 16]. These researches serve as a general background for our current study, but more relevant are a number of recent studies that do include a reservation possibility. Some of these later studies have analyzed the impact of parking reservation in off-street parking facilities [17–22], while others have studied reservation of on-street parking places using mathematical and game-theoretical approaches and thus without taken into account the inevitably spatial nature of parking search [23–25]. The latter is highly problematic, because space fundamentally shapes parking search time as was demonstrated by Levy et al. [11].

Four recent studies have employed a spatially explicit simulation model to study the impacts of bottom-up information provision in combination a reservation system, each using a different experimental setup [7, 26–28]. These studies show that the combination of information and reservation may yield benefits in terms of reduced search time but also that the size of the benefits depends heavily on the conditions. The most detailed study along this line was carried out by Tasseron and Martens [7]. They employed an agent-based model to study the impact of a reservation system in a highly stylized grid-style simulation environment. The results of their study show that users of a reservation system benefit in terms of reduced search time and reduced walking distance under virtually all simulated circumstances. However, societal benefits are not as clear-cut. This is so, because the benefits in search time for the users of the system come at a cost to the regular drivers, which see a nearly identical increase in search time. In contrast, users of the reservation system do experience a substantial reduction in walking distance, without affecting other drivers. Tasseron and Martens conclude that the introduction of a reservation system for on-street parking results in a more efficient distribution of available parking spaces among drivers searching for parking.

The aim of the current study is to analyze in detail whether these findings regarding the (limited) benefits of a reservation system also hold in a real-world case. Two circumstances in particular suggest that the results may be more significant in such a case. First, parking demand and supply vary strongly across time and space, which may increase the advantage of a reservation system. Second, the street network in real cities may lead to relatively long search times due to inefficiencies in route choice and search behavior. At the same time, two other circumstances may reduce the benefits of a reservation system: parking pricing and the availability of off-street parking places. As argued extensively by Shoup [29] and empirically supported by Van Ommeren et al. [30], the introduction of parking pricing may lead to a more efficient use of parking space and thus to lower average search times. The availability of off-street parking facilities

may have the same impact, as it reduces demand for on-street parking and drivers selecting off-street parking typically experience little to no search time at all [9]. Given these opposing "forces," the goal of this paper is to estimate the impacts of a parking information and reservation on parking performance in a real-world situation. For this purpose, we analyze a single case study: the inner city of Antwerp, Belgium.

3. Methodology

Our current study is largely in line with the most recent study of Tasseron and Martens [7], in which they test the impact of parking information provision in combination with a reservation system. Like these authors, we employ the PARKAGENT model to simulate parking search behavior. In order to be able to employ this model for the real-life case of Antwerp, we combine PARKAGENT with an advanced activity-based transport model called FEATHERS [31, 32]. Based on the latter model, we have obtained detailed estimates of parking demand as it changes over time and space, substantially increasing the realism of our simulations. Note that we assume no impact of the parking information system on overall parking demand.

In what follows, we briefly describe the essentials of the PARKAGENT and FEATHERS models. We then briefly present the simulation area and period. We subsequently turn to a description of parking supply, demand, and the parking choice heuristics employed by the agents in our simulations. We then describe the parking information and reservation system used by the smart cars in their search for a parking place. We end with a brief description of the simulation setup and performance indicators.

3.1. PARKAGENT. PARKAGENT is an agent-based model for simulating parking search and choice behavior in a spatially explicit environment [33]. The model generates data on cruising time, cruising distance, walking distance, and spatial distribution of parked cars. The model is built by means of a geosimulation approach [34]. PARKAGENT consists of static objects (such as streets, buildings, parking places) and dynamic objects or agents (i.e., vehicles). Both are represented using a layer of features in a high-resolution geographical information system (GIS).

PARKAGENT enables a highly detailed simulation of the parking choice and search behavior of agents. For this study, two types of agents are distinguished: regular agents (cars) and smart agents (cars). The difference between the two agents is that smart cars are capable of sending information as well as receiving information from parking sensors and other smart cars. As information reduces the inherent uncertainty related to the parking process, this allows the smart agents to make a more informed decision on where to park. The parking choice heuristic will be described in detail in what follows.

A further description of the key features of PARKAGENT can be found in Appendix A in Supplementary Material available online at https://doi.org/10.1155/2017/1812045.

3.2. FEATHERS. The FEATHERS model is an advanced activity-based travel demand model for the Flanders region (Belgium) [31, 32]. In line with the well-known activity-based approach to travel demand modeling, FEATHERS predicts which activities are carried out at what location, at what time, for how long, with whom, and the used transport mode, resulting in a coherent sequence of trips for each simulated individual.

The FEATHERS model uses a synthetic population of agents that represents the actual Flemish population. The synthetic population is based on an extensive Flemish survey (carried out between September 2007 and September 2008) that gathered data on demographic, socioeconomic, household, and travel characteristics. Additionally, different aggregate household and personal data for the Flanders region were used to estimate the characteristics for the entire synthetic population. For each agent/person with its own attributes, the model generates whether a specific activity is pursued or not. If so, the location of the activity, the duration of the activity, and the transport mode are determined based on the characteristics of this individual as well as on the characteristics of the transport network and the spatial environment.

In order to run FEATHERS for the Antwerp study area, several data layers had to be prepared and developed. Where FEATHERS is normally run at the level of transport activity zones, PARKAGENT requires more detail. Therefore, data have been translated from the zonal level to the level of statistical zones. Where the average size of the smallest zone employed in a typical FEATHERS application is 5.7 km^2, the average size of a statistical zone is only 1.3 km^2 (Figure 1). As will be discussed below, parking demand at the level of these statistical zones is translated into parking demand at the level of individual addresses in PARKAGENT.

3.3. Simulation Area and Period. In our analysis, we simulate parking search in the old city center of Antwerp, which encompasses the main pedestrianized shopping area of the city, numerous restaurants, cafes and bars, a number of main tourist attractions, a variety of businesses and services, and residential buildings (Table 1). In total, the area is home to about 8,200 buildings which serve as the destinations of the cars in the PARKAGENT model. The area provides over 9,000 on-street parking places, three free off-street surface lots, and nineteen for-pay parking facilities. We simulate the parking dynamics for 24 hours on a typical Saturday, starting at 03.00 h in the night between Friday and Saturday. We will present data for the "parking rush hours" between 16.00 h and 19.00 h, when visitors to the city are leaving and residents return home. During this period, the availability of on-street parking places is highly unpredictable and bottom-up information and parking reservation services are thus likely to be beneficial for individual drivers as well as society as a whole. The demand for parking is derived from the FEATHERS model, which generates a set of activity schedules for a synthetic population for the entire Flanders region for an entire week. For our study, we only simulate the relevant schedules for the selected area and time period.

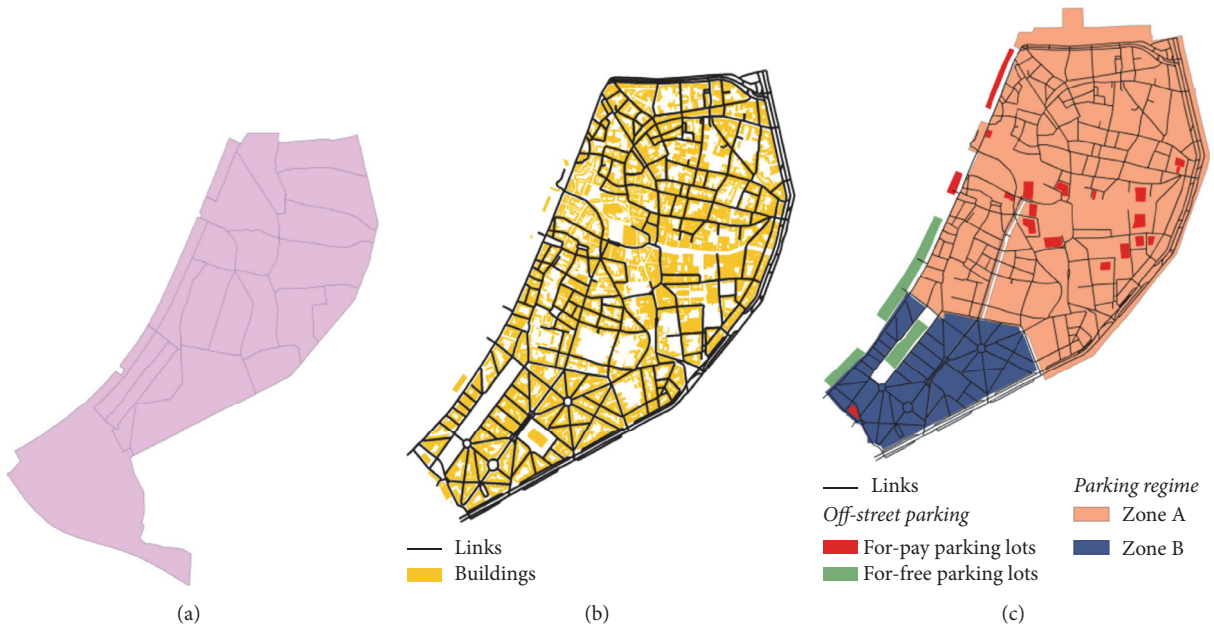

Figure 1: Maps representing (a) the 22 statistical zones used for the Antwerp simulation, (b) the road network and buildings, and (c) parking zones and off-street parking facilities.

Table 1: Characteristics of the study zone.

Type	Number of elements
Buildings	~8200
Residential buildings	~5600
Commercial/public buildings	~2600
Street links	~1100
On-street parking places	~9000
Public off-street facilities	22
Public off-street parking capacity	~9100
Statistical zones	22

3.4. Parking Supply. The parking supply in the study area encompasses on-street and off-street parking places. Based on satellite imagery data, the number and location of on-street parking places were obtained. These parking places fall under one of two street parking regimes. For the pedestrian shopping district and the surrounding area there is a maximum parking limit of 3 hours, indicated by Zone A in Figure 1. The parking costs for this parking zone are € 2.70 per hour. To the south of this zone lies parking Zone B, which has a maximum parking limit of 10 hours and costs € 1.10 per hour. Most residents in the simulated area in Antwerp who own a car have a parking permit for the zone in which they reside, which allows them to park for free for an unlimited time at an on-street parking place.

The simulated area also features three for-free parking lots, located in the southwest of the area. For these parking lots there is no maximum parking duration. Furthermore, nineteen for-pay parking facilities are located in the area. These parking facilities are owned by different parking operators and the prices vary in a range from €2.00 to € 2.90 per hour.

3.5. Estimating Parking Demand Based on FEATHERS. The demand for parking in the study zone is directly derived from the activity schedules which are generated by the FEATHERS model. The model generates schedules for an entire week. For our purposes, we only use the activity schedules for one particular day (i.e., Saturday) that involve travel by car and have origin and/or destination in the study zone. For this set of activity schedules, the FEATHERS model generates a list of all arrivals and departures for every 5 minute interval. Each entry consists of a unique agent ID, the type of activity, the duration of the activity, and an origin-destination (OD) pair.

The FEATHERS model distinguishes nine types of activities. PARKAGENT can only portray four archetypes of parking agents, that is, resident, worker, guest, or visitor. Therefore, the FEATHERS activities are converted into one of the four basic agent types used in PARKAGENT (Table 2). The OD-pair consists of the origin and destination combination on the level of statistical zones. Agents arriving to or moving within the study area are randomly assigned to one of the actual destinations (addresses) within their destination zone. This assignment is based on the type of land use and capacity of the building, as derived from the GIS layer of the city. Guests and residents are assigned to residential destinations, while visitors and workers are assigned to public and commercial destinations. Agents departing from one of the zones in the study zone area are picked based on their

Table 2: Activity translation table.

FEATHERS activity	PARKAGENT activity
Being at home	Resident
Work	Worker
Bring/get	Visitor
Shopping (daily)	Visitor
Shopping (nondaily)	Visitor
Services	Visitor
Social visits	Guest
Leisure	Visitor
Touring	Visitor
Others	Visitor

unique ID. Besides trips that are planned within the simulated environment, many trips have an origin or destination that lies outside this area. To this end, one unique additional zone is used for agents arriving from, or departing to, the area outside the study zone.

In order to adequately estimate the demand for *public* parking (on-street or off-street), it is important to identify the agents who can make use of a private parking place. In the simulation, we assume that only residents and employees may have a private parking place available. We use the fraction of privately parked vehicles within each statistical zone to define stochastically whether an agent entering the zone will park at a private parking place or at a public parking place. Due to the absence of detailed information on private parking spaces for employees, the fraction of employees that park at a private parking place is estimated for the entire simulation area. This employee fraction is based on a small-scale, unpublished survey that has been carried out by the parking authority of Antwerp. We furthermore assume that guests and visitors always park at a public parking place. The demand for parking thus consists of (1) residents and employees entering the study zone who do not have a private parking place available and (2) all guests and visitors entering the study zone. Only these agents are being simulated and only these agents contribute to the overall results on search time and walking distance.

Obviously, overall parking demand in a specific area is determined not only by cars entering the area, but also by the number of stationary cars (i.e., cars that are parked during the entire simulation period). Furthermore, the balance between parking supply and demand is influenced by the number of cars leaving the study area during the simulation. The number of stationary cars can be derived from the estimate of the initial occupancy rate (Appendix B) minus the cars that either travel within or leave the area during the simulation period. These stationary cars are distributed randomly over the statistical zones and do not receive a FEATHERS ID so that they will not be "activated" during the simulation run. The number of cars leaving the simulation area is derived directly from the trip data provided by the FEATHERS model. The relevant FEATHERS IDs are again randomly distributed over the cars located in each statistical zone. A car will leave its parking place in accordance with the FEATHERS trip data and will be directly removed from the simulation environment (i.e., the actually driving is not simulated).

3.6. Parking Choice Heuristics. The parking choice heuristic that is employed in this paper combines elements of a rational approach and a bounded rationality approach to model choice behavior [35, 36]. The starting point of the parking choice heuristic is the assumption that drivers have information on a set of parking options available to them. This is in line with the traditional rational utility approach to model choice behavior and has also been assumed in similar parking models, such as Sustapark [37] and Pamela [38]. However, in line with the notion of bounded rationality, it is assumed that driver agents neither have full information on all parking options nor necessarily choose the best available option. Rather than using the principle of utility maximization a different decision rule is employed as will be described below. Our approach is largely in line with the choice model proposed by Ottomanelli et al. [36].

The implementation of the approach starts with the creation of the relevant parking choice set. This is done when the agent is initialized. The exact set depends on the type of agent but only includes parking options within the maximum walking distance of 1,000 meter. For resident agents, the relevant set includes only on-street parking in the zone for which they hold a parking permit (see Section 3.4) and free off-street parking, as we assume that resident agents are not willing to pay for parking at all. Guest agents and commuter agents are assumed to have some knowledge of the local parking situation. Therefore, their relevant set includes the on-street parking options, the free off-street parking facilities and two randomly selected for-pay off-street facilities within the maximum walking distance to the destination (one kilometer). Finally, it is assumed that visitor agents are the least knowledgeable of the local parking situation and therefore know about the (price of) on-street parking locations and two random off-street parking facilities (for-free or for-pay) within walking distance. The choice set is different for smart cars, irrespective of the exact driver type (resident, guest, commuter, or visitor). Since smart cars receive information on all parking options through the bottom-up information system, *all* parking options within the maximum walking distance of 1,000 meter are included in their choice set.

Once the parking options are known, the relative utility of each option can be calculated. For every element in the set of parking options the relative utility is calculated based on the price and the distance to the destination, in relation to the activity duration. For each on-street parking option with a distinct parking regime the best parking place (in terms of distance to the destination) is selected and acts as a reference point. This reference point is used to calculate the relative utility of this parking alternative and in case the on-street parking option is selected from the option set, to navigate the car to the right location. For all agent types and all parking options, the distance to the destination is multiplied by two, to account for the fact that agents have to walk this path twice. Additionally, the activity duration is taken into account for cost and distance. The distance is divided by the activity duration in hours to address that agents are willing to

walk further the longer the activity duration, to calculate the distance value ($v(d)$):

$$v(d) = \frac{\text{distance}}{\text{activity duration}}. \quad (1)$$

The cost value ($v(c)$) is multiplied by the activity duration, where parking costs are expressed in terms of a basic cost per unit duration (price per hour). The cost value consequently reflects the overall parking cost:

$$v(c) = \text{parking cost} \cdot \text{activity duration}. \quad (2)$$

Subsequently, the calculated cost and distance values are standardized separately using feature scaling:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}. \quad (3)$$

The cost and distance attribute values are normalized to generate a value per parking option between 0 and 1. This value is used to calculate the probability of selecting a particular parking option according to the following exponential function:

$$p = e^{-\lambda * x}, \quad (4)$$

where p is the probability of the normalized value x (the lambda value for cost is 2, for distance 0.5). Choice probabilities are used instead of raw utility functions so they are easier to compare and are convenient to use for modeling bounded-rational behavior of human agents [34]. The overall probability vector is created with p_i for each available alternative i, given $i = 1$ to $i = j$, where j is the total number of alternatives. By combining the cost vector and the distance vector an overall probability vector is created. For worker agents the relative weight between the cost and distance vector is 1 : 25, while for the other agent types this is 1 : 10. The overall probability vector contains the choice probability of each parking option, totaling to one. To account for bounded rationality in decision behavior of the agents, a similar method as the *random proportional* rule is used [39]. According to this rule, the agents do not automatically choose the alternative with the highest utility. The vector is compared to a random value, r, between 0 and 1, and the chosen parking option will be the first alternative that has a cumulative probability that is greater than r. For example, when the probability vector is [0.7, 0.2, 0.1] for three parking options, the first option is chosen for every value of r that is smaller than 0.7, option two is chosen for a value of r between 0.7 and 0.9, and finally when r is greater than 0.9 option three is chosen.

Based on the chosen alternative the agent calculates which route to take (see Figure 2). By default the model calculates the route for each agent to its destination, but the end point of the route in case a parking option is selected located some distance away from the destination. If an off-street parking facility is chosen, the route is automatically changed to the location of the off-street parking facility. If the chosen alternative is an on-street parking location, the route is only changed if the on-street parking location is farther than 25 meters away from the destination. Note that the on-street parking location at this moment is the best on-street parking place associated with the chosen parking regime. For regular cars, the decision on which actual on-street parking place to park the car is based on the standard parking choice heuristic included in PARKAGENT. According to this heuristic, a car may move through three stages: estimate on-street parking availability while driving to the destination, search and select an available parking place when approaching the destination, and search for parking after passing the destination. This heuristic assumes that the driver monitors the occupancy level while driving in a street. The driver then uses this information to estimate the number of expected vacant parking places between the driver's current position and the destination. The lower the estimation, the higher the chance the agent will park at the next vacant parking place. When the driver fails to find a parking place before reaching the destination, the driver will pass the destination and make circular movements around the destination looking for an empty spot, while slowly expanding its search radius. The driver will park at the first empty spot which is within the search radius. In case the driver has selected an on-street parking place at a distance from the destination, this parking

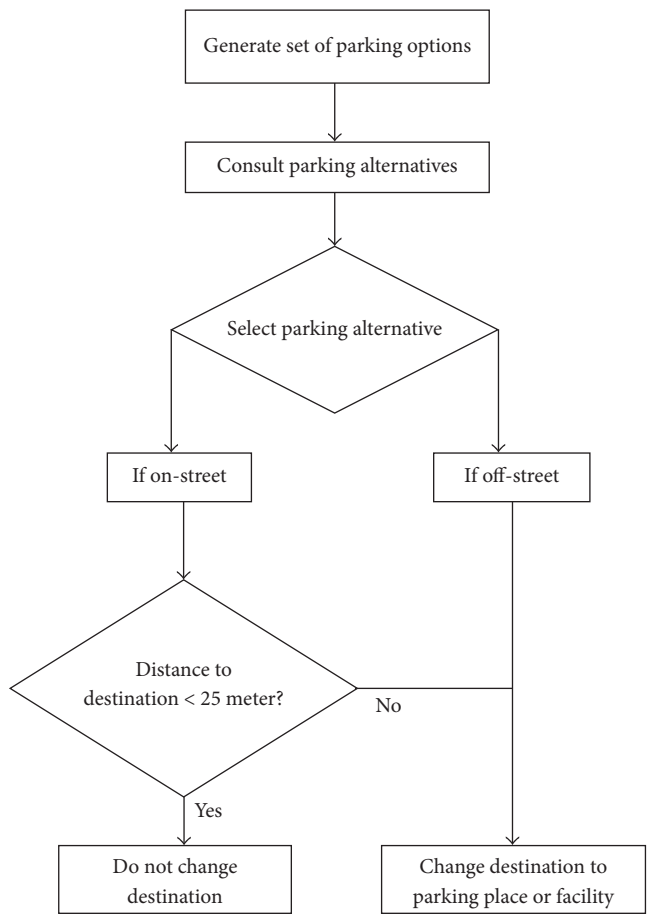

Figure 2: Graphical representation of the parking choice heuristic.

Table 3: Simulation parameters.

Parameter	Value
Number of on-street parking places	9,483
Number of off-street public parking places for free	3,280
Number of paid for off-street public parking places	6,034
Number of departing/arriving vehicles	~17,000
Driving speed while in search	12 km/h
Walking speed	3 km/h
Simulated time	24 hours
Communication range	200 meters
Communication interval	5 seconds
Initial preferred maximum walking distance	120 meters ("as the crow flies")
Maximum tolerable walking distance	1000 meters
Request expiration time[1]	50 seconds
Reservation expiration time[1]	150 seconds

[1]For a definition of these terms, see Appendix B.

place serves as the end point of the route and the same parking heuristic applies. For more detail, see Appendix A.

Since smart cars receive information on the availability of parking places, their parking choice heuristic is somewhat different and will be described in detail below.

3.7. Parking Information Provision and Reservation System. Smart cars have a substantial advantage over regular cars because they can receive information on vacant parking places and can send out requests to reserve an available parking place.

The bottom-up information system is based on both transmitting capabilities of the smart cars and parking sensors. Smart cars are capable of sending messages to other smart cars within a transmission range of 200 meters [40]. Every on-street and off-street parking space are equipped with a sensor, which is capable of sensing the current status of the parking space (vacant or occupied) and is able to communicate (within 200 meters) with smart cars. The transmission interval of messages is set to 5 seconds for both smart cars and sensors. The messages consist of the following attributes: (1) the timestamp at which the parking space became vacant and (2) the location of the parking space, stored as a coordinate.

Upon receiving a message on an available parking space, a smart car will process the message. Messages can be stored in two different databases: a private database and a public database. When looking for a parking space, incoming messages are ranked according to their usefulness and, if useful, stored in the private database. In addition, all incoming message are stored in a public database, which is regularly shared with other smart cars. Both databases have a limited capacity and store the best-scoring messages.

The reservation system is administered in a similarly distributed fashion. Important to note is that the whole process of receiving and sending information, requests, and reservations is executed automatically by the smart car without actual interference needed by the driver. Likewise, each parking space manages the reservation process on its own. Cars can send out at most two pending requests to reserve a parking place. However, at any given time, each car can have at most one reserved parking location. By allowing cars to send out a reservation request even when a successful reservation has been made, it is possible for the car to improve the parking location by making a different reservation. To restrict the number of messages that are sent over the network, cancelation of reserved parking places is not implemented in the model. The earlier reserved parking place is automatically made available for regular cars and smart cars after a fixed amount of time has elapsed (see Table 3).

Upon reception of a confirmation message, a smart car calculates which confirmed parking option is considered the best for the current situation (given the current location of the car, the parking location, and the destination), based on the choice heuristic described in Section 3.6. The car then selects the best ranking parking place.

It is important to note that the reservation system does not always lead to an actual reservation of a parking space. Therefore, it is important to describe the parking process of smart cars in more detail. Like regular cars, smart cars that select on-street parking from the choice set may move through three stages: estimate on-street parking availability while driving to the destination, search and select an available parking place when approaching the destination, and search for parking after passing the destination. In the first stage, smart cars collect data on available parking spaces through bottom-up information provision, as described above. Towards the end of this stage, a smart car may send out reservation requests in case they have received information on the availability of a relevant free parking space. In the second stage, smart cars are willing to park at a vacant spot if it is within their initial preferred walking distance (set at 120 meter) and if the car has not received a confirmation on a reservation request. However, if a smart car has already received a confirmation for a parking space, the car will only park at the encountered parking spot if it is closer to the destination than the reserved parking space. A car enters

the last stage of the parking process, when the destination is passed without finding a parking place. In that case, a car will always park at an empty parking space it encounters along the way, regardless whether it has received a confirmation on a requested parking space or not. The route depends on the situation. If a smart car has successfully reserved a parking space it will keep on driving towards the suggested location. If no reservation has been made, the smart car behaves as a regular car in this stage and will search around the destination with increasingly large circular movements.

Note finally that we assume perfect enforcement of the parking reservation system, implying that no (regular or smart) car will park on a parking place if it is reserved by another car.

3.8. Simulation Setup and Performance Indicators. For reasons of feasibility, our simulation of the center of Antwerp is limited to a limited time period on a typical Saturday. In what follows, we will present results of the impacts of bottom-up information provision and parking reservation for the period between 16.00 h and 19.00 h. These are the Saturday evening peak hours, with the highest number of arrivals (and departures). For technical reasons, the simulation runs for 24 hours (03.00 h–03.00 h), while information gathering and disseminating are enabled one hour before the actual monitoring of parking dynamics is started (so at 15.00 h).

In line with other studies, we are interested in the impact of bottom-up information provision and parking reservation under different levels of technology uptake or "technology penetration levels." In our simulation, we have analyzed the base situation in which no information provision and no reservation system are available and scenarios with a varying penetration rate, increasing from 0.2 to 1.0, with increments of 0.2. This means that 20% to 100% of the vehicles in the simulation are so-called smart cars, that is, being able to send and receive messages on parking place vacancies and able to make reservations. In all scenarios except the base case we assume that all on-street and off-street parking places are equipped with a smart parking sensor.

We have carried out two simulation runs for every simulation setting. This low amount of runs is the result of the extensive simulation time required for each run (on average ~5 hours), which is strongly related to the high number of vehicles included in the simulation (~17,000 cars) and the rapid increase in computing time as the penetration rate, and thus the number of messages goes up. The results presented in what follows always relate to the average for two runs of the same simulation settings.

Parking performance is assessed at the individual level and at the system level. Both are based on three indicators: search time, walking distance, and total parking time. In line with Tasseron et al. [16], search time is defined as the excess time needed to find a parking space from the moment the car enters the simulation environment (i.e., at a distance of 400 meters from the destination), in comparison to the optimal travel time to the most optimal parking location with respect to the destination. All drivers that park within that optimal time frame on the optimal parking space or on a parking space en route to the optimal parking space are considered to be drivers with zero search time. While this way of estimating search time has some problems for off-street parking, it does enable a comparison between regular and smart cars, which is the focus of our analysis. Walking distance is defined as the air distance between the destination and the selected parking space. Total parking time, in turn, is the summation of search time and the time necessary to walk to the destination and back at a speed of 3 km/h.

At the individual level, search time walking distance and total parking time are averages across the two types of agents (i.e., regular and smart cars) in order to assess the benefits of an information and reservation system for smart agents. At the system level, the values are calculated for all cars together.

3.9. Model Calibration and Validation. We have calibrated the parking choice heuristic of regular drivers based on a comparison between the observed parking occupancy rate at night in the simulation area and the occupancy rate as generated by our simulations. We have obtained the observed overnight occupancy rate per statistical zone from the Municipality of Antwerp. The occupancy rate as generated by our model depends on three key factors: parking supply, parking demand, and the parking choice heuristic. Each of these has been described in detail above. The estimate of parking supply is considered to be very reliable, as it is based on data from the Municipality of Antwerp (for off-street parking facilities) and from analysis of satellite imagery data (for on-street parking). The estimate of parking demand is derived from FEATHERS, which has been validated in a separate publication [32]. In our trial runs, parking supply and parking demand have thus been considered fixed, while we have adjusted the relative weights of parking costs and walking distance in the parking choice heuristic to generate parking occupancy rates at 03.00 h in the night. We have adjusted these relative weights and the values of λ for cost and distance, until the generated occupancy rate for the 22 statistical zones was largely in line with the observed occupancy rate. Furthermore, the occupancy rates for each statistical zone at the start of the simulation (3:00) should be similar to the occupancy rates at the end of the simulation run (24 hours later), assuming that people have returned to their homes and workers and visitors left after finishing their activity. These settings have subsequently been used in all simulation runs presented below.

4. Results

In this section the results from the simulation runs are presented, first at the individual level (Section 4.1), then for the overall system (Section 4.2), and finally for a selected area in the city center of Antwerp (Section 4.3).

4.1. Results for Smart Cars and Regular Cars. Against expectations, the simulation runs show that bottom-up information provision to smart cars does not lead to a reduction in search time for smart cars for on-street parking (n = 6,132, totaled for all six penetration rates) (Figure 3). This is in contrast with the results from earlier papers [6, 16]. The main reason for the difference is the average on-street occupancy rate.

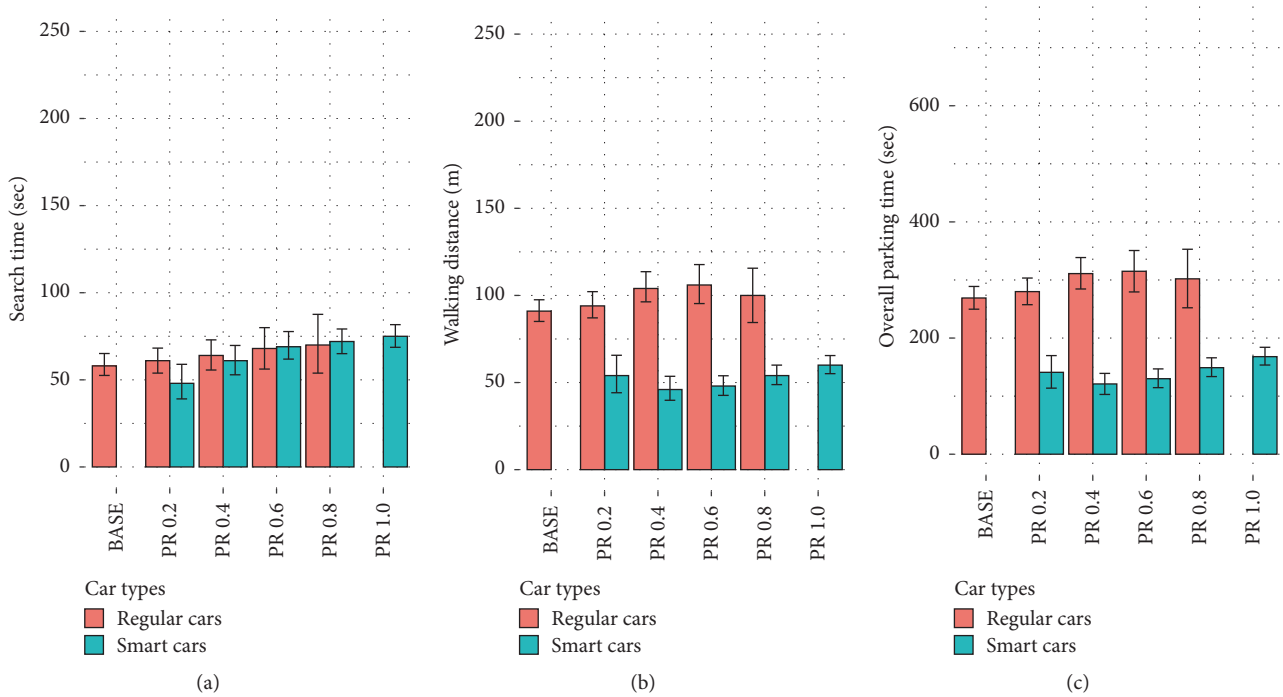

Figure 3: Results for individual drivers for on-street parking: (a) search time, (b) walking distance, and (c) total parking time, for regular cars and smart cars, for a 95% confidence interval at afternoon peak hours.

The average occupancy rate of the entire simulation area is around 65%, which is well below the "threshold values" of 85% or 90%, above which cruising is likely to occur [3, 41]. Furthermore, due to the low occupancy rate regular cars have a higher chance of parking their car before reaching the destination (which implies zero search time) in comparison to smart cars (who may be able to reserve a parking place close to but also after the destination, which implies a search time according to our definition of search time).

In contrast to search time, performance in terms of walking distance does improve for smart cars, for all penetration rates. The walking distance is reduced by about 50%, irrespective of the penetration rate. Walking distance for regular cars is not significantly affected by the introduction of smart cars, again irrespective of the penetration rate.

When search time and walking distance are combined in the total parking time, results are fully in line with expectations: smart cars outperform the regular cars under all circumstances (Figure 3). Regular cars show a large variation in total parking time and are confronted with a slight negative effect on performance. The performance of smart cars shows much less variation, irrespective of penetration rate, underscoring that the reservation system improves not only total parking time, but also reliability of parking time. The latter, in turn, also may also imply a decrease in the uncertainty and anxiety that may go hand in hand with parking search. These possible "psychological" benefits for smart cars, however, go hand in hand with a decrease in reliability and thus an increase in "parking stress" for regular cars.

Results regarding search time and walking distance for off-street parking facilities show a clear benefit for smart cars (Figure 4). Recall that regular cars only have knowledge about two to five off-street parking facilities (depending on the agent type) that are within walking distance of their destination, while smart cars (regardless of agent type) have knowledge about all parking facilities. Thus, the smart car is able to choose the best parking location in relation to its driving route, the location of parking facilities, and the location of the destination, which enables the smart car to select an option that limits both travel time and walking distance. The results indeed show that smart cars are confronted with lower search times than regular cars. However, due to the low number of observations (cars that park at the off-street facilities in the studied time slot) the difference is not significant ($n = 286$, totaled for all six penetration rates).

The results furthermore show that smart cars parking at an off-street parking facility do benefit in terms of a reduced walking distance to the destination. The variation in results is high, as indicated by the error bars. This is due to the low number of agents that park in a parking lot during the afternoon peak hours. The walking distance to the destination is on average higher than the walking distance to the destination when parking on-street. Again, due to the high variation it is not possible to draw conclusions on the development of walking distance over the various penetration rates.

4.2. Overall System Results. The impact of parking information on the overall system is obtained by combining the

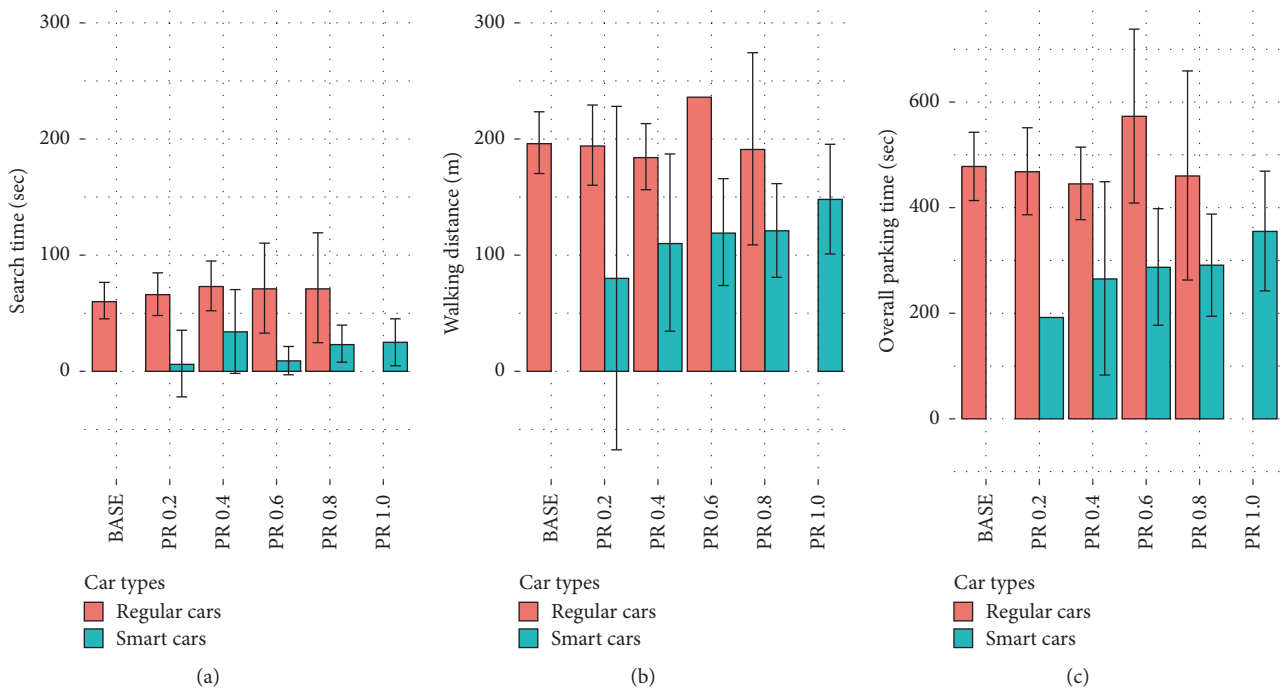

Figure 4: Results for individual drivers for off-street parking: (a) search time, (b) walking distance, and (c) total parking time, for regular cars and smart cars, for a 95% confidence interval at afternoon peak hours.

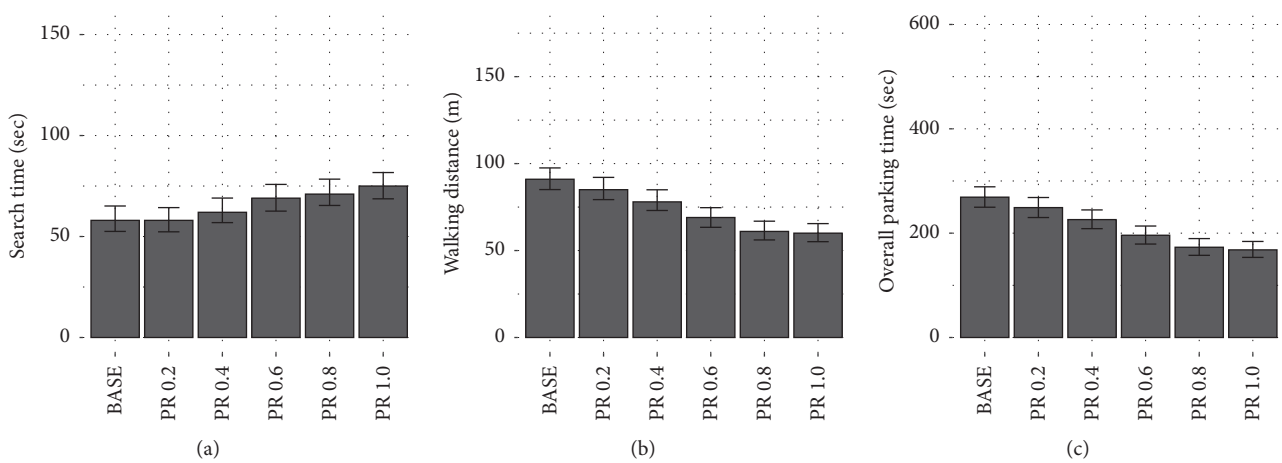

Figure 5: Results at the system level for on-street parking: (a) search time, (b) walking distance, and (c) total parking time, for regular cars and smart cars, for a 95% confidence interval at afternoon peak hours.

results for regular cars and smart cars. The results show that, for every increment in penetration rate, overall search time increases, overall walking distance decreases, and total parking time (search time combined with the time needed to walk to and from the destination) decreases (Figure 5). These results can be explained by the combined effect of three key factors: first, by the parking choice heuristic of smart cars: given the relative weights of search time and walking distance, smart cars typically prefer parking close to the destination over a reduction in search time; second, by the low average occupancy rate; third, by the way in which parking search time is defined (see Section 3.8). In combination, these factors are likely to lead to an increase in search time for smart cars vis-à-vis regular cars, as regular cars are very likely to find a parking place before reaching the destination under conditions of a low occupancy rate (resulting in zero search time), while smart cars are willing to accept some search time to obtain a shorter walking distance.

These observations are underscored by an analysis of the differences in search time across the entire study area. For this purpose, search time for regular and smart cars has been calculated at the level of a single on-street parking place. This value is determined by averaging the search time for each type of car for all parking places within a radius of 100

Figure 6: Spatial variation in search time for on-street parking: difference in seconds between regular cars and smart cars, at afternoon peak hours and for a penetration rate of 0.2.

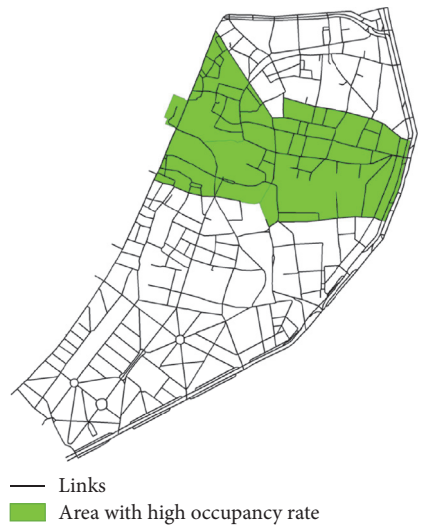

Figure 7: Part of the simulation area with a high occupancy rate throughout the simulation period.

meters. For each parking place, this results in one search time value for regular and smart cars. By comparing the value between both, it is possible to create a "heatmap," which indicates the size of the difference in search time between regular and smart cars. Figure 6 shows the results. A positive difference means that smart cars have, on average, a shorter search time than regular cars, while they have a negative difference points at the opposite. Zone A, where parking is restricted to a maximum of 3 hours, has a relatively high parking turnover and a relatively high occupancy rate (see Figure 7). Under these conditions, a parking information and reservation system provides a considerable advantage, as a random search for on-street parking is relatively inefficient [see [6, 7]]. The same conditions apply in a small part of Zone B. This area is relatively close to a high demand area in Zone A but offers a more attractive parking regime that Zone A, in terms of both lower time restrictions and lower prices. As a result, the area highlighted in Figure 6 is a hotspot for cars that do not want, or are not eligible, to park in Zone A, in particular visitors to the city. Because of the high demand for parking in this area, smart cars benefit from the available information and the possibility of reserving a parking place. In contrast, the remaining part of Zone B shows a benefit in search time for regular cars. This is the result of the lower occupancy rates, which allow regular cars to exchange the certainty for a parking place on the way to the destination against a relatively long walking distance: they tend to park at a parking place before reaching their destination resulting in zero search time in the model.

These findings are in line with earlier studies, which have shown that the crucial impact of the occupancy rate on parking search time and on the relative benefits of a parking information and reservation service on search time at the system level [7, 11, 42]. For this reason, we now analyze the impact of parking information and reservation in more detail for an area within the city center of Antwerp with particularly high occupancy rates.

4.3. Results for Areas with High Occupancy Rates. Earlier studies have shown that smart cars generally only benefit in terms of search time if the parking occupancy rate is above 90% [6, 7]. In our case, these occupancy rates occur mostly in the central area of the study zone, which contains the main, pedestrianized, shopping streets of Antwerp (see Figure 7) and is characterized by a very high occupancy rate (average of 98.6%) during the simulation period (16.00–19.00 h).

The results for this area show that the smart cars indeed benefit in this situation from being better informed than regular cars (n = 1,087, totaled for all six penetration rates) (Figure 8): the former experience lower search times and shorter walking distances than the latter. Both smart and regular cars are faced with a substantially higher search time in this particular area in comparison to the entire study zone, but the difference is much higher for regular than for smart cars (~130% versus ~95% higher). However, when the penetration rate of the technology increases, the search time benefit for smart cars drops, due to the increased competition between smart cars. Furthermore, the reduction in walking distance for smart cars is less pronounced as compared to the results for the entire city center. This shows that, in case the number of vacant parking places is limited, also smart cars have trouble finding a parking place close to their destination within a reasonable amount of time.

The benefits at the system level for the specified area are limited but nonnegligible (Figure 9). While search time is hardly influenced in comparison to the base situation, overall walking distance does show some decrease specially for higher penetration rates (≥0.6), even though the decrease

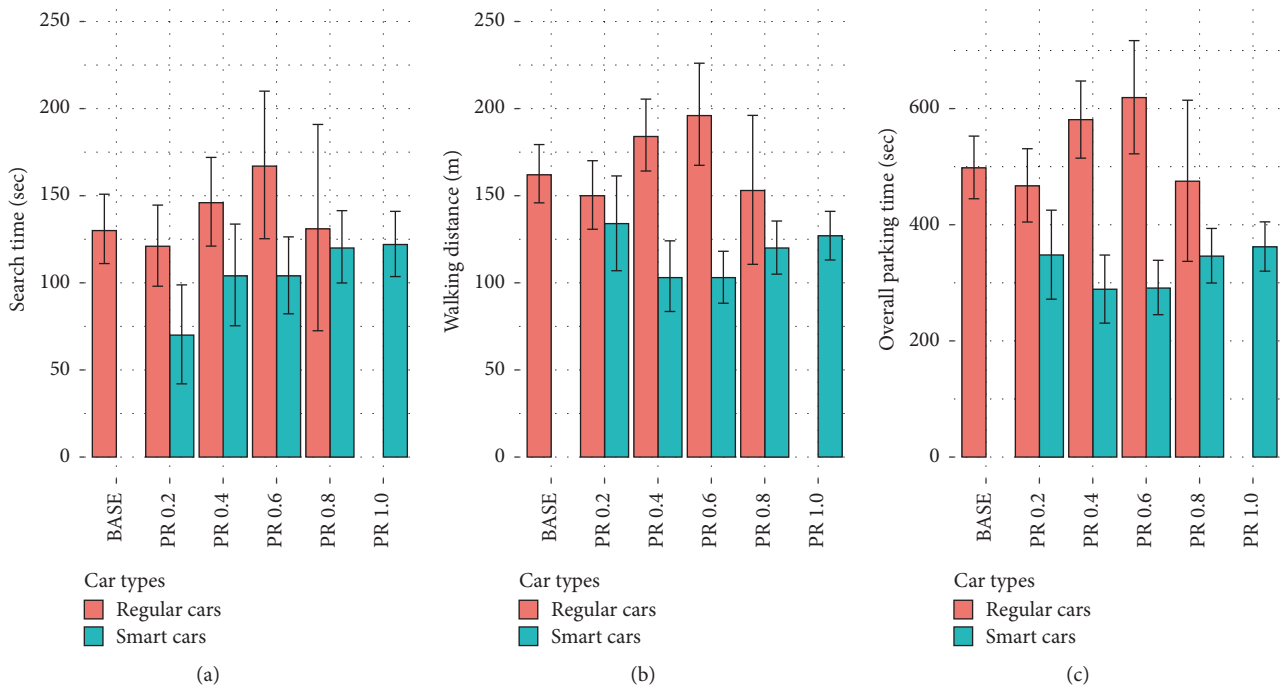

Figure 8: Results for individual drivers for on-street parking in high occupancy area only: (a) search time, (b) walking distance, and (c) total parking time, for regular cars and smart cars, for a 95% confidence interval at afternoon peak hours.

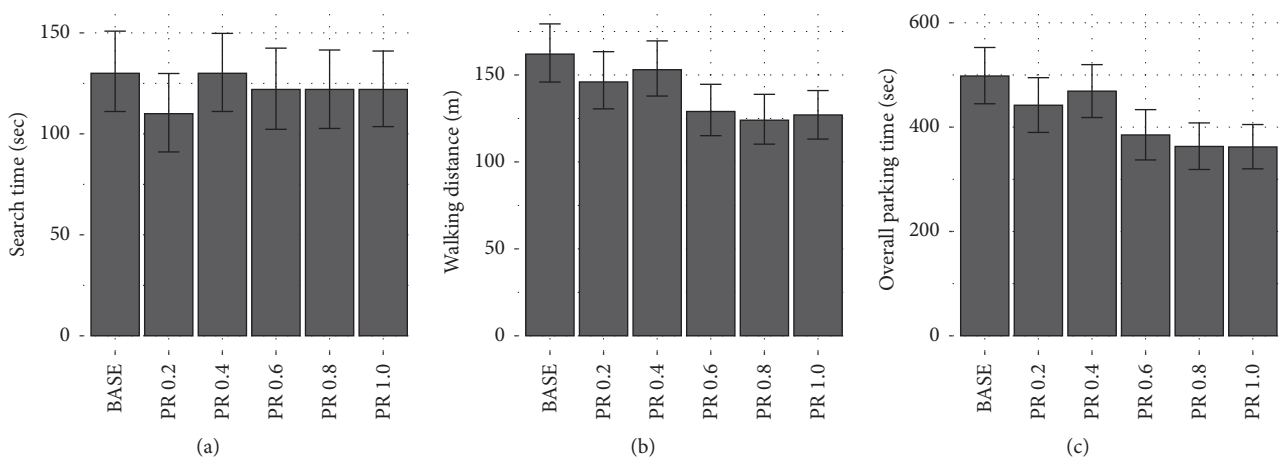

Figure 9: Results for at the system level for on-street parking in high occupancy area only: (a) search time, (b) walking distance, and (c) total parking time, for regular cars and smart cars, for a 95% confidence interval at afternoon peak hours.

is less pronounced than for the entire simulation area. Total parking time shows a small but significant reduction at the system level.

5. Conclusions and Discussion

In this paper the impact of information provision and reservation in a realistic, real-world simulation environment was studied. While our analysis only relates to a specific period and area (i.e., a Saturday afternoon in historic city center), the findings do provide a first assessment of the potential benefits of a bottom-up parking information system in a real-life setting.

The results are perhaps against expectations. Smart cars did not experience a significantly lower average search time than regular cars, while at the system level the introduction of smart cars even lead to an increase in overall search time. In contrast, walking distance did improve significantly for smart cars. When all cars are equipped with communication technology the average walking distance decreases by more than 30%. Combining search time and walking distance leads to a reduction in total parking time under all penetration

rates. If all cars are equipped with information technology, total parking time is even reduced by about 35%.

The benefits are different in the central part of our study zone, which is characterized by very high parking occupancy levels during the period of simulation. For this specific area, smart cars gain in terms of *both* search time and walking distance. However, the search time gains for smart cars come at the expense of regular cars. This negative externality hardly occurs for walking distance, with the result that total parking time still shows a substantial reduction with every increase in the share of smart cars. When all cars are able to receive information and reserve a parking place, average walking distance decreases by ~22% and total parking time by ~27% in contrast to the base situation with zero smart cars.

The counterintuitive results in terms of search time are the result of two interacting factors: the particular parking conditions in the simulated area and the employed parking heuristics. First, and as shown in previous research, parking information is especially effective in case of high competition over parking places. This condition only occurs in part of our simulation environment. Substantial parts of the inner city of Antwerp show relatively low occupancy rates, implying that also regular cars will be able to find a parking place without much search time. This condition of low occupancy level interacts with the way in which smart cars select a parking place. In our heuristics, smart cars aim to minimize total parking time, which leads to a preference for nearby parking places in order to reduce walking distance. This preference often implies that smart cars do not park *before* reaching the destination but rather continue driving to select a more nearby parking place after passing the destination, resulting in slightly longer drive and park times for smart cars. Since we have defined search time as the difference between the minimal time to drive to and park as close as possible to the destination on the one hand and the actual drive and park time on the other, this parking heuristic is likely to result in relatively long search times vis-à-vis regular cars that select a parking place *before* reaching the destination.

The overall benefits in terms of total parking time are impressive, certainly in contrast to the minimal benefits in terms of search time, but it should be taken into account that they accrue to the population of drivers only. Society would primarily benefit from a bottom-up information and reservation system if such a system would lead to a reduction in *overall search time*, as search time is related to multiple externalities (congestion, traffic (un)safety, air and noise pollution). The increasing literature on transport and health even suggests that a decrease in walking distance may well have societal costs, as "active travel" (i.e., walking in this case) is strongly correlated with positive health outcomes. Thus, the societal case for a bottom-up parking information and reservation system is weak at best.

Clearly, our findings should be interpreted with care, for at least four reasons. First, the smart cars are optimized to select the parking place that requires the driver the lowest possible time to reach the destination, taking into account driving and walking distance. As a consequence, smart cars are more likely to benefit in terms of walking distance than in terms of the time they need to search for a parking place. If the decision mechanism is changed to stronger value search time than walking distance, the results will change more in favor of a shorter search time (and longer walking distance). It is expected, however, that it would not fundamentally change the total sum of benefits of a bottom-up information and reservation system.

A second remark concerns the PARKAGENT simulation model. This model makes no explicit distinction between drivers that are making a regular shopping trip and drivers on a nonregular shopping trip. Van der Waerden [38] shows that there is a significant difference between these two groups: nonregular visitors tend to park for a longer period of time, are willing to accept a longer walking distance, and have a lower aversion to pay for parking. This could potentially result in different outcomes for these two different agent groups. On the other hand, due to the stochastic choice behavior and considering the fact that the agents in our model take into account the activity duration when choosing a parking location, the parking choices of our agents may well reflect the differences observed between these the two groups of agents.

Third, our results only relate to the "objective" benefits of a parking information and reservation system, in terms of search and walking time. Such systems may well have additional psychological benefits, as they may reduce car drivers anxiety about finding an available parking place, thus generating substantial additional benefits for users of the system (and possibly also for other users of the street space through improved behavior of drivers searching for parking).

Finally, we have only analyzed the added value of a bottom-up information provision for a limited time period, in part due to software restrictions. It may well be that the information system delivers more benefits during other time periods, for instance, on Sunday's when parking is for free in some parts of the inner city, or in evening hours when residents returning home may have difficulty finding a free on-street parking place. Clearly, more research is needed to gain a more complete understanding of the potential benefits of a bottom-up parking information system for individual drivers and the wider society. However, our findings do show that benefits in terms of search time may only be expected under conditions of high occupancy rates.

Disclosure

This paper is based on a chapter of the Ph.D. thesis of one of the authors [43].

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Research Article

Cooperative Multiagent System for Parking Availability Prediction Based on Time Varying Dynamic Markov Chains

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Traffic congestion is one of the main issues in the study of transportation planning and management. It creates different problems including environmental pollution and health problem and incurs a cost which is increasing through years. One-third of this congestion is created by cars searching for parking places. Drivers may be aware that parking places are fully occupied but will drive around hoping that a parking place may become vacant. Opportunistic services, involving learning, predicting, and exploiting Internet of Things scenarios, are able to adapt to dynamic unforeseen situations and have the potential to ease parking search issues. Hence, in this paper, a cooperative dynamic prediction mechanism between multiple agents for parking space availability in the neighborhood, integrating foreseen and unforeseen events and adapting for long-term changes, is proposed. An agent in each parking place will use a dynamic and time varying Markov chain to predict the parking availability and these agents will communicate to produce the parking availability prediction in the whole neighborhood. Furthermore, a learning approach is proposed where the system can adapt to different changes in the parking demand including long-term changes. Simulation results, using synthesized data based on an actual parking lot data from a shopping mall in Geneva, show that the proposed model is promising based on the learning accuracy with service adaptation and performance in different cases.

1. Introduction

The problem of traffic congestion in urban cities has been one of the very distressing issues. In order to arrive to a destination people need to start their trip well ahead of their scheduled program and will be forced to spend more time on the way. In addition, it has economical impact with incurring significant amount of cost. For example, in USA, studies show that traffic congestion costs about 124 billion US dollar (USD) annually with an expectation of rising to 186 billion USD in 2030 [1], while it was about 48 billion USD in 1990s [2].

It is also one of the major players in air pollution [3]. The emission of different air pollutants degrades air quality significantly [4]. This pollution in turn results in health problems including worsening asthma symptoms, asthma development in children, lung cancer, and heart disease [4]. Health problems, which are not related to the air pollution, are also reported including psychophysiological stress of the drivers [5, 6].

Studies suggest that on average one-third of the traffic jam is created by cars searching for a parking place [7, 8]. Hence, the study of parking problems and their corresponding solution methods have been one of the major issues for researchers in the field. Price based controlling approach for the parking demand by analyzing different pricing strategy where the cost increases when the number of available parking spaces decreases has been one method proposed [8]. However, organizations, like universities, develop an optimization model of the problem and try to optimize the parking slot allocation, thus helping with proper planning and design of parking spaces [9].

In busy centers or part of a city, drivers are not well aware of the parking situation and availability. This gap of

information can be bridged using a proper statistical prediction approach based on previous experience and a multi-agent-based service to communicate among parking places in the neighborhood and with drivers. Prediction approaches have been one of the essential tools used to analyze and forecast different scenarios based on limited information. It has been used in different areas including financial market, agriculture, environmental issues, and engineering [10–14]. With the rapidly growing studies on transportation planning and management [15–17], prediction is playing a vital role. Markov chain theory can be useful for learning based prediction purposes. The Markov property is when one can make predictions for the future of the process based solely on the knowledge of its present state. It has been used for prediction in different applications. Hence, in this paper, based on previous data transition matrices of the Markov chain will be constructed and used to predict the next state of the available level of parking space. The states will be the level of available parking places. Since the demand for parking place varies and depends on different issues, a time varying Markov chain will be used. In addition, the transition matrix will "learn" through iterations and adapt itself for long-term changes in the demand for parking. An opportunistic space- and time-related multi-agent-based service then compiles all these predictions, generates a cumulative prediction for a neighborhood of interest, and supports and answers drivers queries for parking space availabilities. This will relax the traffic jam as the drivers will no longer wander around looking for vacant parking slot. To summarize, the main aims and objectives of this paper are (1) to propose an approach of constructing a dynamic time varying Markov chain approach based on previous data for parking availability prediction, (2) to use the Markov chain based approach for the prediction of parking availability in a given parking place, (3) to use multiagent systems in order to construct a cumulative prediction of the neighborhood of multiple parking places, and (4) to introduce a learning approach where the Markov chain or the prediction can adapt for changes in the environment which affects the parking place demand.

The paper is organized as follows. The next section discusses related works. Section 3 presents an opportunistic parking service based on the notion of spatial services we developed in previous works. Section 4 discusses the parking prediction mechanism we propose. This is followed by an evaluation of the approach in Section 5. Section 6 provides a discussion and possible future works.

2. Related Works

Smart commercial solutions for dynamically finding parking places usually involve sensors reporting parking occupancy to a central server gathering all this information. Drivers are then provided with dynamic notifications, active route guidance, or an overview map of available parking spaces (http://www.mobility.siemens.com/mobility/global/en/urban-mobility/road-solutions/integrated-smart-parking-solution/pages/integrated-smart-parking-solution.aspx). These sensors can be either overhead radar sensors, or on the ground sensors located at the different parking places reporting their current occupancy. Such services can be combined with others services to provide multimodal solutions (e.g., mixing public and private transport solutions). Advanced research solutions involve the use of agent-based systems for negotiating parking spaces in advance, or vehicular communication to provide information within a parking lot [18]. Solutions can be central solutions, opportunistic, aiming at searching parking spaces, guiding drivers towards such spaces, or providing e-payment solutions [19].

Some studies suggest a mechanism of current parking availability information delivery to the user. Reference [20] discusses information manipulation and delivery, with objectives including walking distance, thus aiming at decreasing the emission of toxic gases. Space availability information delivery mechanism is based on what they call PARC (parking access and revenue control) [21]. It is useful, especially when the parking garage is huge, to use information management delivery systems to locate vacant spaces. However, still it tells the current situation and it does not predict the likelihood of the parking situation in the future. Hence, the best way to address this problem is to couple these ideas with appropriate prediction system.

Hence, the development of parking space prediction approaches has also been one of the research focus areas. A number of studies have been reported on parking availability prediction. Based on the turnover rate for each parking lot, a parking demand was generated in [22]. The land use per unit area is used to forecast a cumulative demand value which may be useful for road and parking management, but not for guiding drivers according to their parking needs. Calibrated discrete choice model was used for parking space prediction with a parking reservation mechanism, in [23].

Recently, based on queuing theory and Laplace transform a parking prediction approach was proposed [24]. They combined real time cloud-based analysis and historical data trends that can be integrated into a smart parking user application. A multivariate autoregressive model for parking prediction is also proposed in [25]. They used both temporal and spatial correlations of parking availability. The spacial and temporal aspects of parking prediction were also addressed in [26]. Back-end model is used to learn historical models of parking availability which can be stored in the map in the vehicle.

Neural network is another method used in the domain. Prediction of parking occupancy mainly by studying the relationship between aggregating parking lots and predicting parking occupancy, using feedforward neural network, is studied in [27]. Similarly, [28, 29] use neural network coupled with Internet of Things (IoT) for predicting parking availability with backpropagation. Another research on parking availability prediction using neural network is done in [30]. They develop a prediction mechanism for sensor enabled cars using regression tree, neural network, and support vector regression. Their analysis is based on calculating the occupancy rate of a parking, which is the ratio of the number of slots occupied by the number of slots which are operational.

Unlike the success of Markov chain analysis in different prediction applications, a limited number of researches are reported which use Markov chain for parking availability prediction. Queuing theory and continuous Markov chain are used in [31] to predict the parking availability before the arrival of the driver. However, they did not propose a way of applying the method for different situations or times where the demand fluctuates. Reference [32] used a continuous time Markov chain to predict the available parking spaces through communication between the parking garage and the navigation system of the cars. The demand for parking depends on different issues including time of the day and day of the week. Hence, the discussions and models used are not considering these issues. Furthermore, a system which adapts with the change in the environment has not been explored, which is one of the contributions of this paper.

3. Smart Opportunistic Parking Service: Overview

The opportunistic parking service we propose is based on the notion of spatial services we developed in previous works, as will be discussed below.

3.1. Spatial Services. Spatial services are new generation of services that exploit spatially distributed data, enable smart environments, or exploit Internet of Things (IoT) scenarios. This is a new category of decentralised services based on data propagation among stationary or mobile devices and where the functionality of the service is provided as a result of the collective interactions among multiple entities, involving processes and calculations taking place across several geographically distributed computational nodes. Spatial services are built and composed on demand. When users query to retrieve the closest vacant parking place in a smart city, sensors, connected objects, and services spontaneously collaborate to query the spatially distributed data and to provide the answer, going well beyond traditional location-based services requiring a central server gathering all data and providing the computation.

The systems are composed of several agent-based entities, geographically distributed across the city, each with their local perception and learning and predicting capabilities, exploiting their own locally available data. They work in a decentralised manner and their functionality is the result of the collective interactions among multiple agent-based entities, possibly spatially (geographically) distributed across several stationary or mobile nodes [33].

In our case, each parking lot agent interacts with its neighboring parking lot agents or any other connected agent-based objects, propagating away information about itself (i.e., its predictions) or gathering information about other parking lots (e.g., using spreading or gossip mechanisms) or any traffic or road network disturbance in the traffic or route network.

3.2. Smart Parking Service. To illustrate our discussion, we consider a smart parking service guiding drivers across the city towards a parking lot close to their destination. It takes into account parking spaces availability as well as any unforeseen circumstance (road works, accident) blocking the access and preventing the use of a predetermined route or predetermined parking lot. The place in question will be connected to the system and injects data in the system (e.g., hole in the ground, closed path). The smart parking service aggregates data spatially and delivers the information to the driver.

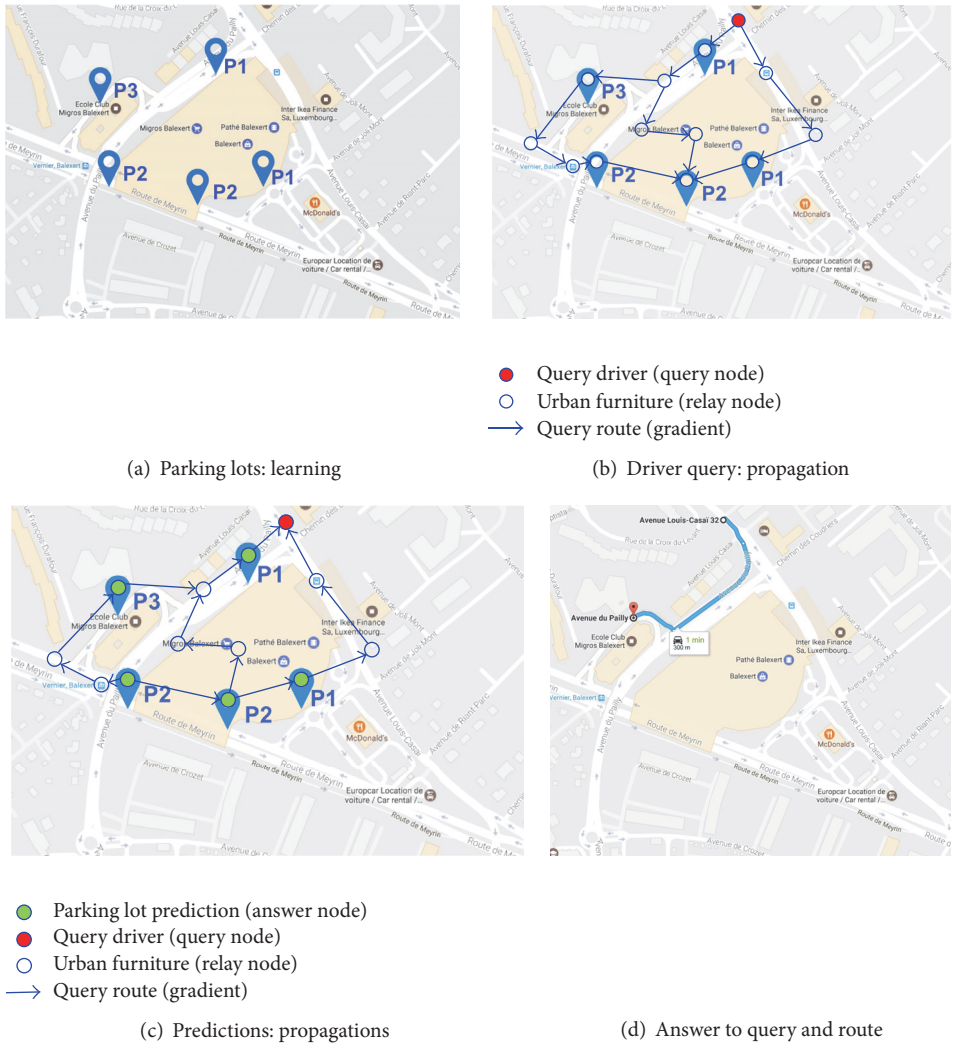
Figure 1(a) shows the case of a parking service in the area of Balexert (the biggest shopping mall of the French speaking area of Switzerland) in Geneva. The Balexert shopping mall has 3 parking spaces (https://www.balexert.ch/parkings/, https://www.geneve-parking.ch/fr/parkings/pr-balexert): $P1$ occupies the whole first basement of the shopping mall and $P2$ occupies the same space at the second basement both with two other entrances, and $P3$ is outside with 4 levels. $P1$, $P2$, and $P3$ have capacities of 925, 890, and 348 parking places, respectively. The parking service we envision is composed of different parts.

3.2.1. Parking Lot: Learning and Prediction of Availability. Each parking lot (e.g., public garages, park and ride, airports or trains stations, and street parking areas) predicts, through a permanent learning activity, its availability patterns for each time-period of the day, for each day of the week. This learning phase brings in and adapts to three aspects: (a) learning of on-going availability based on actual occupancy of parking places; (b) adaptation to seasonal changes (e.g., school holidays period or developments taking place in the area); (c) adaptation to sudden changes in availability due to weather changes (e.g., snow falling, heat wave); (d) foreseen changes (e.g., conference with 5000 participants).

3.2.2. Propagation of Driver Query and Parking Space Prediction. A driver queries for a suitable parking lot, specifying the likely arrival time in the area (e.g., in 5 mins or 40 mins). Connected urban furniture (e.g., lamp posts, traffic lights) propagates the driver query across the different connected objects in the environment, using a gradient or spreading spatial service. Objects sensitive to the query (i.e., those matching with parking availability requests, in our case devices linked to $P1$, $P2$, and $P3$ entrances) inject in the system their predicted availability corresponding to the time the driver will arrive in the area (e.g., availability in the next 15 mins). Figure 1(b) shows the propagation of a driver query across connected urban furniture.

Figure 1(c) shows how predicted availability of a given parking lot propagates across different connected objects, reaching along the way the other parking lots, as well as the driver itself. At the different parking lots, data aggregates to provide parking space availability over the whole Balexert area. To do so, the different nodes involved send the answer to the driver. This information evaporates and spontaneously disappears from the involved computation nodes after a while depending on user profile and length of route.

3.2.3. Answer to Query. Predicted availability of a given parking lot and that of larger areas propagate across different



(a) Parking lots: learning

(b) Driver query: propagation

(c) Predictions: propagations

(d) Answer to query and route

Figure 1: Driver query, prediction propagations, and answer.

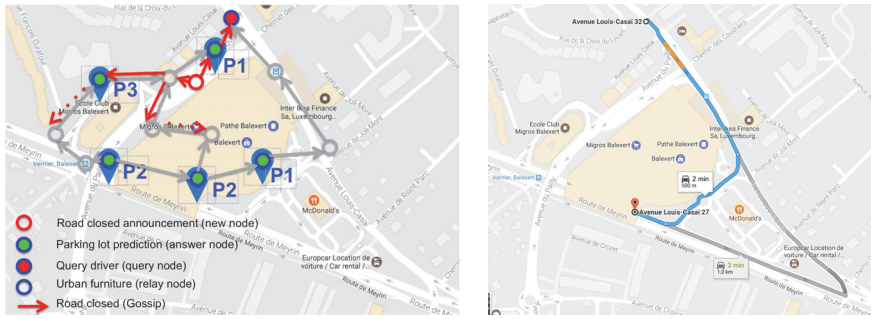
connected objects, eventually reaching the driver car. The driver's car matches the answer to the query it injected. The corresponding agent then informs the driver and a route is calculated. Figure 1(d) shows the case where $P3$ provides the closest availability for our driver. It is interesting to note that the system works independently of the actual objects along the route or whether or not they move.

3.2.4. Spatial Service Announcing Unforeseen Events or Changes in Network. Figure 2(a) shows further interactions involving closed roads or unexpected events. A new connected object (red node) spreads information about road works and informs about a closed path. This information spreads around using the gossip spatial service (interacting nodes share their respective information and update their local information accordingly). If other such objects would convey information about the state of the routes, that information would be aggregated as they reach the different intermediary nodes. Finally, in Figure 2(b), the driver agent eventually receives both parking availability predictions and closed path information and is able to calculate a new route (e.g., to reach $P2$ from the open road section).

4. Parking Availability Prediction

A Markov chain or Markov model consists of countable family of random variables, $S_i's$ also called states, that satisfies the Markov property. That is, the probability of the next state depends only on the current state but not on previous states. The collection of these probabilities of transition from one state to another can be represented in a matrix form, called transition matrix, where the rows represent current state and the columns represent the next state.

4.1. Properties of Parking Demand. Since a single transition pattern is not valid all the time and parking demand depends on different conditions, a homogenous Markov chain is not suitable for predicting parking place availability. Parking demand depends on the day of the week and the time of the day. The demand of parking place, and consequently



(a) Spatial service: unexpected changes (b) Spatial parking service: new route

Figure 2: Overview of the intelligent parking space system. The red dotted arrows are the road closed (gossip) just like the solid red lines (it is broken to show that there could be multiple agents in the process); filled blue circles are parking places; and the grey circles are agents.

availability of parking place, may vary on week days and weekends. Furthermore, in considering a specific day of the week, the demand varies through time. For instance, according to city of Portsmouth transportation report in 2012 [34], the demand in the city increases around midday (12 pm) and evening (8 pm) on working days and in the evening (6–8 pm) on weekends. This is similar to what we observed with the Balexert shopping mall. Similarly, the demand is seasonal. That is, the parking availability changes based on the season or period of the year. If it is a holiday season the demand near a recreation center increases whereas the demand around work places will more likely decrease [35]. Weather can be another factor which the parking demand depends on. Furthermore, the development of the neighborhood (e.g., construction of a new or the closure of an old parking place) and relocation of people in the neighborhood affect the parking demand.

In addition to those mentioned, other short term circumstances can affect the demand. These can be categorized into two categories as foreseen and unforeseen circumstances. Foreseen circumstances include planned events like international or national conferences, meetings, and similar events. The information regarding the number of participants is known or can be estimated, which again gives sufficient information to estimate the additional increase in the parking demand. On the other hand due to different unexpected circumstances, unforeseen circumstances, the parking demand may also be affected and the availability of parking place can change. In this category we can mention events like international events which come rarely without sufficient information about the additional demand for parking and road block due to different reasons including road works, accidents, and the like.

A reliable prediction system needs to incorporate all these concepts and update itself with the dynamic changes of the environment. A driver at a particular time may want to ask three basic questions: (1) is there available parking place in a particular location? (2) Will there be available parking place soon (when I arrive)? (3) What about other parking places near the place of interest? The first question is a direct question and can easily be answered by counting the actual available places. The second question needs a prediction approach based on current state of parking availability for a particular parking garage. The third question can be solved by communicating with other parking garages in the neighborhood and providing the requested information to the user.

4.2. Parking Availability Prediction Setup. The probability of changing states depends on the demand for parking. Hence, the prediction model is a function of the season, the day of the week, the time of the day, and the weather condition. There are as many matrices as different combinations of days, time, season, and weather.

The following three steps are used to develop a Markov chain model.

Discretizing Time. For a given day, the time horizon needs to be discretized to accommodate the change on the demand through different times of the day. Let Δt be the *time width* used for this purpose. That means a given parking demand situation will be represented by a given transition matrix for Δt duration of time and replaced by another. Some researchers used five minutes of time width [27]. The smaller the time window the better the prediction results, however an increase in complexity.

State Characterization. One possible way of state characterization is using the exact number of available parking slots. However, it increases the complexity especially in cases where there are hundreds of parking spaces. Therefore, another possible way to overcome this limitation, is to determine different classes of parking space availability and classify the situation. One possible way is based on percentage of available parking space; for example, more than 40% available parking places result in no traffic congestion, then one class or state can be more than 40% parking places available, and the rest of the states can be 0%, from 0% to 20%, and so on available parking places. Suppose, in general we have n states, say $S_1, S_2, \ldots, S_n$.

Transition Matrix Construction. Once the time width and the states are defined, the transition matrix needs to be constructed for each time duration of interest. It is constructed using previous experience (i.e., collected data) and expected knowledge of the situation when data is not sufficient. Consider current time is in the duration $[t_i, t_{i+1})$. Let us call the state at t_i an *entering state* and at t_{i+1} a *leaving state*. From the previous same time of similar days (i.e., similar refers to the same season, the same day of the week, and the same weather condition) a data will be summarized based on the available parking slots at times t_i and t_{i+1}. Data is summarized in a matrix form with entries $\overline{p_{jk}}^{(i)}$, representing the number of times the state changes from j to k in the given interval (i.e., at time i the state is j and at time $i+1$ the state is k). There could be cases in which one of the states never occurs in the data of the initial states. In such cases the initial data can be generated using previous experience and rule of thumb and through nonconventional data collections [36] from users (i.e., drivers who regularly use the parking lots are asked regarding the parking situation for the particular scenario of interest). It will later update itself and evolve based on the initial values and learning from experience.

Hence, in the constructed matrix $\overline{p}^{(i)}$, each row and column represent the states where the entries $\overline{p_{jk}}^{(i)}$ represent the number of times the state changes from state j to state k in the given time interval. This matrix will be normalized row-wise (i.e., the summation of entries in each row will be 1 and each entry is nonnegative, to construct the final transition matrix, p).

4.3. Learning Mechanism. Since the model can be affected by gradual and long-term changes like relocation of people, a learning mechanism needs to be used. That is, the system needs to be adaptive by incorporating the newly read data. That can be done by adding additional data to reconstruct or update the transition matrix. One of the possible ways to do that is to record previous data and replace old data by a new one in each iteration. However, saving all previous data used to construct the transition matrix is memory expensive. Hence, based on a parameter called the *learning window*, the new information can be magnified over the rest. Suppose N is the learning window and the current state is j; then the learning is done by multiplying the jth row by N, adding 1 to the entry corresponding to the leaving state, and normalizing the row by dividing each entry by $N+1$. The resulting matrix will be the new transition matrix.

The degree of learning depends on the parameter N. If N is set to be large, it means the updating is highly affected by old and outdated data and the new entry will have a small or negligible effect, producing slow learning. On the other hand if it is set to be very small, it means it will highly be affected by current conditions. However, different changes can happen due to different nonrepeating reasons and the learning to be affected in a higher degree for such changes may produce unreliable results. However, if proper tuning of this learning window is set, the matrix will adapt itself easily to long-term changes.

In the other case, if there is a nonrepeating demand fluctuation which is planned ahead, like organized conferences or meetings, a user modification needs to be involved to update the transition matrix accordingly. This also includes accidents and unplanned big events. In such cases as user feed inputs will be used for the prediction or warning information system needs to be set up.

4.4. Parking Availability Prediction. Suppose at t_i the state is j; then the probability of the next state at $t_{i+\Delta t}$ to be k is p_{jk}. For simplicity let us represent Δt by a unit; hence $t_{i+\Delta t} = t_{i+1}$ and $t_{i+n\Delta t} = t_{i+n}$ for any n. k with the highest probability p_{jk} shows that state k has the highest probability to be the next state. If we are interested to make a prediction not at t_{i+1} but at t_{i+m}, then the transition matrices will be multiplied consecutively from t_i up to t_{i+m} to produce a single matrix predicting the next state at t_{i+m}. However, if the current state is known, rather than multiplying the whole matrix it will be easier and more efficient to multiply the corresponding row of the current transition matrix by the next matrix and continue like that. That is, if the current state is known and is, say, k, then the probability of the occurrence of the other states after m time duration can be computed simply by multiplying the kth row vector of the current transition matrix by the next transition matrix which will produce a row vector and multiply that by the next transition matrix and so on. The resulting vector of probabilities tells us the probability of the state after the m time intervals.

4.5. Cooperation of Prediction Agents. A user requesting the prediction on the availability of parking in a given parking place or garage may be informed that the place is likely to be full in the next couple of time intervals. In this case, a driver may be interested to know the situation in the neighboring parking places. Hence, the parking places communicate with each other to produce the necessary information.

A parking place is powered with an autonomous agent that controls its information, collects new information, updates its matrix, sends predictions, and interacts whenever necessary with other agents in its neighborhood. A neighborhood for a given parking garage is a set of other parking garages where it can send and receive information. Suppose d is the distance a driver can compromise to park away from the place of interest. Hence, the agent communicates with other agents which are at most d distance from itself, provided there are no other constraints that prevent the driver to park there. Agents communicate with other agents and produce a cumulative prediction regarding parking availability situation in its neighborhood. Suppose there are $Q-1$ agents, say $A_2, A_3, \ldots, A_Q$, in the neighborhood of agent A_1, and the parking availability in each of these agents is $j_1, j_2, \ldots, j_Q$ at a given time. Suppose A_1 is the place of interest of the driver. When a request by agent A_1 is sent to collect information to produce a cumulative prediction, each of the other agents will send the row of their transition matrix corresponding to their state prediction in the requested time; that is, an agent A_q will send $p_q(:) = \left[p^q_{j_q 1} \;\; p^q_{j_q 2} \;\; \cdots \;\; p^q_{j_q n}\right]$.

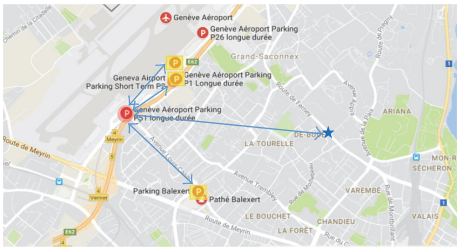


FIGURE 3: A communication scenario between three parking places represented by P and a user represented by a star. The red circle is the place of interest for the user whereas the yellow rectangles are the parking in the neighborhood where the user needs to get information from.

This row vector gives the probability of occurrence of each of the states from the current state j_q. This means the nonoccurrence can be given by $P_N(q) = 1 - p_q(:)$. Hence, there will be Q nonoccurrence vectors, say $P_N(1), P_N(2), \ldots, P_N(Q)$. The nonoccurrence cumulative vector can be computed by applying an entry-wise multiplication of these vectors, resulting in a vector, say P_N. Hence, the cumulative prediction vector will be the normalized vector of $P = 1 - P_N$.

It should be noted that, in some cases, the states in one parking garage may not be the same with the other. For example, in one of the parking spaces there could be a total of 100 parking places and 500 in the other. If a percentage representation is used in the state construction stage, state i will have different parking capacity in the two parking garages. This problem can be dealt with in the state construction step by having similar states for all parking places and assigning zero probabilities for nonexisting states in some of the parking places.

Figure 3 shows a communication scenario where a user is situated at the black cross point requesting the status of parking places around the red parking place. The red parking place communicates with the neighboring blue parking places, computes the cumulative prediction, and communicates back with the user.

4.6. A Numerical Example. To demonstrate the approach proposed, consider a scenario with two parking places, namely, parking places a and b. Suppose the there are three defined states, S_1, S_2, and S_3, where S_i represents a parking situation where the number of available parking spaces is between $((i-1)/3)100\%$ and $(i/3)100\%$. At $t = t_0$ when the state is S_1 the number of times it changes to S_1, S_2, and S_3 based on the fifty data items collected is 40, 10, and 0 times, respectively. Similarly if the initial state (the state at t_0) is S_2, it is 10, 25, and 15, respectively, and if it is S_3, 0, 15, and 35, respectively. Hence, the data can be summarized as follows:

$$\overline{p_a}^{(t_0)} = \begin{pmatrix} 40 & 10 & 0 \\ 10 & 25 & 15 \\ 0 & 15 & 35 \end{pmatrix}. \tag{1}$$

Similarly, a collected set of data for the next time intervals is given as

$$\begin{aligned} \overline{p_a}^{(t_1)} &= \begin{pmatrix} 45 & 5 & 0 \\ 25 & 20 & 5 \\ 10 & 25 & 15 \end{pmatrix}, \\ \overline{p_a}^{(t_2)} &= \begin{pmatrix} 45 & 5 & 0 \\ 30 & 15 & 5 \\ 15 & 30 & 5 \end{pmatrix}. \end{aligned} \tag{2}$$

Similarly, suppose the data for the second parking place is given as follows:

$$\begin{aligned} \overline{p_b}^{(t_0)} &= \begin{pmatrix} 45 & 5 & 0 \\ 20 & 30 & 0 \\ 10 & 20 & 20 \end{pmatrix}, \\ \overline{p_b}^{(t_1)} &= \begin{pmatrix} 50 & 0 & 0 \\ 30 & 20 & 0 \\ 20 & 25 & 10 \end{pmatrix}, \\ \overline{p_b}^{(t_2)} &= \begin{pmatrix} 50 & 0 & 0 \\ 35 & 15 & 0 \\ 20 & 25 & 5 \end{pmatrix}. \end{aligned} \tag{3}$$

After normalizing, the final transition matrices for the two parking place can be given as follows:

$$\begin{aligned} p_a^{(t_0)} &= \begin{pmatrix} 0.8 & 0.2 & 0 \\ 0.2 & 0.5 & 0.3 \\ 0 & 0.3 & 0.7 \end{pmatrix}, \\ p_a^{(t_1)} &= \begin{pmatrix} 0.9 & 0.1 & 0 \\ 0.5 & 0.4 & 0.1 \\ 0.2 & 0.5 & 0.3 \end{pmatrix}, \\ p_a^{(t_2)} &= \begin{pmatrix} 0.9 & 0.1 & 0 \\ 0.6 & 0.3 & 0.1 \\ 0.3 & 0.6 & 0.1 \end{pmatrix}, \\ p_b^{(t_0)} &= \begin{pmatrix} 0.9 & 0.1 & 0 \\ 0.4 & 0.6 & 0 \\ 0.2 & 0.4 & 0.4 \end{pmatrix}, \\ p_b^{(t_1)} &= \begin{pmatrix} 1 & 0 & 0 \\ 0.6 & 0.4 & 0 \\ 0.4 & 0.5 & 0.1 \end{pmatrix}, \\ p_b^{(t_2)} &= \begin{pmatrix} 1 & 0 & 0 \\ 0.7 & 0.3 & 0 \\ 0.4 & 0.5 & 0.1 \end{pmatrix}. \end{aligned} \tag{4}$$

The prediction at t_1, t_2. and t_3 can be done by using $p_a^{(t_0)}$, $p_a^{(t_0)}p_a^{(t_1)}$, and $p_a^{(t_0)}p_a^{(t_1)}p_a^{(t_2)}$, using matrix multiplication as given below:

$$p_a^{(t_0)}p_a^{(t_1)} = \begin{pmatrix} 0.82 & 0.16 & 0.02 \\ 0.49 & 0.37 & 0.14 \\ 0.29 & 0.47 & 0.24 \end{pmatrix},$$
$$p_a^{(t_0)}p_a^{(t_1)}p_a^{(t_2)} = \begin{pmatrix} 0.84 & 0.142 & 0.018 \\ 0.705 & 0.244 & 0.051 \\ 0.615 & 0.314 & 0.071 \end{pmatrix}. \quad (5)$$

Similarly for the second parking place, we have

$$p_b^{(t_0)}p_b^{(t_1)} = \begin{pmatrix} 0.96 & 0.04 & 0 \\ 0.76 & 0.24 & 0 \\ 0.60 & 0.36 & 0.04 \end{pmatrix},$$
$$p_b^{(t_0)}p_b^{(t_1)}p_b^{(t_2)} = \begin{pmatrix} 0.988 & 0.012 & 0 \\ 0.928 & 0.072 & 0 \\ 0.868 & 0.128 & 0.004 \end{pmatrix}. \quad (6)$$

Based on the initial state a prediction can then be made. For example if the state at t_0 in parking a is S_3 then there is a high probability that the state at t_1, t_2, and t_3 is S_3, S_2, and S_1, respectively. As mentioned earlier, it is worth noting that if the initial state is known, rather than multiplying the whole matrix, the corresponding row vector to the current state can be used to multiply the matrices in the next time stamp to do the prediction.

In addition to a prediction by one of the parking places, consider the initial state of the parking place a is S_3 and for parking place b is S_2. By the end of the third time interval, that is, at $t = t_3$, the prediction by parking places a and b is given by $p_a = [0.6 \;\; 0.36 \;\; 0.04]$ and $p_b = [0.928 \;\; 0.072 \;\; 0]$, respectively. The nonoccurrence vectors will be $p_N(a) = 1 - p_a = [0.4 \;\; 0.64 \;\; 0.96]$ and $p_N(b) = 1 - p_b = [0.072 \;\; 0.928 \;\; 1]$. The entry-wise multiplication of these two vectors will be $p_N = p_N(a) * p_N(b) = [0.0288 \;\; 0.5939 \;\; 0.96]$. Hence, $1 - p_N = [0.9712 \;\; 0.4061 \;\; 0.04]$ and its normalized value becomes $[0.6853 \;\; 0.2865 \;\; 0.0282]$. Therefore the cumulative prediction is S_1 with highest probability of 0.6853.

5. Evaluation of the Proposed Approach

5.1. Data Set. As discussed in Section 3.2, Balexert shopping mall has three parking places labeled as $P1$, $P2$, and $P3$. Data was collected between 19 December 2016 and 9 January 2017 on Monday mornings. However, since the data was not complete a linear interpolation method is used to compute the missing data, as given in Table 1.

5.2. Time Discretization and Simulation of Parking Occupancy. Time is discretized based on a time width of 5 minutes, as done by [27], with t_0 = 7h55, a data span for one hour, and a final time at t_{12} = 8h55.

The states are constructed based on the percentage of available parking. We then have six states as shown in Table 2.

The data only tells that there is a high probability of moving from S_6 to itself in the first four time intervals. In the collected data, the initial state is state 6. Hence, to construct the complete transition matrix addition data or information where the starting state is different from 6 is needed. Based on informal data collection gathered from enquiries with some drivers as well as parking management personnel, the pattern of arrival of cars does not depend on the availability of parking or the initial state. Hence, final transition matrices are given below, for the first four time intervals and the fifth time interval in (7) and for the next six intervals and for the last time interval in (8).

$$p^{(i)} = \begin{pmatrix} 0.45 & 0.25 & 0.15 & 0.1 & 0.05 & 0 \\ 0.1 & 0.25 & 0.35 & 0.1 & 0.1 & 0 \\ 0 & 0.15 & 0.4 & 0.35 & 0.1 & 0 \\ 0 & 0 & 0.15 & 0.4 & 0.25 & 0.2 \\ 0 & 0 & 0.05 & 0.15 & 0.3 & 0.6 \\ 0 & 0 & 0 & 0.05 & 0.15 & 0.8 \end{pmatrix},$$
$$p^{(4)} = \begin{pmatrix} 0.45 & 0.35 & 0.15 & 0.05 & 0.05 & 0 \\ 0.3 & 0.4 & 0.2 & 0.1 & 0 & 0 \\ 0 & 0.35 & 0.35 & 0.25 & 0.05 & 0 \\ 0 & 0 & 0.35 & 0.4 & 0.2 & 0.05 \\ 0 & 0 & 0.05 & 0.4 & 0.3 & 0.25 \\ 0 & 0 & 0 & 0.05 & 0.6 & 0.35 \end{pmatrix}, \quad (7)$$

$$p^{(j)} = \begin{pmatrix} 0.45 & 0.25 & 0.15 & 0.1 & 0.05 & 0 \\ 0.1 & 0.25 & 0.35 & 0.1 & 0.1 & 0 \\ 0 & 0.2 & 0.4 & 0.3 & 0.1 & 0 \\ 0 & 0 & 0.25 & 0.4 & 0.25 & 0.1 \\ 0 & 0 & 0.05 & 0.2 & 0.45 & 0.3 \\ 0 & 0 & 0 & 0.05 & 0.3 & 0.65 \end{pmatrix},$$
$$p^{(12)} = \begin{pmatrix} 0.8 & 0.15 & 0.05 & 0 & 0 & 0 \\ 0.4 & 0.4 & 0.1 & 0.1 & 0 & 0 \\ 0.05 & 0.4 & 0.4 & 0.1 & 0.05 & 0 \\ 0 & 0.1 & 0.4 & 0.3 & 0.1 & 0 \\ 0 & 0.05 & 0.2 & 0.6 & 0.15 & 0 \\ 0 & 0 & 0.05 & 0.15 & 0.45 & 0.35 \end{pmatrix} \quad (8)$$

for $i = 0, 1, 2, 3$ and $j = 5, 6, 7, 8, 9, 10, 11$.

5.3. Prediction Results of a Single Agent. To run the simulation, simulation parameters need to be set, including algorithm parameter. Hence, the learning window N is set to be 100. Big number of algorithm runs gives reliable results and hence the algorithm runs for 500 iterations with initial random state.

Table 1: Collected and synthesized data for $P2$ of Balexert parking with average number of available parking spaces.

Time	7h55	8h00	8h05	8h10	8h15	8h20	8h25	8h30	8h35	8h40	8h45	8h50	8h55
Data collected	775	769.5	—	754	739.5	—	—	—	—	685	669	—	—
Interpolation results	775	769.5	762	754	739.5	698	692	690	688	685	669	580	521

Table 2: States from the data set.

States	$S1$	$S2$	$S3$	$S4$	$S5$	$S6$
Number of available parking spaces	0	[1–178]	[179–356]	[357–534]	[535–714]	[715–890]
Percentage of available parking	0%	0%–20%	20%–40%	40%–60%	60%–80%	80%–100%

In order to check the performance of the simulation, the arrival of cars or parking demand is also randomly generated based on the transition matrix. It is done by using a normal distribution where the entries of the states with high probability in the transition matrix will have high probability of occurrence. We tested three types of performance: *consecutive prediction* (the performance on consecutive time), *prediction ahead*, (the performance in the future predictions, not in consecutive time), and *learning property* (performance by injecting a demand change and simulating long-term changes).

Consecutive Predictions. Based on the transition matrix of the corresponding states, normal distribution is used to generate the number of cars arriving to the parking place. Based on that the prediction error is computed. Figure 4 shows the percentage of correctness of the prediction. It is computed based on the eleven predictions done in a day for the 500 days.

For each of the runs with different initial state, the prediction becomes stable in final iterations. The error of the simulation results within every 50 iterations is given in Figure 5. As expected, we observe better results when the initial state is in line with data used for building the matrix (i.e., State 6).

Prediction Ahead. Based on each initial state, the prediction is done at the end of all of the time intervals. The accuracy of the prediction is then compared with the actual situation (i.e., based on random car arrivals from a normal distribution as discussed) until the last time interval (as shown in Figure 6). Due to consecutive matrix multiplications, errors accumulate along the computation, and results tend to be less accurate than for the case of consecutive predictions. Again, the case of $S6$ as initial state provides better predictions.

Adaptation to Long-Term Changes. The learning mechanism plays a role in adapting to long-term changes. We tested a scenario where the demand for parking occupancy increases after 200 iterations (i.e., 200 days) by about 100 more parking demands. We use the same initial transition matrix for prediction. We simulate a parking occupancy similar to the previous case up to 200 iterations and then added an increase of 100 in the parking demand. The approach runs for 1000 iterations and results are provided in Figure 7.

We observe a loss in the accuracy of predictions when a new data is added (iteration 200), followed by an adaptation, and a success rate of the prediction returned to the top around iteration 400. The learning window N is 100, we observe that, after 200 iterations, the system has finished adapting to the new conditions.

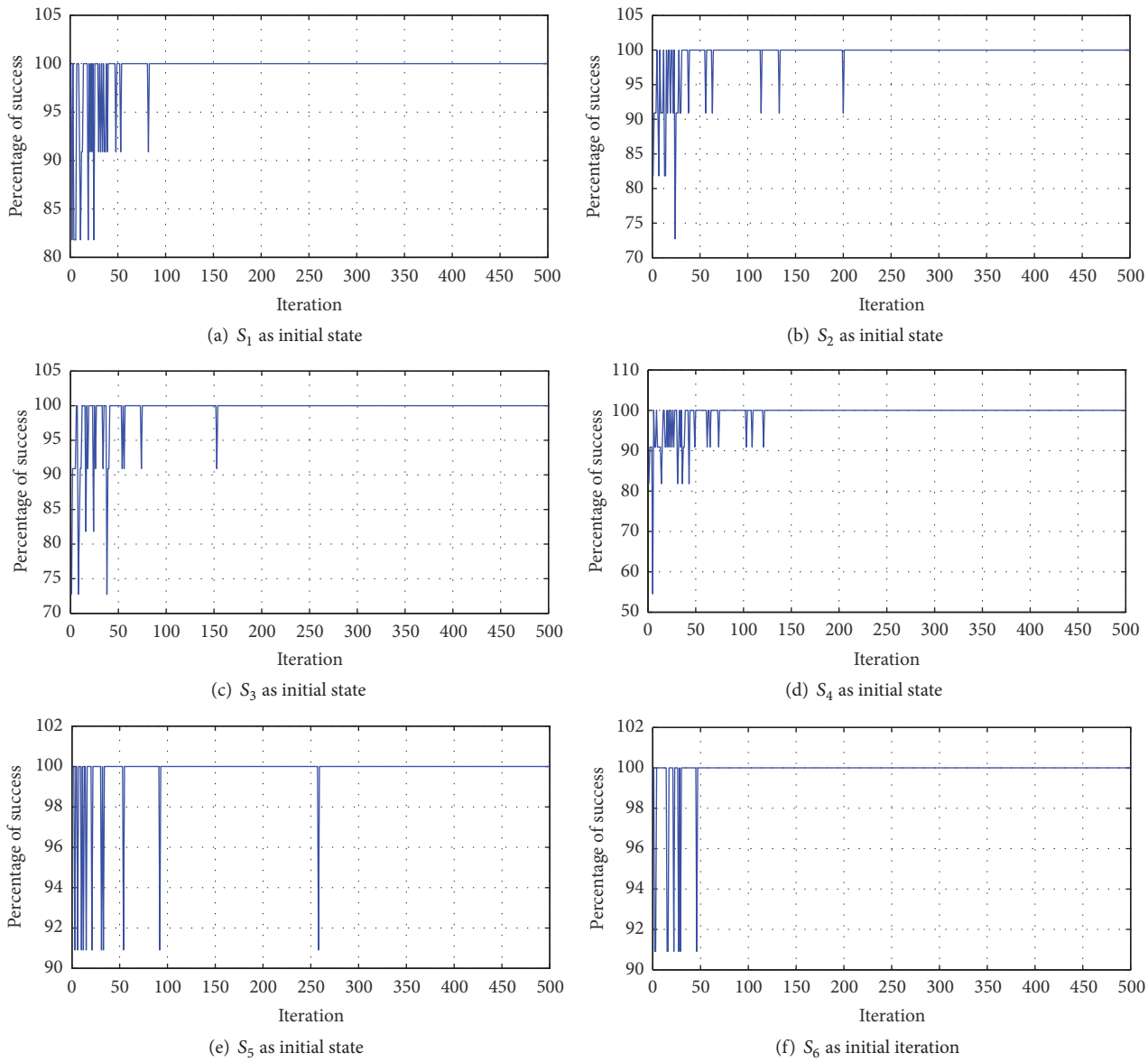
5.4. Smart Parking Service

5.4.1. Data Set. As presented in Figure 8, there are three parking places in Balexert. Suppose the place of interest for a driver is parking $P2$. Let the neighborhood radius d be as given in Figure 8.

The agent in parking $P2$ communicates with the agent in parking $P1$, which is in its neighborhood (radius area including both $P1$ and $P2$). The total number of parking places under consideration in $P1$ is 925. Table 3 provides the data for parking place $P1$.

5.4.2. Simulation and Evaluation. One of the steps after discretizing the time is to define the states. Note that the states in the two parking places need to be the same. Since the number of parking places in $P1$ and $P2$ differs only by 35 slots, let $S6$ be the number of available parking places more than 713. This makes the states used for both parking places be the same. The transition matrix for $P1$ at time interval i, $p^{(i)}$ is the same with $p^{(1)}$ (used for $P2$), for all i except the last matrix $p^{(12)}$. For $p^{(12)}$, it is equal to the fifth interval matrix of $P2$, that is, $p^{(5)}$ of $P2$.

Based on the collected data at 7h55 of the day, the parking places will be in state $S6$. When a driver sends a request to $P2$ where the center of interest is located, agent at $P2$ will request information on parking places availability prediction to other parking places in its neighborhood with radius d (i.e., to $P1$). Since the agents are predicting the situation by the end of the first interval or the beginning of the second interval their first matrix will be used. That is, in both cases, row $(0, 0, 0, 0.05, 0.15, 0.8)$ corresponding to state $S6$ of $p^{(1)}$ will be used. The agent then compute the nonoccurrence of the row given; that is, $P_N(1) = P_N(2) = 1-p = (1, 1, 1, 0.95, 0.85, 0.2)$. The nonoccurrence cumulative vector is computed applying an entry-wise multiplication, producing $P_N = (1, 1, 1, 0.9025, 0.7225, 0.04)$. Finally, the normalized cumulative prediction vector $P = 1 - P_N = (0, 0, 0, 0.0730, 0.2079, 0.7191)$. Therefore, the prediction for



(a) S_1 as initial state

(b) S_2 as initial state

(c) S_3 as initial state

(d) S_4 as initial state

(e) S_5 as initial state

(f) S_6 as initial iteration

Figure 4: Simulation results for different initial states.

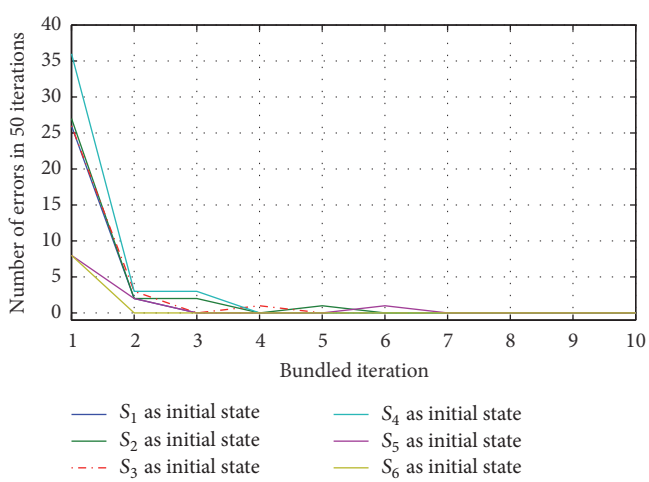
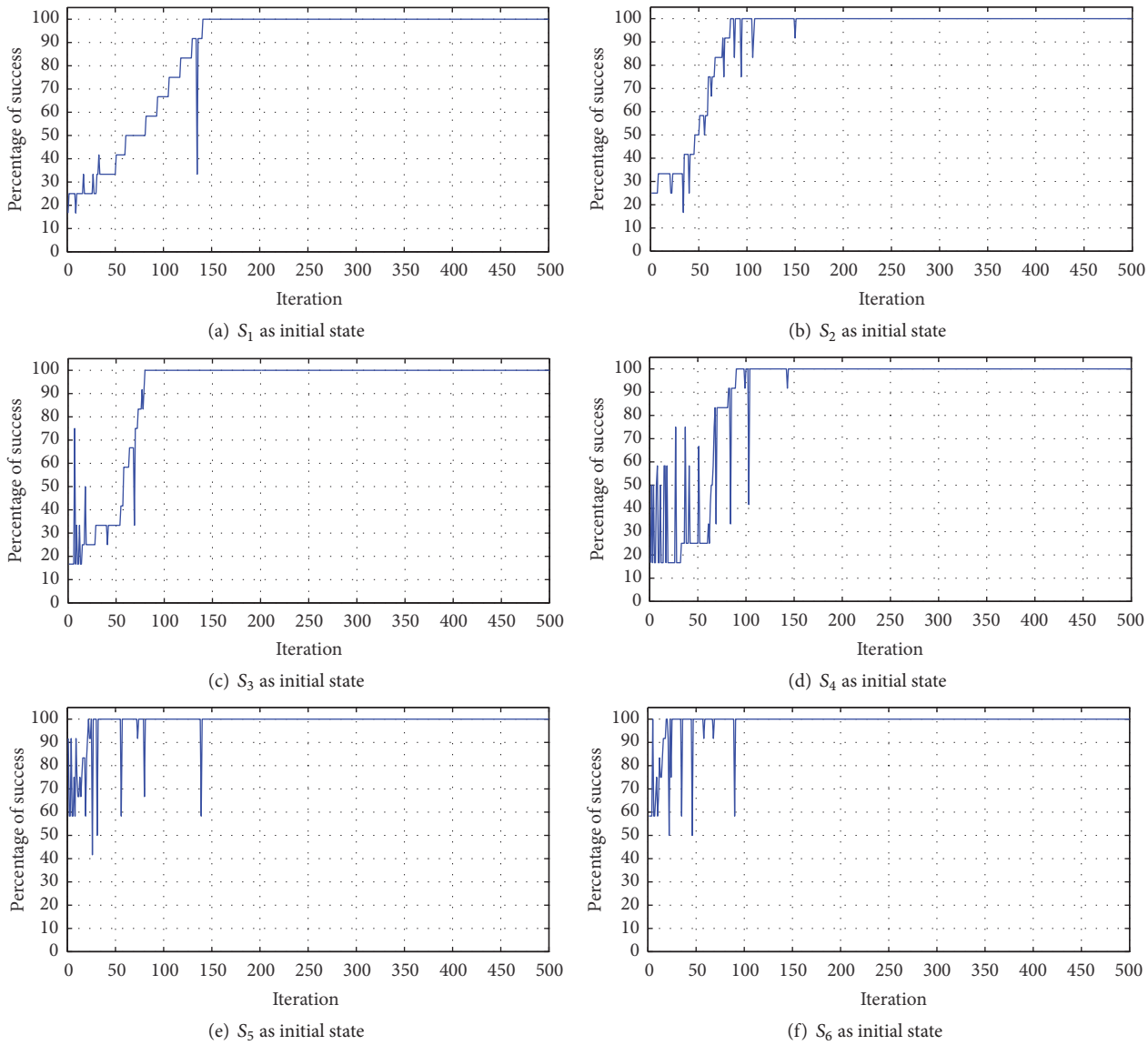


Figure 5: Error in iterations bundled in 50 for different runs with different initial states.



(a) S_1 as initial state

(b) S_2 as initial state

(c) S_3 as initial state

(d) S_4 as initial state

(e) S_5 as initial state

(f) S_6 as initial state

Figure 6: Simulation results for different initial states.

Table 3: Data for $P1$ of Balexert parking with average number of available parking spaces.

Time	7h55	8h00	8h05	8h10	8h15	8h20	8h25	8h30	8h35	8h40	8h45	8h50	8h55
Parking	905	883.5	878	874	864	854	844	834	825	823	816	788	700

the neighborhood parking availability at 8h00 is $S6$ with highest probability of 0.7191.

Suppose the prediction is needed at 8h05. In that case the agent at $P2$ will request the agent at $P1$ its prediction at 8h05. It also computed its own prediction; its prediction will be the row vector of the current matrix, $p^{(1)}$ multiplied by $p^{(2)}$. The nonoccurrence vector for both agents will then be 1 − (0, 0, 0.0150, 0.0825, 0.1775, 0.7400) = (1, 1, 0.9850, 0.9175, 0.8225, 0.2600). The product of these nonoccurrence vectors will be (1, 1, 0.9702, 0.8418, 0.6765, 0.0676). Hence the cumulative prediction will be (0, 0, 0.0206, 0.1096, 0.2241, 0.6458).

Suppose a driver, who is 30 minutes away from the target parking place ($P2$), requests parking availability information at the current time; let it be 7h55. The prediction vector 30 mins ahead, calculated by the agent in $P1$, will be (0.0009, 0.0082, 0.0478, 0.1293, 0.1996, 0.7029).

In a similar way the agent at $P2$ will produce the vector (0.0021, 0.0167, 0.0976, 0.2033, 0.3668, 0.3632). The cumulative nonoccurrence vector will be (0.9970, 0.9753, 0.8592, 0.6936, 0.5069, 0.1892). Hence, the cumulative prediction will be (0.0030, 0.0247, 0.1408, 0.3064, 0.4931, 0.8108). Hence after 30 minutes, at 8h25, the prediction for the neighborhood

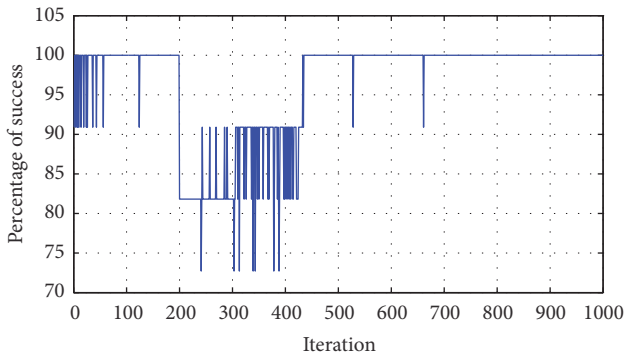


Figure 7: Simulation result on the learning of the approach with increased demand.

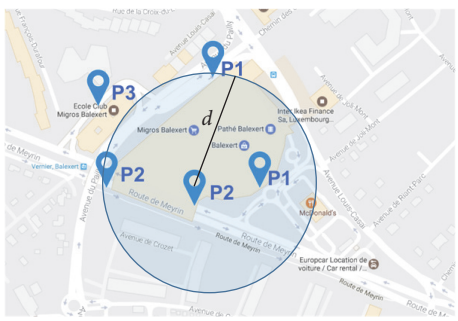


Figure 8: Smart parking for Balexert (two entrances for each of $P1$ and $P2$).

parking availability will be in state $S6$ with a probability of 0.8108.

5.5. Results. With similar argument, Table 4 presents the prediction for the neighborhood parking availability around $P2$. The table is computed with the same initial state for both $P1$ and $P2$.

Note that even though Table 4 shows both parking places starting with the same states, they can possibly start with different states. For example, parking place $P1$ starts with $S1$ and $P2$ with $S2$; the resulting prediction for the given time interval from 8h00 to 8h55 will then be $S1$, $S3$, $S4$, $S6$, $S6$, $S6$, $S6$, $S6$, $S6$, $S6$, $S6$, and $S5$.

We performed a simulation generating random initial states for the two agents. Different scenarios can be recorded. For example, the predicted states for the first and the second agent can be k_1 and k_2, and the combined prediction can be k. To evaluate the simulation result we define the success of a prediction. Since the parking availability increases with the state number, we consider that a cumulative prediction of state k is better than individual predictions by the agents, say k_1 and k_2, if either of these predictions is greater than or equal to k, that is, $k_1 \geq k$ or $k_2 \geq k$. Based on random initial states, a prediction is performed for 500 iterations; in each iteration, the prediction for all the time interval is compared against the demand which is randomly generated based on the transition matrix. Hence, in each iteration there will be 13 predictions and their accuracy is checked if it agrees

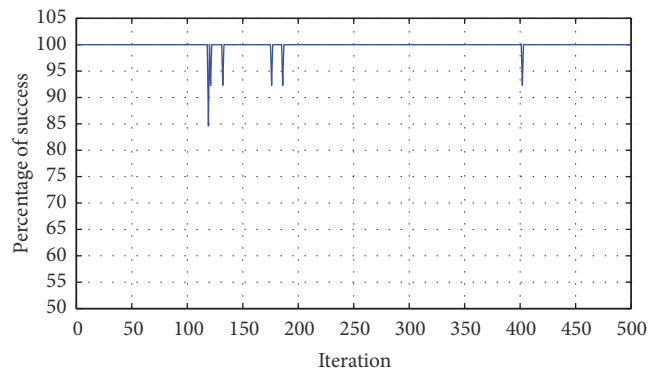


Figure 9: Agent-based prediction performance of the parking places.

with random demand. The result as presented in Figure 9 is promising with high success rate.

6. Discussion and Conclusion

6.1. Summary. An agent-based service combined with a learning and prediction system, as a solution to ease parking place search and thus relieve traffic congestion, is proposed. Agents predict the parking availability in a given parking garage and communicate with other agents to produce a cumulative prediction. Each agent uses a time varying Markov chain to predict parking availability of an individual parking garage based on actual situation using a transition matrix constructed from previous data. Transition matrices are constructed for each time interval, for each weekday, season, and weather condition, based on previous experience and gathered information. Transition matrices vary through time to represent long-term changes in demand and thus adapt with changes in the neighborhood. A multi-agent-based spatial service collects and propagates queries and predictions in the whole neighborhood.

We evaluated our approach on the parking garages of the Balexert shopping mall in Geneva, Switzerland. Preliminary data was collected, which we synthesized based on the observed pattern of data. We conducted four types of simulations. The first predicts the consecutive state based on the actual state. With an average initial prediction accuracy of about 83% it gradually increases while learning and adapting the matrix. The second concerns prediction beyond the consecutive time. In this case, predictions starting from about 34% of accuracy on average at the beginning improve gradually. The third case illustrates long-term changes in the demand occurring in the neighborhood. In this case also, the prediction adapts to the change and returns to accurate predictions again. The last simulation considers multiple agents and predicts the parking space availability in the neighborhood (in total). Given the limited set of data at our disposal, which results in a limitedly accurate transition matrix, simulations show that the matrix gradually evolves and gives high quality prediction.

Table 4: Neighborhood prediction. The 1st column indicates the initial states for $P1$ and $P2$.

Time	8h00	8h05	8h10	8h15	8h20	8h25	8h30	8h35	8h40	8h45	8h50	8h55
$S1$	$S1$	$S3$	$S3$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S5$
$S2$	$S3$	$S3$	$S4$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S5$
$S3$	$S3$	$S4$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S5$
$S4$	$S4$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S5$
$S5$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S5$
$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S6$	$S5$

6.2. Future Works. This paper does not consider the cost of parking. One possible research issue for future work involves designing a decision aiding tool for minimizing the cost based on the prediction of parking space availability.

Different parking space categorization can also be studied. Parking spaces are designed and reserved for a group of people like disabled, high-level management personnel, or for specific cars (e.g., electric cars).

The time window and the time width are made fixed, in this paper. It is worth exploring the effect of these parameters on the speed of learning and the quality of prediction.

External learning mechanism for short duration nonrepeating changes is not explored. Future issues can consider possible ways of external learning, identifying parameters, their values, and their effect on predictions.

Integrating the proposed model with an online service like smart phone applications can also be another interesting research issue to explore. Possibly a parallel computing approach in computing cumulative predictions where there are a huge number of parking places and demands can be studied to deal with possible increase in computational time.

The work performed in this paper for parking places availability shares many similarities with public transport prediction of occupancy. Indeed, occupancy depends on days, time, season, and weather and is similarly affected on the long-term by new constructions, or new public transport routes. Translating this work on public transport may be worth exploring.

An additional venue for future works involves actual simulations and visualisation of spatial services propagation. A prototyping tool supporting vehicles simulations and actual agents code is already available for such studies [37].

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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Research Article

Designing Dynamic Delivery Parking Spots in Urban Areas to Reduce Traffic Disruptions

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Pick-up and delivery services are essential for businesses in urban areas. However, due to the limited space in city centers, it might be unfeasible to provide sufficient loading/unloading spots. As a result, this type of operations often interferes with traffic by occupying road space (e.g., illegal parking). In this study, a potential solution is investigated: Dynamic Delivery Parking Spots (DDPS). With this concept, based on the time-varying traffic demand, the area allowed for delivery parking changes over time in order to maximize delivery opportunities while reducing traffic disruptions. Using the hydrodynamic theory of traffic flow, we analyze the traffic discharging rate on an urban link with DDPS. In comparison to the situation without delivery parking, the results show that although DDPS occupy some space on a driving lane, it is possible to keep the delay at a local level, that is, without spreading to the network. In this paper, we provide a methodology for the DDPS design, so that the delivery requests can be satisfied while their negative impacts on traffic are reduced. A simulation study is used to validate the model and to estimate delay compared to real situations with illegal parking, showing that DDPS can reduce system's delay.

1. Introduction

Urban logistic facilities, devoted to the loading and unloading operations from transport companies, are essential for efficient urban deliveries [1]. Thus, urban logistic facilities are widely used and typically placed in city centers with a high level of commercial activities [2]. The existence and the proper management of these facilities are crucial to serve cities' needs. To minimize their negative effects on the surroundings, loading and unloading facilities are normally placed outside driving lanes. However, this is not always feasible due to the limited public space in downtown areas. In some areas, illegal parking is highly used in freight operations. For example, in Paris, illegal double parking is used for up to 50% of the freight movements [3]. Local authorities often face a dilemma on how to allocate public space among loading/unloading activities, traffic, parking, public transport, and so on. To address that, multiuse lanes have become an innovative yet pragmatic solution. At different times of the day, these lanes can be devoted to different usages such as general traffic, buses only, loading/unloading activities, or residential parking. In Spain, for example, it has been successfully implemented in Barcelona [4] and Bilbao [5]. The multiple uses of the lane can accommodate different activities in a day. However, they block the whole lane (within a given link or potentially across links), even when there is not enough demand of the specific activity to use the entire space. In the case of loading and unloading activities, the demand is rarely high enough to occupy a whole lane throughout a link, not to mention across multiple links. Additionally, on the traffic side, the blockage of the whole lane is simply unwise since the capacity of the street drops drastically. To address that, in this paper, we investigate the provision of Dynamic Delivery Parking Spots (DDPS). DDPS occupy only a portion of the driving lane, and the allowed area changes dynamically over the day to guarantee proper

traffic performance, according to different levels of traffic demand.

DDPS can provide many benefits in practice. The number of dedicated (i.e., fixed) loading/unloading spots can be reduced, since some of the operations might happen in DDPS. Additionally, the city can make a better use of the existing space, for example, by devoting part of the traffic lanes to freight activities when the traffic demand is low. Additionally, DDPS could be regulated with a prebooking parking system [6, 7] that guarantees the optimal use of the devoted space.

Moreover, DDPS can be easily implemented: only few and inexpensive infrastructure changes are required, technological equipment is available, and the existing traffic/parking management and control strategies can be used. For infrastructure, in-pavement lights in the shoulder lane can clearly indicate the area where delivery is allowed, similar to the use of Bus Lane Intermittent Priority (BLIP) [8]. Apart from the use of in-pavement lights, vehicle detectors can be placed at the different spots of the DDPS, for detecting the presence of vehicles. Such detectors can also be used to control the correct use of DDPS. For example, when a vehicle is using incorrectly DDPS, a signal could be automatically sent to the control authorities.

This paper aims to provide basic guidelines for DDPS on urban areas, so that the deliveries can be carried out while traffic disruptions are kept to a minimum. DDPS provide space for loading/unloading activities on the shoulder lane of the street, but they are only allowed if the traffic delay is kept local (i.e., traffic delay is kept on the link and does not spread over the network). In other words, traffic must pass smoothly the upstream intersection, the lane drop at the delivery spot, and the downstream intersection, with no queue spillover to other links in the network. Using the hydrodynamic theory of traffic flow, we analyze the traffic discharge rate at both the upstream and the downstream intersections, taking into consideration that a portion of the shoulder lane is blocked. In particular, we model the relation between the delivery location within the link, the traffic demand arriving from upstream, and the disruptions to traffic. Based on such relation, the location of the DDPS can be regulated as a function of the traffic demand, to reduce the traffic disruptions as much as possible. In order to validate the developed model, show its applicability in a more realistic situation, and analyze the effect of stochastic arrivals, a simulation study is performed. The simulation is also used to evaluate the performance of DDPS in comparison to illegal delivery parking.

The rest of this paper is organized as follows. Section 2 lists and describes the existing literature, highlighting the differences to this paper. Section 3 shows the analytical model where generalized suggestions concerning the location of DDPS are made. Section 4 shows a numerical example to illustrate how the model is applied to a particular case. Section 5 validates the model with simulation in a set of scenarios. Then, it compares the overall delay between the system with DDPS and the current situation with illegal parking. Section 6 summarizes the findings of this study.

2. Literature Review

On-street parking highly influences urban traffic performance, mostly from three different perspectives. First, the parking lanes occupy road space, leading to reduced traffic capacity on the road and the neighboring network [9, 10]. Second, the parking/unparking maneuver itself generates a temporary traffic bottleneck, which blocks vehicles arriving from upstream and causes extra travel time [11–15]. Third, special parking behaviors such as illegal (e.g., double) parking or loading/unloading trucks/buses take space from driving lanes, reducing the road capacity unreasonably and causing inconvenience and confusion to other travelers [16, 17].

As a special case, delivery vehicles can cover all these three negative aspects, and, more importantly, their loading/unloading processes and the ensued traffic issues occur recurrently. It is, therefore, of great importance to improve and optimize the loading and unloading operations to reduce their effects on the traffic performance. To that end, multiple researchers have developed different control schemes [18, 19]. Recent work [20] evaluated the effects of pick-up maneuvers on traffic flows near maximal capacity, which were proved to have a major impact on traffic conditions. In order to evaluate the effects on travel times, a potential tool was developed in [21], and some additional investigations can be found in [22]. Very recently, the macroscopic impacts of deliveries in double lane parking in an arterial corridor were assessed with a simulation study [23]. Our paper, with a different approach, is focused on providing guidelines on the location and the number of spots, avoiding the negative effects at the network level.

Other researchers have evaluated the traffic effects of parking maneuvers [24, 25]. They have proposed a model to analyze the impact of parking maneuvers on a road segment and their influence on the capacity of nearby intersections and the overall network. It is shown that, under certain conditions such as low traffic demand or optimum parking location, parking maneuvers do not affect traffic throughput, even in cases when one-lane road is analyzed. Similar patterns are observed for curbside bus stops [26]. Evidently, loading/unloading operations last normally much longer [2, 27] than the time needed for parking maneuvers and bus stops, but they happen less frequently, and a prebooked schedule, as studied in [6], can be implemented.

From the network perspective, [28, 29] have shown that, at a network level, it is possible to remove lanes or even links to a certain extent without reducing much of the network capacity. Such findings are encouraging, as they indicate that temporarily removing some portions of a lane might not be very disruptive if the effects are kept local.

Implementation of various Information and Technology Systems (ITS) strategies, such as parking guidance or traffic signal control, has proven to be very beneficial for traffic operations at the network level [30]. For example, [31] presented a model for determining the optimal display of parking guidance and information sign configuration that minimizes queue lengths and distance traveled while searching for parking. Similarly, in the fuzzy logic-based model developed by [32], each delivery vehicle can receive information on

whether to park or not, based upon the current given state of the parking (e.g., space availability).

On the other hand, as an important element of ITS, traffic signal systems have been one of the most cost effective investments [33]. For example, an Adaptive Traffic Control System (ATCS) has been developed as the most advanced traffic signal system technology for coordinated network control. ATCSs systems continuously make small adjustments to signal timing parameters in response to changing traffic demand and patterns [34]. These adjustments aim to improve network-wide efficiency by dealing with fluctuations in traffic demand. These systems could also improve the performance of DDPS in case of nonrecurring traffic conditions [35].

The study of urban freight transport and city logistic policies requires specific site-oriented studies to collect data. For example, [2] compared the cities of Rome, Barcelona, and Santander regarding the current distribution patterns and regulations. In different cities, policies to reduce the number of commercial vehicles have been studied and implemented such as urban consolidation centers or off-hour deliveries. Freight flows are determined by the interactions among different actors: shippers, carriers, and receivers. Some of these policies have failed to reduce the demand, as they targeted carriers, which do not usually have enough decision power to change the delivery performance (delivery time, location, etc.). The problems of parking in urban areas considering the specific challenges for freight have been studied in [36]. The work analyzed the balance between the demand for parking and the available on-street supply in a case study on the city of New York. In New York City, off-hour delivery programs have been fostered with money incentives for receivers in a pilot test, providing significant benefits and demonstrating a high potential for full implementation [37]. This paper, on the other hand, focuses on the provision of more parking spaces, when some capacity of the traffic lane is available, but the demand for delivery parking operations remains unchanged.

Recently, [38] developed a simulation framework for planning, managing, and controlling urban delivery schemes. Last-minute reservations were proved to significantly improve the system in terms of the total service time, compared to a scenario without booking. To the best of the authors' knowledge, there is no study modelling the specifics on dynamic usage of a driving lane for loading/unloading purposes. Hence, this paper aims to fill this gap by providing preliminary understanding on how the DDPS could be arranged without significantly affecting the performance of traffic, and by validating the system's parameters in a microsimulation environment. This is considered a first step towards the implementation of DDPS. Further research might be needed to address some more practical issues regarding such implementation.

3. Analytical Model

This section is divided into four subsections: assumptions and definitions; formulations; relaxation of assumptions; summary of the formulations and guidance. In the first subsection, we introduce the scope of the model and the main tools used for the analysis. In the second subsection, we analyze the discharging rate of both the upstream and the downstream intersections, taking into consideration the lane drop at the location of the delivery area. In the third subsection, we discuss the relaxation of some assumptions. Finally, in the fourth subsection, we summarize the formulations and provide a roadmap to guide readers to the correct expression, depending on the local conditions including the traffic demand.

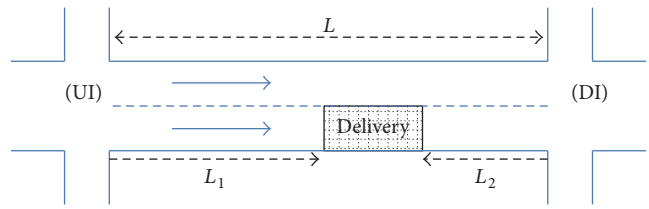

Figure 1: General situation of the DDPS on a given link between the upstream intersection (UI) and the downstream intersection (DI). Notice that, in this example, a 2-lane street is presented, but the methodology is generalized to any number of lanes n ($n \geq 2$).

3.1. Assumptions and Definitions. Our analysis focuses on a street with a number of n ($n \geq 2$) lanes per direction. On this street, a dynamic delivery area (an area can consist of several spots) is placed on the link between two consecutive intersections. The total length of the link is L, the distance between the delivery area and the upstream intersection (UI) is L_1, and the distance between the delivery area and the downstream intersection (DI) is L_2. Figure 1 depicts the situation with an example of a 2-lane street. Notice that the loading/unloading vehicles would temporarily occupy the dynamic delivery area (gridded) and block a part of the lane, reducing the road capacity. All the notation used within the paper can be found in Table 2 in the Appendix.

We assume that the geometry of the street is the same throughout the link. We also assume for simplicity that the intersections are coordinated with a green wave signal control. Due to the green wave, when no delivery operation is conducted (i.e., there is no blockage), the traffic discharged from the UI should be able to cross the DI without any stop or delay. Naturally, the conditions change when a loading/unloading operation takes place on the dynamic delivery area. Some vehicles arriving on the shoulder lane will have to stop upstream of the dynamic delivery area, while some other vehicles might merge into the other lanes and cross the DI. Depending on how large L_1 is, the queue might (or not) spill over into the UI and affect traffic on the upstream links. Therefore, to limit the impacts of DDPS on traffic, we aim to find the conditions such that there is no queue spillback to UI. To analyze these potential effects under the different traffic states, we define several variables below.

We denote c as the length of the signal cycle and g as the length of the green signal. For the analysis, we assume that these parameters are the same for both intersections. Later in this section, we will discuss how the relaxation of these assumptions would affect the model.

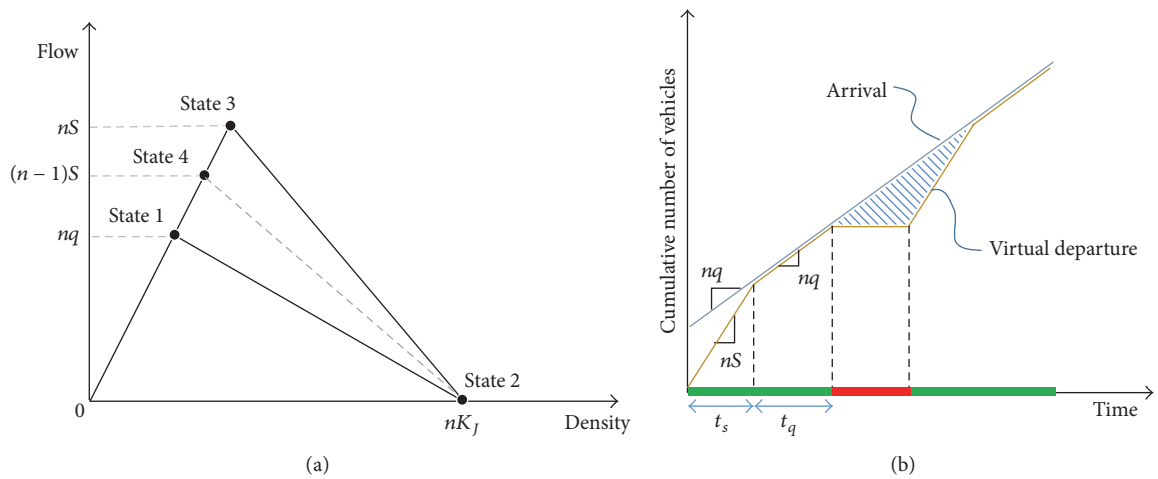

Figure 2: (a) Triangular fundamental diagram for the street with a number of n lanes. (b) Illustrative queuing diagram for undersaturated conditions.

For the purpose of modelling traffic conditions, a triangular fundamental diagram (FD) is assumed, based on the hydrodynamic theory of traffic flow. Such assumption has been previously validated with empirical studies [39–42]. Figure 2(a) depicts an illustrative FD with the different traffic states that might be observed on a link. State 1 represents the traffic flow arriving from upstream (q); state 2 represents the stopping traffic in front of the red light; state 3 represents the traffic discharging from the queue at the intersections (assuming there is no queue spillback from downstream); state 4 represents the capacity of the street at the delivery area, where only a number of $n-1$ lanes can be used. The saturation flow rate per lane is S; thus, nS is the total saturation flow rate of the street, and $(n-1)S$ is the link capacity at the location of DDPS. The jam density per lane is K_J (nK_J for the entire road). Notice that we define the arrival flow rate (i.e., traffic demand volume) for the whole street as q, such that $q \in [0, nS]$.

The queuing diagram in Figure 2(b) is given as an illustrative example. It shows the cumulative number of arrivals and departures at the UI without the interruption of loading/unloading vehicles. One can notice that the arrival has a constant flow of q and the virtual departure rate can be at the maximum of nS (i.e., saturation flow) during the green signal; the shaded area is the delay generated by the red signal within a cycle. The queuing diagram can help in visualizing the delay generated by potential delivery operations and will be used in the following subsection to show different cases.

We also assume that most of the flow is arriving from upstream. In other words, only a rather small number of turning vehicles enter the link during the red signal, (q_t) compared to the flow arriving from upstream, (i.e., $q_t \ll q$). For this reason, their effects on the overall traffic operations can be neglected.

Note that the DDPS concept is developed for loading/unloading operations, as they have shown to be crucial in an urban context. However, the facility could serve similar parking operations for other purposes, such as service trips or on-demand passenger transport services. In cases when other operations are allowed in the area, it is important to ensure that the features of such operations are aligned with the DDPS concept and the model presented here. For instance, the parking duration cannot be unlimited. Long service trips (i.e., more than 2 h) might not be suitable for DDPS locations where the traffic demand changes rapidly, given that the allowed parking area will change accordingly.

3.2. Formulations. In this subsection, we investigate the location of the delivery area, such that no traffic spillover is generated. The location is defined by the distance between the delivery area and the neighboring intersections. We will find the minimum distance values (L_1 and L_2), that guarantee that no traffic spillover is caused to other links. (i.e., minimum values for L_1 and L_2). Denote such minimum distances as d_1 and d_2. To find their formulations, we first define some new variables.

In the absence of DDPS, the maximum number of vehicles (N) that can be discharged during a cycle, in a street with n lanes, can be calculated using (1). If the intersection is undersaturated ($q \le n(Sg/c)$), N is the total traffic demand arriving at the intersection in one cycle (qc), given our assumption that the number of turning vehicles is negligible. If the intersection is oversaturated ($q > n(Sg/c)$), N is the maximum number of vehicles that can discharge (at the saturation flow rate) during the green signal (nSg)

$$N = \begin{cases} qc, & \text{if } q \le n\dfrac{Sg}{c}, \\ nSg, & \text{if } q > n\dfrac{Sg}{c}. \end{cases} \tag{1}$$

In the presence of DDPS, the maximum number of vehicles, which can be discharged at the intersection during a cycle by the $n-1$ lanes that are not blocked, N_d, can be calculated using (2). Note that, due to the merging effects, the number of discharged vehicles will be reduced by a factor of $\beta \in [0, 1]$. A factor equal to 1 represents a perfect merge

of the vehicles on the shoulder lane to the immediate next lane, causing no decrease in the lane capacity. This factor also depends on the number of remaining free lanes: the higher the number of lanes, the smaller the overall effect (i.e., the higher the β). Merging effects and the impact of lane changes have been studied in freeway environments, either with an endogenous model [43–45], simulation [46, 47], or empirical data [48, 49]. In this paper, as it will be later shown, the β parameter can be easily calibrated with a simple simulation experiment performed in a controlled manner.

$$N_d = \begin{cases} qc, & \text{if } q \le (n-1)\dfrac{Sg}{c}\beta, \\ (n-1)\,Sg\beta, & \text{if } q > (n-1)\dfrac{Sg}{c}\beta. \end{cases} \tag{2}$$

Denote $N_i, i \in \{1, 2\}$, as the maximum number of vehicles that could be accommodated in the distance of d_i, in the lane with the delivery area. Its expression is written in

$$N_i = d_i K_J, \quad \forall i \in \{1, 2\}. \tag{3}$$

N_1 and N_2 are the number of queued (jammed) vehicles that could fit into the space before or after the dynamic delivery area on a single lane. Intuitively, the larger N_1 and N_2 are, the less traffic delay the loading/unloading operation causes. In the case of N_1, a larger space can guarantee that the queue will not spill over to the UI. In the case of N_2, a larger space would allow storing enough vehicles in front of the DI, to guarantee that it does not starve from vehicle's flow once the green signal starts.

In other words, to avoid a service rate reduction at the UI, independently of the duration of the operation, N_1 must be equal to or larger than the difference between N and N_d. By formulating $N_1 \ge N - N_d$, we can obtain $d_1 = N_1/K_J$; it is written as (4a), (4b), and (4c) where $\widehat{\beta} = (n - (n-1)\beta)$ represents the overall percentage of capacity lost at the DDPS.

$$d_1 = 0, \quad \text{if } q \in \left[0, (n-1)\frac{Sg}{c}\beta\right], \tag{4a}$$

$$d_1 = \frac{qc - (n-1)\,Sg\beta}{K_J}, \quad \text{if } q \in \left[(n-1)\frac{Sg}{c}\beta, n\frac{Sg}{c}\right], \tag{4b}$$

$$d_1 = \frac{Sg\widehat{\beta}}{K_J}, \quad \text{if } q \in \left[n\frac{Sg}{c}, nS\right]. \tag{4c}$$

In other words, when L_1 is larger than d_1, the service rate at the UI is not affected and the delivery area does not generate lingering delays affecting the upstream traffic performance. Note that, for long links, $L > Sg\widehat{\beta}/K_J$, it will be possible to allow DDPS without affecting the UI.

Figure 3 shows the three pieces of linear curves resulting from the plot of the three subequations above ((4a)–(4c)). Each of the three pieces corresponds to a different scenario according to the traffic demand. The traffic demand is analyzed between 0 and the total capacity of the link (nS). The two relevant traffic demand levels where scenarios change are $n(Sg/c)$, representing the traffic capacity at the intersection when using all lanes, and $(n-1)(Sg/c)\beta$ representing the

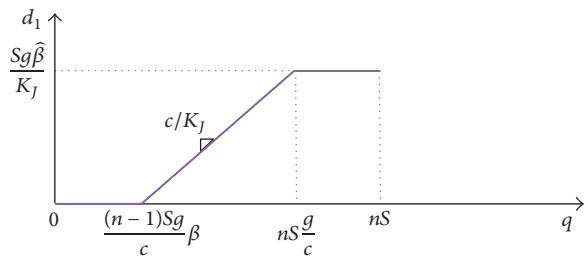

Figure 3: Value of d_1 in relation to the traffic demand volume q.

capacity at the intersection when using one less lane (including the merging effects). Recall that g and c are the duration of green time and the length of signal cycle, respectively. This leads to the three different scenarios described below.

Scenario 1. The UI is very undersaturated, $q \in [0, (n-1)(Sg/c)\beta]$ (4a), as the demand is very low. Recall that $(n-1)(Sg/c)$ represents the capacity of an intersection when using $n-1$ lanes, and β accounts for the merging effects. With such low demand, the site remains undersaturated, even if one lane is completely blocked by DDPS. In other words, the other $n-1$ available lanes can serve all the traffic demand, given that the arrival flow is small enough ($N - N_d = 0$). As a result, d_1 is also zero (i.e., the delivery area can occupy all the way back to the UI, and the UI would still be able to fully discharge the arriving traffic within every cycle).

Scenario 2. The UI is undersaturated in the absence of a delivery area, $q \in [(n-1)(Sg/c)\beta, n(Sg/c)]$ (4b). However, the intersection would become oversaturated if the right lane was to be completely occupied. In other words, the demand is lower than the capacity of the intersection using all lanes, $n(Sg/c)$, but higher than the capacity of the intersection with one lane blocked, $(n-1)(Sg/c)\beta$. Hence, to ensure that the intersection remains undersaturated, we need to provide some storage space, that is, $L_1 > 0$. The storage space required is equivalent to $N - N_d = qc - (n-1)Sg\beta$. The distance, evidently, increases as the traffic demand (q) grows.

Scenario 3. The intersection is oversaturated in any case, with or without the delivery area, $q \in [n(Sg/c), nS]$ (4c). The demand exceeds the capacity of the intersection even with all available lanes, $n(Sg/c)$. In others words, all the lanes discharge traffic at the saturation flow rate (S) during the whole green signal. DDPS can only be allowed if the space remaining on the same lane is able to accommodate the vehicles blocked; that is, the vehicles arriving from upstream that cannot be accommodated in the $(n-1)$ lanes, $N - N_d = Sg(n-(n-1)\beta)$. To guarantee this, we need a minimum distance $d_1 = Sg\widehat{\beta}/K_J$ with $\widehat{\beta} = (n-(n-1)\beta)$. Notice that this is independent of the value of q, as the amount of vehicles entering the intersection is limited by the traffic signal, not by the traffic demand.

With d_1 already defined, we can now formulate d_2, (i.e., the minimum length of L_2, distance between the delivery area and the DI, such that the DI does not starve for traffic).

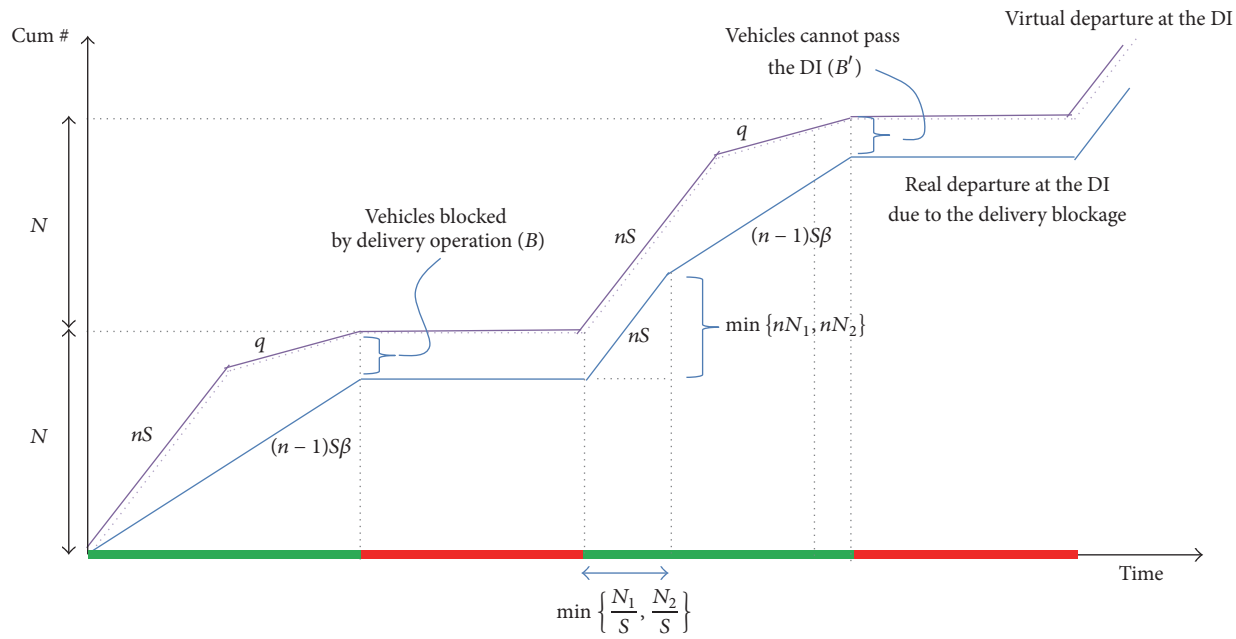

Figure 4: Virtual departure and real departure curves at the DI for the cases where the service rate at DI is not affected.

One should note that the computation of the d_2 distance at the DI is different from the case of the UI, for two reasons. First, the arrival pattern has changed since we need to account for vehicles affected by the delivery operations, which can be stored before or after the dynamic delivery area. Second, the signal control is correlated between these two intersections, that is, green wave. Therefore, the vehicles that successfully departed the UI and are not blocked by the delivery operation can also directly depart the DI. However, the vehicles which are held behind the dynamic delivery area can only arrive at the DI later than they were supposed to (in the worst case, all vehicles will arrive during the following red signal and will be forced to discharge during the next cycle). In any case, even when some vehicles are forced to wait for the next cycle, the right value for d_2 can limit the disruptions to traffic so that the service rate is not reduced. We will find d_2 that satisfies this condition.

The queuing diagram of Figure 4 depicts the virtual departure at the DI and the real departure at the DI due to the delivery blockage. The virtual departure refers to the potential departure at the DI in the absence of DDPS (i.e., the same as the departure from the UI assuming no platoon dispersion and perfect coordination). Due to the traffic signal coordination (i.e., green wave), during the first cycle of blockage, the discharging rate at the DI is $(n-1)S\beta$, since the blockage makes the full shoulder lane useless, and the rest of the lanes will be affected by the merging maneuvers. Some of the vehicles from the first cycle cannot cross the DI in time and are stored in front of the red signal, using all lanes available downstream of the parking area. During the second cycle of the blockage, at the beginning, the DI can discharge at the saturation flow, nS, given that vehicles stored in the L_2 area discharge using all available lanes. This lasts for a period equivalent to the $\min\{N_1/S, N_2/S\}$, as the $\min\{N_1, N_2\}$ is the number of vehicles that will be stored within the link. Afterwards, the discharging rate drops again to the saturation flow of $n-1$ lanes, that is, $(n-1)S\beta$, until either the queue clears up or the green signal ends.

Note that, for the departure curve, we assume that once the green signal is activated, vehicles start discharging at the maximum flow. It is true that the effects of perception-reaction time and acceleration time will make the time discharging at the maximum flow slightly longer. However, this will happen at both intersections (UI and DI) when traffic flows are critical (Scenarios 2 and 3 of Figure 3). With the presence of DDPS, there will be vehicles waiting in front of the traffic light, not only for the UI, but also for the DI.

The queue left at the end of the second cycle depends on the value of L_2 and its relation to L_1. When $L_2 \leq L_1$, the number of vehicles that can discharge DI is limited by the smallest distance, that is, L_2. When $L_2 \geq L_1$, the number of vehicles that can discharge DI is fixed by L_1; that is, N_1 vehicles can discharge. We compare the queue at the DI at the end of the first and second green signal to see if the queue diminishes. We aim to find the critical length of L_2, for which the queue gets smaller over cycles, independently of the duration of the blockage. Geometrically, based on Figure 4, we can obtain the number of vehicles that cannot pass the DI at the end of both the first and the second cycle of blockage. Let us denote B as the number of vehicles queuing at the DI at the end of the first green signal and B' as the number of vehicles after the second green signal. Their expressions are written as

$$B = \begin{cases} 0, & \text{if } q \in \left[0, (n-1)\dfrac{Sg}{c}\beta\right], \\ N - (n-1)\,Sg\beta, & \text{if } q \in \left[(n-1)\dfrac{Sg}{c}\beta, nS\right], \end{cases} \tag{5}$$

$$B' = \begin{cases} 0, & \text{if } q \in \left[0, (n-1)\dfrac{Sg}{c}\beta\right], \\ 2N - 2(n-1)Sg\beta - N_2, & \text{if } q \in \left[(n-1)\dfrac{Sg}{c}\beta, nS\right]. \end{cases} \quad (6)$$

Eq. (5) calculates the number of vehicles queuing at the DI at the end of the first green signal. When q is below the threshold, no vehicles queue, as, even with the blockage, the DI is able to serve all the vehicles within its green signal. Above this threshold, the number of vehicles queuing is given by the difference between N (the maximum number of vehicles that can be discharged during a cycle) and $(n-1)Sg\beta$ (the number of vehicles that can be discharged with one lane blocked).

In a similar way, we calculate in (6) B', the number of vehicles queuing at the DI after the second green signal. Once again, when the demand is below the given threshold, no vehicles queue. Above this threshold, the queuing vehicles are calculated as the sum of the three following components: $+2N$, the maximum number of vehicles that can be discharged during the two cycles (first and second); $-2(n-1)Sg\beta$, the number of vehicles that can be discharged with one lane blocked during the two cycles; and $-N_2$, the number of vehicles that could not pass the DI during the first cycle and were stored in front of the delivery area, ready to be discharged in the second cycle. In both equations, the threshold represents the maximum flow for which no vehicles are delayed during one cycle. Below this threshold, no vehicles queue at the DI at the end of the cycle.

In the case when the number of blocked vehicles decreases after the second cycle, the delay decreases over time. Otherwise, the delay increases over time. From this aspect, if $B' < B$, the delivery operation is acceptable; in the opposite case, the delivery operation should be avoided, since the delay will linger over time and, sooner or later, will spread over the network. Denote d_2 as the minimum distance of L_2 that would allow this to happen; it is written as (7), where $\widehat{\beta} = (n - (n-1)\beta)$:

$$d_2 = \begin{cases} 0, & \text{if } q \in \left[0, (n-1)\dfrac{Sg}{c}\beta\right], \\ \dfrac{qc - (n-1)Sg\beta}{K_J}, & \text{if } q \in \left[(n-1)\dfrac{Sg}{c}\beta, n\dfrac{Sg}{c}\right], \\ \dfrac{Sg\widehat{\beta}}{K_J}, & \text{if } q \in \left[n\dfrac{Sg}{c}, nS\right]. \end{cases} \quad (7)$$

In other words, if $L_2 \geq d_2$, then the service rate at the DI can recover over time. DDPS could also be considered when the lingering delay for the duration of the blockage is not significant and can be cleared some cycles after the blockage ends. However, this is not considered here and will be developed in future work. Although d_1 and d_2 are derived with different approaches, interestingly they lead to the same expression. In other words, for any given traffic demand (q), the minimum distance to the upstream intersection and the minimum distance to the downstream intersection are equivalent to each other. In the end, both intersections have a similar performance with the blockage after the first cycle. Both intersections have exactly the same traffic demand that has to be served within one cycle. The traffic demand is served with the nonblocked lanes plus the storage capacity. Considering that the capacity of the nonblocked lanes is the same, the storage space in front of or after the blockage area is also equivalent.

Figure 5 shows the necessary area to allow the provision of DDPS in relation to the traffic demand (q). As can be seen in Figure 5, there are two possible situations when dynamic delivery areas can be provided:

(i) In Figure 5(a), as the link length is larger than $2Sg\widehat{\beta}/K_J$, the dynamic delivery area is always possible between $Sg\widehat{\beta}/K_J$ and $L - Sg\widehat{\beta}/K_J$. However, if q is smaller than $n(Sg/c)$, the allowed area can be even larger. In the extreme case, where the demand is rather low, $<(n-1)(Sg/c)\beta$, the whole lane between the UI and DI can be used for DDPS.

(ii) In Figure 5(b), when the link length is smaller than $2Sg\widehat{\beta}/K_J$, but the traffic demand is also small, dynamic delivery areas are still possible. Denote $q_{\max}$ as the maximum traffic demand volume with which DDPS are possible; it can be found based on $d_1 = L - d_2$. Its expression is written in

$$q_{\max} = \frac{LK_J + 2(n-1)Sg\beta}{2c}. \quad (8)$$

If the link is seen as between location 0 (the start of the link in the considered traveling direction) and L (the end of the link), the parking area can be provided within $[d_1, L - d_1]$.

3.3. Relaxation of Assumptions. Some of the model assumptions will be relaxed and discussed here. Regarding the signal control, the model assumes equality of signal cycle lengths and equality of green signal lengths for both intersections. The case for different signal cycle lengths requires a new model formulation, which would need to particularly study the traffic behavior within different combinations of signal cycle length. For example, if the UI signal cycle length is twice as long as the DI signal cycle length, the model would need to be adapted to account for the behavior of the traffic flow until the same pattern is repeated. Notice, however, that it is very common for cities to have the same signal cycle length at nearby intersections. In such cases, the DDPS model presented here will be valid.

On the other hand, the same signal cycle length at nearby intersections does not guarantee the same green signal length. However, unless there are specific reasons to define it differently, many consecutive intersections have similar values for the green signal length. Otherwise, bottlenecks or capacity loss would occur, leading to an inefficient signal coordination. In case when the green signal lengths of the UI and the DI are not exactly equal, the results of the model would slightly change. We denote g_1 and g_2 as the green time for the UI and the DI, respectively. In this case, the levels of demand that determine the different possible scenarios of Figure 3 will be computed as in (4a), (4b), and (4c), but substituting $g = \min\{g_1, g_2\}$. In other words, different demand thresholds will be determined by the minimum of the green signal length

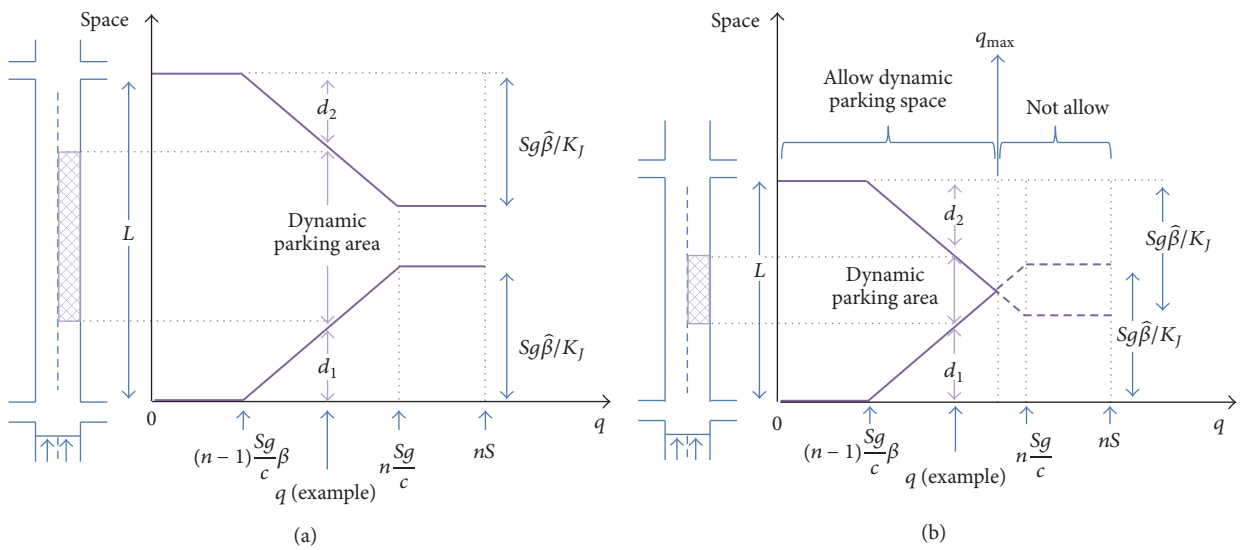

FIGURE 5: Values of d_1 and d_2 in relation to the traffic demand volume q. (a) If $L \geq 2Sg\hat{\beta}/K_J$. (b) If $L < 2Sg\hat{\beta}/K_J$.

between the two intersections. Then, we can still use the three scenarios described before for the DDPS design. In Scenario 1 of Figure 3, for undersaturated states, DDPS can still be provided. In scenario 2, for undersaturated traffic states that could become oversaturated with DDPS, DDPS could be provided, but only under some conditions. When $g_1 > g_2$, it is not advisable to provide DDPS, as the traffic signals already create a bottleneck, which could only be worsened with DDPS. When $g_1 < g_2$, it would be possible to slightly reduce d_2, as the longer green signal at the DI requires less storage space after the DDPS blockage. Finally, in scenario 3, for oversaturated states, DDPS can only be provided when the length of the link is long enough to guarantee sufficient storage space.

Last but not least, we now discuss the possible relaxation of the assumption of a uniform arrival pattern. The arrival pattern has been assumed to be uniform at the UI (i.e., vehicles' arrival is uniformly distributed throughout the length of the signal cycle). However, when the demand arrives in platoons, the model can still be used. For instance, let us assume that the first vehicle of the platoon arrives at the UI in the middle of the green signal. In such case, the first half of the green time is not used, but, during the second half, vehicles discharge at the saturation flow rate until the end of the green or the end of the platoon. It could happen that a part of the platoon could not cross the UI in the same green signal. In that case, this portion of the platoon remains queuing at the UI. At the next green signal, this queue discharges at the saturation rate, until either all incoming vehicles are served or the green signal ends. This behavior is similar to the uniform arrival pattern for our modelling purposes. Another example could be the case when the first vehicle of the platoon arrives during the red signal, leaving one green signal completely unused. During the red signal, vehicles arrive and queue in front of the UI. As in the previous case, at the beginning of the next green signal, the queue discharges at the saturation rate. Hence, even if vehicles arrive in platoons at the UI, the signal pattern will shape how the vehicles arrive at the DDPS, and our model can still be used in these situations.

3.4. Summary of Formulations. Assuming that each delivery space needs a distance of x meters, the number of possible spaces is $(L - 2d_1)/x$, which depends on q and L. Table 1 summarizes the generalized formulations for the area where to provide DDPS and the number of available spaces, based on q and L. This table provides a simplified diagram for the proposed methodology. The description of all the parameters used can be found in Table 2. Under the column scenarios, the specific conditions can be identified, and, for each of them, we specify if DDPS can be provided (column provision); in which space it should be placed (column area to provide); and the number of delivery spaces (last column).

As shown in Table 1 several steps need to be taken in order to define a specific case. First, the length of the link needs to be checked. If $L \geq 2Sg\hat{\beta}/K_J$, there is always an area available to provide delivery parking spots. When the link length is long, the central area of the link can always be used by the delivery vehicles. The exact length of the available area depends on the traffic demand (q). If $L < 2Sg\hat{\beta}/K_J$, DDPS can be provided only if $q \leq q_{\max}$, and the length of the area also depends on q. Finally, in the case where L is comparatively short, that is, $L < 2Sg\hat{\beta}/K_J$, and traffic demand is higher than $q_{\max}$, no delivery parking spot should be allowed.

The applicability of the methodology is illustrated in the next section. However, in order to implement DDPS in reality, the following two conditions are required. First, a reliable tool for traffic flow forecasting is essential in order to estimate traffic flows in the given street. Most medium-sized or big cities already have loop detectors installed, which provide information that can be used to accurately estimate the flow. Second, it should be noted that, in periods with saturation of traffic or in areas with saturated traffic flow within the day, DDPS should not be provided.

Table 1: Provision suggestions on the dynamic delivery areas under various conditions.

Scenarios			Provision	Area to provide	Number of delivery spaces to provide
If $L \geq \frac{2Sg\widehat{\beta}}{K_J}$		Yes	If $q \in \left[0, (n-1)\frac{Sg\beta}{c}\right]$	$[0, L]$	$\frac{L}{x}$
			If $q \in \left[(n-1)\frac{Sg\beta}{c}, n\frac{Sg}{c}\right]$	$\left[\frac{qc-(n-1)Sg\beta}{K_J}, L-\frac{qc-(n-1)Sg\beta}{K_J}\right]$	$\frac{L-2[qc-(n-1)Sg\beta]/K_J}{x}$
			If $q \in \left[n\frac{Sg}{c}, nS\right]$	$\left[\frac{Sg\widehat{\beta}}{K_J}, L-\frac{Sg\widehat{\beta}}{K_J}\right]$	$\frac{L-2Sg\widehat{\beta}/K_J}{x}$
If $L < \frac{2Sg\widehat{\beta}}{K_J}$	If $q \leq q_{\max}$	Yes	If $q \in \left[0, (n-1)\frac{Sg}{c}\beta\right]$	$[0, L]$	$\frac{L}{x}$
			If $q \in \left[(n-1)\frac{Sg}{c}\beta, q_{\max}\right]$	$\left[\frac{qc-(n-1)Sg\beta}{K_J}, L-\frac{qc-(n-1)Sg\beta}{K_J}\right]$	$\frac{L-2\left[qc-(n-1)Sg\beta\right]/K_J}{x}$
	If $q > q_{\max}$	No	—	—	—

Table 2: Parameters, acronyms, and scenarios.

Parameters	
B	Number of vehicles queuing at the DI at the end of the first green signal
B'	Number of vehicles queuing at the DI at the end of the second green signal
K_J	Jam density per lane
L	Total length of the link
L_1	Distance between the delivery area and the upstream intersection
L_2	Distance between the delivery area and the downstream intersection
N	Maximum number of vehicles that can be discharged during a cycle
N_d	Maximum number of vehicles that can be discharged at the intersection during a cycle by the $n-1$ lanes that are not blocked
N_i, $i \in \{1, 2\}$	Maximum number of vehicles that could be accommodated in the distance of d_i in the lane with the delivery area
S	Saturation flow rate per lane
c	Length of the signal cycle
d_1	Minimum distance value of L_1 that guarantees that no traffic spillover is caused to other links
d_2	Minimum distance value of L_2 that guarantees that no traffic spillover is caused to other links
g	Length of the green signal
g_1, g_2	Green time for the UI and the DI
n	Number of lanes per direction
q	Traffic flow arriving from upstream
$q_{\max}$	Maximum traffic demand volume with which DDPS are possible
x	Distance needed for each delivery space
β	Factor that represents the merge effect of the vehicles on the shoulder lane to the immediate next lane
$\widehat{\beta}$	$(n-(n-1)\beta)$.Transformation of the β parameter to simplify the notation
Acronyms	
ACTS	Adaptive Traffic Control System
DDPS	Dynamic Delivery Parking Spots
DI	Downstream intersection
FD	Fundamental Diagram
ITS	Information and Technology Systems
UI	Upstream intersection
Scenarios	
S0	Illegal parking with random arrival and location
S1	DDPS
S2	DDPS with prebooking system
V1	DDPS
V2	One lane blocked

4. Illustration of the Model

In this section, we use a numerical example (divided into two parts), to illustrate the application of the proposed methodology. Given the data for a particular link, we exemplify how the results from the analytical formulation could aid the design of a DDPS. The results show how the model can be used in a two-lane ($n = 2$) link under realistic conditions. The following values are assumed: saturation flow rate $S = 1800$ veh/hr/lane, jam density is $K_J = 150$ veh/km/lane, distance needed for each delivery space is $x = 8.5$ meters [50], and link length $L = 120$ meters. The green signal (g) lasts 35 seconds and the cycle length (c) is 70 seconds.

In the first part, we analyze the traffic demands for which we can allow DDPS on a given link, the location of the parking spots, and the number of spots allowed to be placed. In the second part, we assume a given daily traffic demand pattern and provide an overview of how the DDPS should change over the length of the day.

As mentioned before, the calibration of the β parameter is performed with a simple simulation experiment. We compare the total number of served vehicles on the one-lane link (without a blockage) and the two-lane link (with a blockage). In case of the one-lane link, we simply calculate the total number of vehicles served during the simulation period. Given that the used traffic demand is large enough to saturate the intersection, this is the maximum number of vehicles that the link can handle, due to the signalized intersection. Then, under the same traffic conditions, a two-lane link is simulated with a blockage on the right (shoulder) lane. In this case, we calculate the effect of the merging vehicles. Due to the blockage, the vehicles circulating on the shoulder lane need to merge to the left lane, causing less vehicles (originally arriving at the left lane) to be served, compared to the one-lane link scenario. This reduction was calculated for different simulation settings considering diverse lengths of merging areas, and the average value found was $\beta = 0.92$.

4.1. Location of DDPS. We will first analyze whether it is possible to provide a dynamic delivery area and the locations of such provision. Following Table 1 we detect which are the possible scenarios.

Step 1. $2Sg\widehat{\beta}/K_J = (2 \cdot 1800(35/3600)1.08/150) \cdot 1000 = 252$ meters.

Step 2. Is $L \geq 2Sg\widehat{\beta}/K_J$? No; therefore, we can only provide dynamic delivery when $q \leq q_{\max}$.

Step 3. Based on (8), $q_{\max} = (LK_J + 2(n-1)Sg\beta)/2c = 1290$ veh/hr.

Step 4. Area to provide provision:

(i) if $q \in [0, (n-1)(g/c)S\beta]$, that is, if $q \in [0, 828]$ veh/hr, the area to provide dynamic delivery is within $[0, L]$, that is, $[0, 120]$ meters.

(ii) if $q \in [(n-1)(g/c)S\beta, q_{\max}]$, that is, if $q \in [828, 1290]$ veh/hr, the area to provide dynamic delivery is within $[(qc-(n-1)Sg\beta)/K_J, L-(qc-(n-1)Sg\beta)/K_J]$, that is, $[0.13q - 107.33, 227.33 - 0.13q]$ meters.

Step 5. Number of delivery spaces to be provided:

(i) if $q \in [0, (n-1)(g/c)S\beta]$, that is, if $q \in [0, 828]$ veh/hr, we can provide L/x, that is, 14 spaces.

(ii) if $q \in [(n-1)(g/c)S\beta, q_{max}]$, that is, if $q \in [828, 1290]$ veh/hr, we can provide $(L - 2(qc - (n-1)Sg\beta)/K_J)/x$, that is, $39.37 - 0.03q$ spaces.

The results of the case study are presented in Figure 6(a).

4.2. Temporal Variations across the Day. In this example, we analyze the link during the entire day and show how the dynamic delivery area changes according to the traffic demand. The graph on the top of Figure 6(b) shows traffic demand variations during a given day (an input to the model), with the two peak hours (morning and afternoon). The graph at the bottom shows the time-space diagram for the dynamic delivery area.

During the times of the day when traffic demand is lower than $(n-1)(g/c)S\beta$, we can allow DDPS on the full link, given that the traffic demand is low enough. In other words, the other free lane can accommodate all the demand. Furthermore, when traffic demand is between $(n-1)(g/c)S\beta$ and $q_{\max}$, the dynamic delivery area is reduced linearly in relation to the demand, until no space can be provided. Finally, during the decrease of the traffic demand after midday, we can provide a delivery area for some hours using the lane capacity that the decrease of traffic demand leaves unoccupied.

5. Validation and Evaluation of the Model

In this section, the results of a simulation study based on the numerical example described above are presented. The objectives of the simulation are twofold: (1) to validate the results of the analytical model in more realistic scenarios (e.g., stochastic vehicle's arrival) and (2) to evaluate the performance of the proposed DDPS concept through a comparison with the current situation of illegal delivery parking. This section is divided into two subsections, one for the model validation and one for the DDPS performance evaluation.

Simulation experiments are conducted using a VISSIM microsimulation platform [51]. To account for the stochastic nature of vehicles' arrival in the simulation model, multiple VISSIM simulation runs with various random seeds were executed for all scenarios. Each simulation was one hour and 15 minutes long, with a 15-minute warm-up time and one hour of evaluation time.

5.1. Model Validation. For the validation of the analytical model, two different scenarios representing different management strategies of the delivery parking operations are analyzed. The first scenario (V1) considers the provision of DDPS in the central part of the link, with the length (number of spots) determined according to the analytical formulation. The length for DDPS is determined in each case according to

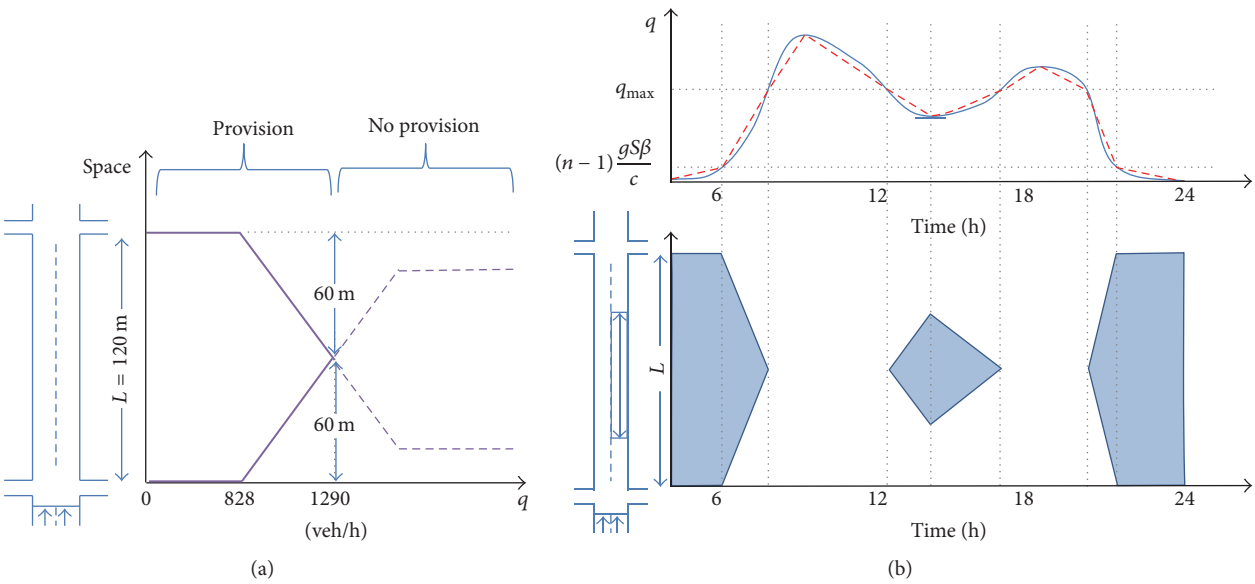

FIGURE 6: (a) Values of d_1 and d_2 in relation to the traffic demand volume q. (b) Dynamic delivery area variations across the day.

the traffic demand and signal timing parameters (see Table 1). In this scenario we also assume that the spots are occupied all the time due to a prebooking system. Secondly, we evaluate a hypothetical scenario (V2) in which one lane is completely devoted to the delivery parking. In total, three levels of traffic demand (988, 1090, and 1190 veh/h) are used as an input in the simulation platform, for each scenario. The levels of demand are chosen such that they correspond to the provision of 9, 6, and 3 DDPS spots of 8.5 meters, respectively, in the case of V1.

For comparison purposes, we analyze two performance measures: the average queue length in the UI and the latent demand. The latter represents the number of vehicles that cannot be served during the simulation (i.e., due to the spillback at the UI).

Results reveal that no latent demand is generated in scenario V1, suggesting that the presence of DDPS does not cause spillbacks. However, when the portion of the road space devoted to DDPS is larger than what is recommended by the proposed analytical model (the case of V2 scenario), there is a latent demand at the end of the simulation (2%, 15%, and 24% for the traffic demand of 988, 1090, and 1190 veh/h, resp.), causing spillbacks. In addition, one can observe from Figure 7 the average queue length in each scenario and for each traffic demand. In the V2 scenario the queue length nearly reaches the length of the upstream link, which is another sign of the spillback effect.

In reality, when parking is not available, delivery vehicles might park illegally to perform loading and unloading operations, affecting the overall network performance. Therefore, we conduct another set of simulation experiments in order to investigate the benefits of DDPS, compared to the potentially illegal parking maneuvers. Tested scenarios and the results of these experiments are provided in the next subsection.

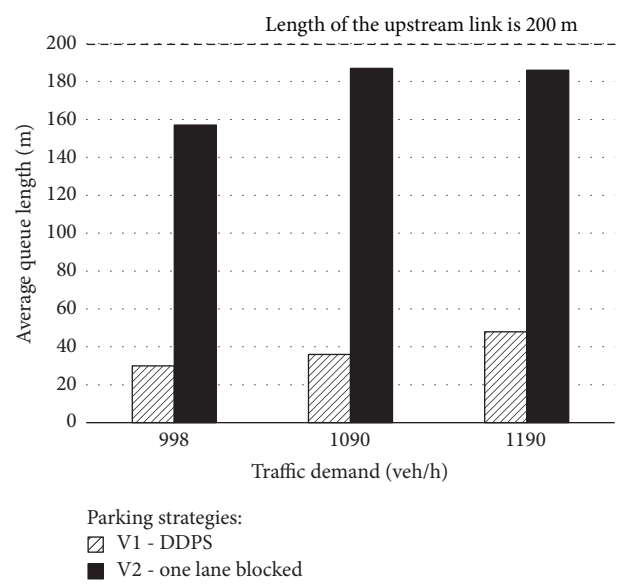

FIGURE 7: Average queue length (m) in the validation scenarios: V1 and V2.

5.2. DDPS Performance Compared to Illegal Parking. In this subsection the performance of DDPS is analyzed with the three following scenarios:

(1) S0 scenario, representing the current situation, where some delivery vehicles perform random illegal parking in the shoulder lane (see Figure 8(a)). In reality, the delivery parking location is usually chosen based on the proximity to the destination. In our simulation, we assume that delivery vehicles choose a random location within the link, arriving with a random pattern during the simulation period. From that

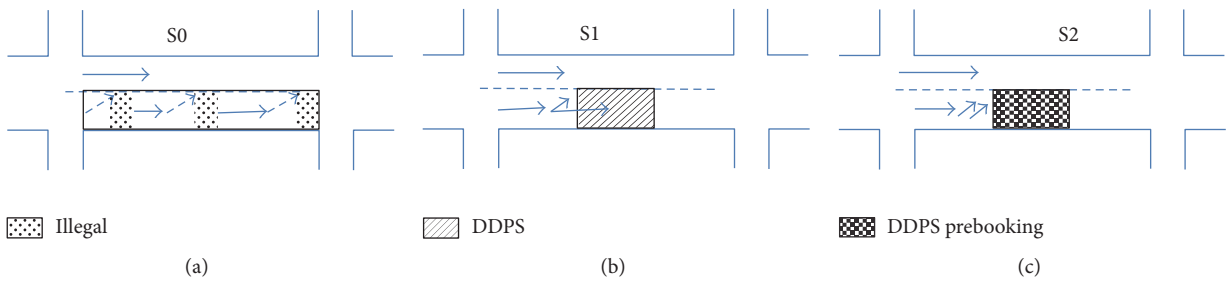

Figure 8: (a) S0, illegal parking with random arrival and location; (b) S1-DDPS; (c) S2-DDPS with prebooking system.

perspective, five different random arrival patterns are tested.

(2) S1 scenario, representing the dynamic operations of DDPS, where the shoulder lane is blocked only when there are delivery vehicles operating (see Figure 8(b)). Vehicles operate only in the DDPS area determined according to the given traffic demand and signal timing parameters. In other words, delivery vehicles do not park at a random location, but within the area assigned according to the DDPS formulation (Table 1). The same random arrival patterns of delivery vehicles from the previous scenario are used.

(3) S2 scenario, representing the operation of a DDPS combined with a prebooking system. When a prebooking system is used, delivery vehicles are assigned a given parking time in advance, according to their preferences, which respects the capacity of the facility at all times [6]. Given the provision of DDPS spots with a prebooking system, we assume that the delivery parking demand can be higher and uses the facility during most of the time (at the maximum capacity). For that reason, in this scenario, other vehicles cannot use this part of the lane at all (see Figure 8(c)). In this case, delivery vehicles have a preassigned time; therefore the arrival pattern is not random.

In scenarios S0 and S1, we assume that there will be a demand of 9 delivery vehicles per hour, which will perform delivery operations at the studied link. In the S0 scenario, delivery vehicles decide to park illegally, as no facility is available at all; in the S1 scenario, delivery vehicles use one of the available parking spots provided. In contrast, S2 can serve an increased number of delivery vehicles per hour, as the DDPS is used with a prebooked assignment and parking spots can be used all the time.

The average duration of loading/unloading operations varies depending on the type of goods and also across different cities. For example, in the city of Barcelona, the average delivery time is around 18 minutes [25] and vehicles are allowed to park in dedicated areas for a maximum of 30 minutes. Other cities such as Valencia, Lyon, Rome, or Westminster have similar time restrictions for delivery parking [2, 3, 52]. In the city of New York, the average parking time can reach 1.8 h [37], as multiple customers are served from the same parking location. Also, some cities allow other activities such as service vehicles to use these parking facilities. In general, DDPS is a solution for parking times up to a maximum of 30 minutes, given that, for longer parking periods, traffic conditions might change and DDPS might not be available anymore. In cases where parking time is much longer, other alternatives should be considered for parking. In this simulation study, we consider three different parking times (10, 20, and 30 minutes) and analyze their impact on the traffic performance. Note that the variation of parking times would not affect the provision of DDPS, but the number of vehicles that could be served, that is, the capacity of the parking facility.

To investigate the impact of each scenario (S0, S1, and S2) on the traffic performance, the average delay per vehicle is used, as shown in Figure 9. Note that the average vehicle delay of scenario S0 (illegal parking) is significant. A system without delivery parking (enforced regulation) was also simulated, and the average delay registered ranged from 16 to 17 sec/veh. Moreover, the average delay increases with both the length of the loading/unloading operations and the traffic demand.

With DDPS in S1 scenario, we show that this delay can be significantly reduced, if the same delivery demand uses the facility located in the center of the link (defined according to the analytical method in Table 1).

Nevertheless, when the traffic demand is high and/or loading/unloading operations last long, DDPS might not have enough capacity to serve the randomly arriving delivery vehicles, (i.e., it might not be possible to position all delivery vehicles within DDPS spots at a given time). These cases for S1 have not been simulated and are represented with ∅ symbol. Instead, the S2 scenario where DDPS is combined with a prebooking system is a much better option, as it allows us to optimally assign the delivery demand to parking spots and increase the capacity of DDPS. In this case, we assumed that the DDPS area will be blocked for the total simulation period, so that other vehicles cannot use it. The delay caused in the system with a prebooking DDPS (in dashed lines in Figure 9) is lower than illegal parking, except for only one case: when traffic demand is low and parking time is only 10 minutes. In all other cases, DDPS with a prebooking system causes lower delay in the system, and, in exchange, it offers much more delivery parking capacity for the DDPS users.

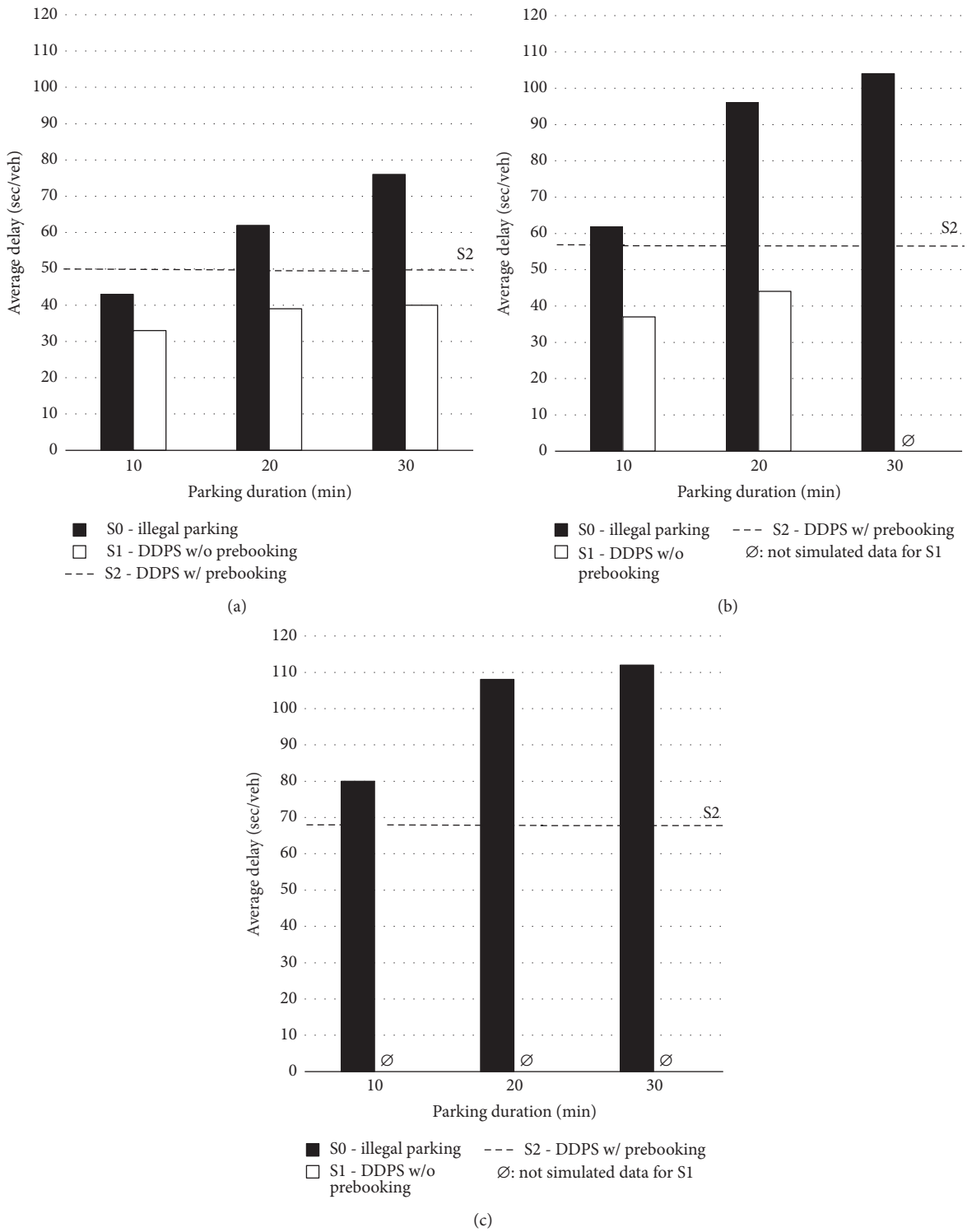

Figure 9: Average delay (sec/veh) in scenarios S0, S1, and S2 in case of traffic demand: (a) 988 veh/h; (b) 1090 veh/h; (c) 1190 veh/h.

6. Conclusions

In this paper we have introduced the concept of Dynamic Delivery Parking Spots (DDPS), a novel solution for loading and unloading operations in urban areas. DDPS are delivery facilities located on the shoulder lane of a link that are activated dynamically, keeping the traffic delay to a minimum.

Current loading and unloading operations happen either in dedicated areas outside traffic lanes or, when these lanes are full or nonexisting, in curbside parking or illegally, as

in-lane parking. DDPS can be a solution to provide delivery operations, reducing the negative effects on traffic at the same time.

DDPS temporarily block the shoulder lane, creating traffic disruptions. However, within certain conditions, it is possible to keep these disruptions at the local level, that is, without generating network effects. Thanks to this, DDPS can make a more efficient use of the scarce urban space, that is, taking traffic lane capacity for loading/unloading activities when possible.

In this paper, we develop the detailed analytical formulations to quantify the traffic effects of DDPS and find the conditions required to keep the delay at the local level. Some simplifications are needed, but with this, clear guidelines on where and when to allow DDPS are provided.

Simulation experiments are carried out to validate the results of the formulation and to further show the applicability of the proposed concept in realistic scenarios. Moreover, we are able to compare the delay caused by the DDPS to the real situation, where there might be illegal delivery parking in the shoulder lane.

In summary, DDPS can be located on a link if, even with the blocked lane, the remaining capacity of the link plus the storage capacity of the blocked lane is able to cope with the traffic demand. If this criterion is met, then DDPS should be located at the center of the link, that is, far from intersections, and leaving some capacity of the blocked lane for traffic that will later merge or diverge to other lanes of the link. As shown with the simulation experiments, DDPS can reduce the vehicle delay compared to the case when delivery vehicles park illegally.

Future research steps could extend the analytical model to incorporate different assumptions. For example, the effects of turning vehicles or pedestrian crossings could be incorporated. Additionally, small lingering delays could also be accepted to allow DDPS. The accumulated delays can be quantified to allow a number of DDPS that minimize or limit the delay, given the number of cycles of the blockage.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

A Dynamic Information-Based Parking Guidance for Megacities considering Both Public and Private Parking

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The constantly increasing number of cars in the megacities is causing severe parking problems. To resolve this problem, many cities adopt parking guidance system as a part of intelligent transportation system (ITS). However, the current parking guidance system stays in its infant stage since the obtainable information is limited. To enhance parking management in the megacity and to provide better parking guidance to drivers, this study introduces an intelligent parking guidance system and proposes a new methodology to operate it. The introduced system considers both public parking and private parking so that it is designed to maximize the use of spatial resources of the city. The proposed methodology is based on the dynamic information related parking in the city and suggests the best parking space to each driver. To do this, two kinds of utility functions which assess parking spaces are developed. Using the proposed methodology, different types of parking management policies are tested through the simulation. According to the experimental test, it is shown that the centrally managed parking guidance can give better results than individually preferred parking guidance. The simulation test proves that both a driver's benefits and parking management of a city from various points of view can be improved by using the proposed methodology.

1. Introduction

While automotive transportation (hereafter called "car") is of vital importance in everyday urban life, the constantly increasing number of cars has, however, become a messy problem in big cities. In particular, the parking problem has been considered as one of the most urgent issues to be solved, since it is hard to meet the rapidly growing parking demands with the limited parking resources within a city. It is not unusual to see many cars circling around parking facilities hunting for an available parking space, which causes severe energy losses, environmental pollution, and other irritating problems. Since the high cost of spatial resources limits the construction of new public parking in a city, increasing the parking supply has not been always a good solution for the parking problems. Therefore, over the past few decades, several parking management systems and policies have been proposed and implemented as alternative solutions in many big cities.

To solve the parking problem, many cities are already utilizing intelligent transportation systems (ITS) that include parking management functions for efficient transportation management. However, the parking management functions in the current version of ITS are still in their infancy. Recent advances in information and communication technologies (ICT) such as overhead sensors, wire/wireless networks, and smart phones have made it possible to provide very useful parking information to drivers. For example, modern parking buildings equipped with parking spot monitoring sensors that are already purchasable from the market are assisting drivers to find vacant parking spots within the buildings. Widening our lens to the parking management throughout an entire city, parking guidance information systems (PGIS) characterized by variable message sign (VMS) are frequently

deployed in major cities. The current VMS provides drivers with only brief information, such as the number of vacant parking spots and the distance and the direction to parking facilities. Based on this information and driver's experience (i.e., prior knowledge), drivers should decide the best parking facility by himself/herself. However, this decision is vague and erratic, since there is no clear way of rank-ordering the parking facilities to find the best one with respect to multiple decision criteria, such as the current number of available parking spots, parking cost, distance, or traffic conditions. Furthermore, the direction guidance provided by the current VMS is too imprecise to find a parking facility easily. These limitations must be taken into account when developing a new intelligent parking guidance system, so that it helps the drivers' decision-making by providing dynamic routing guidance obtained by considering both the driver's preference in selecting parking and real-time parking data.

From the perspective of parking supply, a policy called parking sharing has been introduced to maximize the utilization of the existing parking resources by using private parking spaces within a city. In big cities, there are many private parking spaces which are unused by owners during specific time periods. If other drivers are allowed to use these unoccupied private parking spaces, the shortage of parking spaces can be relieved. To connect the owners of private parking spaces with drivers, some cities are operating parking sharing programs. Mostly, the parking sharing is done by a contract between the owner of the private parking and the driver who needs the parking space regularly. However, parking sharing according to the scheduled plan by contract sometimes fails to instantly respond to the dynamic parking demand within a city. In this sense, an integrated information service of private parking spaces and public ones will help drivers in finding better parking places. In other words, the extension of parking management to the private parking as well as public parking can increase the available parking resources of a city without additional cost regarding construction, so that the utilization of the spatial resource can be improved. To do this, it is indispensable to develop and integrate various ICT, such as parking spot monitoring sensors, communication networks to transfer monitored data, management systems for real-time updates of the availability of parking spots, effective algorithm to provide the best parking spot to drivers, and a personal navigation device to guide a driver to the designated parking. Among these, in this paper, the authors aim to present an overview of system architecture to operate an intelligent parking guidance program, highlighting a new methodology to provide information of the best parking spot available to drivers based on the collective real-time parking status, including both public and private parking.

The rest of this paper is organized as follows. The second section describes the advantages and shortcomings of existing parking guidance models. Recent advances in ICT for a parking management system are also introduced in this section. Section 3 presents the overall system architecture that underpins the proposed parking guidance methodology, while the detailed description of the main algorithm and newly defined functions to search, assess, compare, and determine the best parking space is made in Section 4. Simulation-based validation has been conducted to evaluate the proposed methodology, and its results are discussed in Section 5. The conclusion and future works are summarized in the last section.

2. State of the Art

2.1. Sensor Network for Intelligent Parking Guidance. For the intelligent parking guidance, it is necessary to collect and use dynamic parking information, such as currently available vacant parking spots, parking fees, and parking usage history. Recently developed ICT makes it possible to monitor parking in real-time and remotely transfer parking status to a parking management system. To do this, two kinds of technical support are crucial: (1) monitoring sensors and (2) communication networks. To check parking status, different types of sensors are developed and implemented. The most used types of monitoring sensors are ultrasonic, magnetic, and video camera. Some of the studies propose a single type sensor system, which adopts one of these three sensors to implement the intelligent parking system [1–4], while some introduce a combined sensor system with heterogeneous input signals [5–8]. From the previous works, different types of sensors are applied to monitor the availability of parking according to the working environment, accuracy, and cost. Depending on the objective and operational algorithm of a parking guidance system, it is important to choose the most appropriate type of sensor with the consideration of data modality.

Another research interest has been building sensor network to transfer sensing data. For the communication of sensor data, both wire and wireless solutions are considered and implemented. Shin et al. [9] selected ZigBee as a communication protocol due to its low cost of installation. Boda et al. [10] implemented specially developed wireless sensor nodes (mica2) which were manufactured by Crossbow Technologies. Srikanth et al. [11] applied RF communication into the sensor network in transferring sensor data. Silva et al. [12] implemented a wireless network based on the IEEE 802.15.4 standard. Caliskan et al. [13] introduced a vehicular ad hoc network (VANET) which was used to transfer the status information of a parking lot through cars and proposed an application of VANETs into parking data transmission.

Different kinds of communication protocols are considered in the previous works, and wireless solutions are mostly preferred due to their low installation cost. Considering the previous research works regarding sensors and sensor networks, an intelligent parking guidance system using ubiquitous environment to monitor and control parking is quite tangible and applicable. In reality, however, the current application of collected data through these technologies is quite limited. Most of the applications are restricted to the management of a single parking facility. Few of them consider parking management from the perspective of a city. To extend parking management from a single parking facility to multiple parking facilities and private parking within a city, the reliability of sensors in an outdoor environment should be improved, and long-range communication should be considered in the sensor network.

2.2. Parking Guidance for a City. Even though the technical developments to monitor and communicate parking data are well established, their applications into parking management throughout a city are still immature. Most installed parking guidance information systems (PGIS) in many cities have a form of message board which is called a variable message sign (VMS). The main research issue regarding the operation of VMS is to enhance the information quality of the parking lot's availability, such as information updating intervals and the expected number of available parking spaces. Mei and Tian [14] studied the available parking spaces on VMS to be presented to drivers in periods of high demand. A new parking guidance information configuration model based on parking choice behavior was proposed, and the optimized configuration of VMS to get the shortest total vehicle kilometers of travel was calculated using a mathematical program. Thompson et al. [15] also studied the best car park availability information. In their work, the influence of parking information from PGI signs on the overall performance of the traffic system was estimated using a behavioral model [16] of parking choice. Their study proved that the driving distance of an automobile could be reduced by the optimized configuration of PGI display intervals, which showed a possibility of relieve the parking problem by providing better parking information. Caicedo [17] studied the effect of parking information given by a VMS. A demand assignment model to evaluate the benefits of manipulating the information on a VMS was developed and tested in this research.

Various researchers are interested in the enhancement of VMS configuration to provide better parking information. However, in spite of the usefulness of PGIS based on VMS, the effect on the system-wide reduction in travel time throughout a city and vehicle benefit may seem to be relatively small [18, 19]. The parking guidance relying on VMS has several drawbacks: (1) drivers may not find near vacant parking spots by merely following the VMS, (2) drivers may miss a better parking spot while heading to a specific parking spot, due to the temporal discrepancy, (3) parking resource utilization becomes imbalanced, and (4) parking guidance itself causes new traffic congestion. The provided information by VMS becomes outdated during driving, since it cannot respond dynamically to the information update. Moreover, considering the characteristics of VMS, the deliverable information is limited

To overcome these limitations, an advanced parking guidance system that can provide intelligent parking information is required. To extend deliverable parking information and enhance parking management of a city, Chou et al. [20] proposed a parking management system based on an agent-based platform. The proposed system used an intelligent agent system, which helps a driver to negotiate parking prices with car parks so that the driver can find better and cheaper parking. For this propose, the authors showed a possibility of extending the function of PGIS by adding a negotiation process between the parking facility and the driver based on the parking fee. Teodorović and Lučić [18] adopted a reservation concept combined with parking revenue management system. The reservation system was designed to maximize the revenue of a parking facility, so the parking request from a driver could be accepted or rejected as decided by the facility. Unlike Chou et al.'s work, their system focused more on the operation perspective of a parking facility. Srikanth et al. [11] also proposed a reservation function through the Internet or GSM (Global System for Mobile Communications) for the convenience of the driver. Within the proposed system, a driver could reserve a parking spot remotely through a client application. The reservation could secure a parking spot until the driver arrives. However, these systems may not be suitable for helping the driver's decision-making for finding the best parking space.

To help the decision of the optimal parking selection, Caliskan et al. [13] proposed an estimation method of future parking lot occupancy using the information collected from the developed vehicular ad hoc networks (VANETs). Since the delivered information of parking lot status through VANETs can be outdated when a driver arrives at the parking lot, it is necessary to predict occupancy in advance. An occupancy prediction based on the Markov model was proposed in their work. By these works, more intelligent information supporting finding parking spaces was studied and introduced for enhanced parking management throughout a city.

In a similar vein, some research works have been interested in the behavior of the driver in parking selection. The choice of parking is closely related to parking guidance, so many researchers tried to make a model to explain parking selection. For example, Bonsall and Palmer [21] studied parking choice behavior using a travel choice simulator. Jonkers et al. [22] also showed driver behavior in searching for parking places. Mei et al. [23] explained the parking searching process and related factors in parking choices. As an advanced system to provide intelligent parking guidance, new parking management systems have been introduced by several researchers. Giuffrè et al. [24] proposed an advanced parking guidance system as a conceptual architecture of an IPA (Intelligent Parking Assistant) aiming at overcoming current parking management solutions for smart cities. Jonkers et al. [22] introduced an intelligent parking service (IPS) which was connected with PGIS. Using the IPS, drivers could be assisted with navigation, reservation, and payment. As a driver approaches a destination, he/she is advised of an available parking place which can be reserved. Moreover, the payment is automatically handled by the IPS.

E-parking, as an innovative platform which allows drivers to obtain parking information before or during a trip and to reserve a parking spot, was proposed and evaluated in the study by Rodier and Shaheen [25] for the evaluation of the impact of smart parking systems. Geng and Cassandras [26] proposed a smart parking system designed for an urban environment. The proposed system performed a smart allocation between drivers and parking and provided a reservation function. The best parking was suggested considering proximity to the destination, parking cost, and overall parking capacity. In their work, the central server assigns a proper parking spot to each driver and the driver could decide to accept the reservation. If the driver is not satisfied with the suggested parking, he/she should wait until the next

assignment. The parking guidance by this system is based on reservations, so there is lack of consideration of drivers who do not want to use reservation. The system proposed by Geng and Cassandras is similar to the developing system in this paper in that the decision support of the parking selection and reservation function is implemented in the parking guidance system. However, the considering factors in finding the best parking are limited, and the guidance based on reservation confines drivers' preference, so there is still the need to improve parking guidance system intelligently.

As the recent application of an intelligent parking management system in the field, San Francisco, USA, built a new system called the SFpark Pilot Program in order to help drivers who are seeking a parking space. Under this program, drivers can check available parking spaces around them through the Internet. However, this application shows its early stage of intelligent parking guidance system so that the decision support to find the best parking is still missing.

Considering previous efforts to improve parking management, the available providing information becomes diverse, and some developing systems try to adopt new functions to increase driver's convenience. However, most of them are lacking decision support in the selection of the best parking space, considering various factors related parking choice. Only a few consider user preference in the selection and suggestion of the best parking place. None of them considers private parking in the parking management of a city. Moreover, the parking guidance in real-time environment is still regarded as a challenging issue due to the large amount of data processing.

3. System Architecture

3.1. Overall System Architecture. The intelligent parking guidance system presented in this paper is composed of diverse IT components, such as advanced sensors to monitor parking spot occupancy, wire/wireless communication to transfer parking data, a central server to manage and generate parking information for the whole city, and personal navigation devices to handle the parking requests and guide the drivers. The overall system architecture and the role of each component are depicted in Figure 1. The detailed constitution of the developing system will be omitted in this paper since the focus here is to propose the methodology framework of a system at the operational level and to verify the model in providing a driver with the best parking spot in a real-time manner.

Unlike the existing parking management systems, the presented system is designed to include private parking in the parking management of a city, as well as public parking facilities. To do this, the data of private parking should be also traced by the central server. The status of private parking is monitored by a sensor installed at the request of the owner. The available parking time and expecting parking cost are registered to the central server by the owner through the provided web interface. Whenever the availability schedule of private parking is changed, the owner can update it to the central server. The registered private parking is considered as a candidate of available parking spots in the parking selection, along with public parking. By providing private parking, the owner can have monetary benefits, and the city can extend parking resources without any further construction costs and investment.

3.2. Data Flow of Intelligent Parking Guidance System. Under the introduced system architecture (refer to Figure 1) in Section 3.1, various kinds of data are collected and manipulated in order to generate the best parking guidance information. The two main streams of data are from parking spot monitoring sensors and personal navigation devices. The parking spot monitoring sensor checks the parking spot status in real time and transfers it to the central server. The central sever collects all parking spot status data throughout a city and stores it in the equipped database. Some statistical data regarding parking spot occupancy are generated by the central server using historical data and used in the parking selection by the personal navigation device. On the other hand, the personal navigation device handles locational data of the car using the installed map data and GPS. The most important part that assesses and selects the parking spot is also processed by the personal navigation device. The detailed process and related data flow are depicted in Figure 2 using the data flow diagram [27].

According to Figure 2, the parking guidance is triggered by a driver through the personal navigation device. To request parking guidance, the driver should input the destination and preference level of decision factors that will be used in the assessment and selection of the best parking. As soon as parking guidance is requested, the personal navigation device sends the driver's destination and expected parking duration to the central server. The central server finds available parking spots, including both public and private parking, near the destination. Then, the parking and related data (e.g., cost and current occupancy status) are transmitted from the central server to the personal navigation device. A software module in the personal navigation device assesses parking spots and selects the best one with a reservation option as the first step. The driver can decide whether he/she will use the reservation option or not. In the case that the driver accepts the reservation option, the personal navigation device sends a reservation request to the central server so that the provided parking spot is reserved until the driver arrives. Otherwise, the software module reassesses parking spots with different decision factors which are designed to suggest the best parking spot without reservation option. Unlike the evaluation for a reservation, in this parking selection, the uncertainty of finding a vacancy when the driver arrives at the suggested parking spot is considered.

4. Parking Guidance Methodology

An important part of the intelligent parking guidance system from the operation viewpoint is the development and validation of a method to find the best parking spot considering both the driver's preference and the public benefit for the city. Geng and Cassandras [26] defined a user's objective function that combines the proximity to the destination with the parking cost, while also ensuring that the overall parking

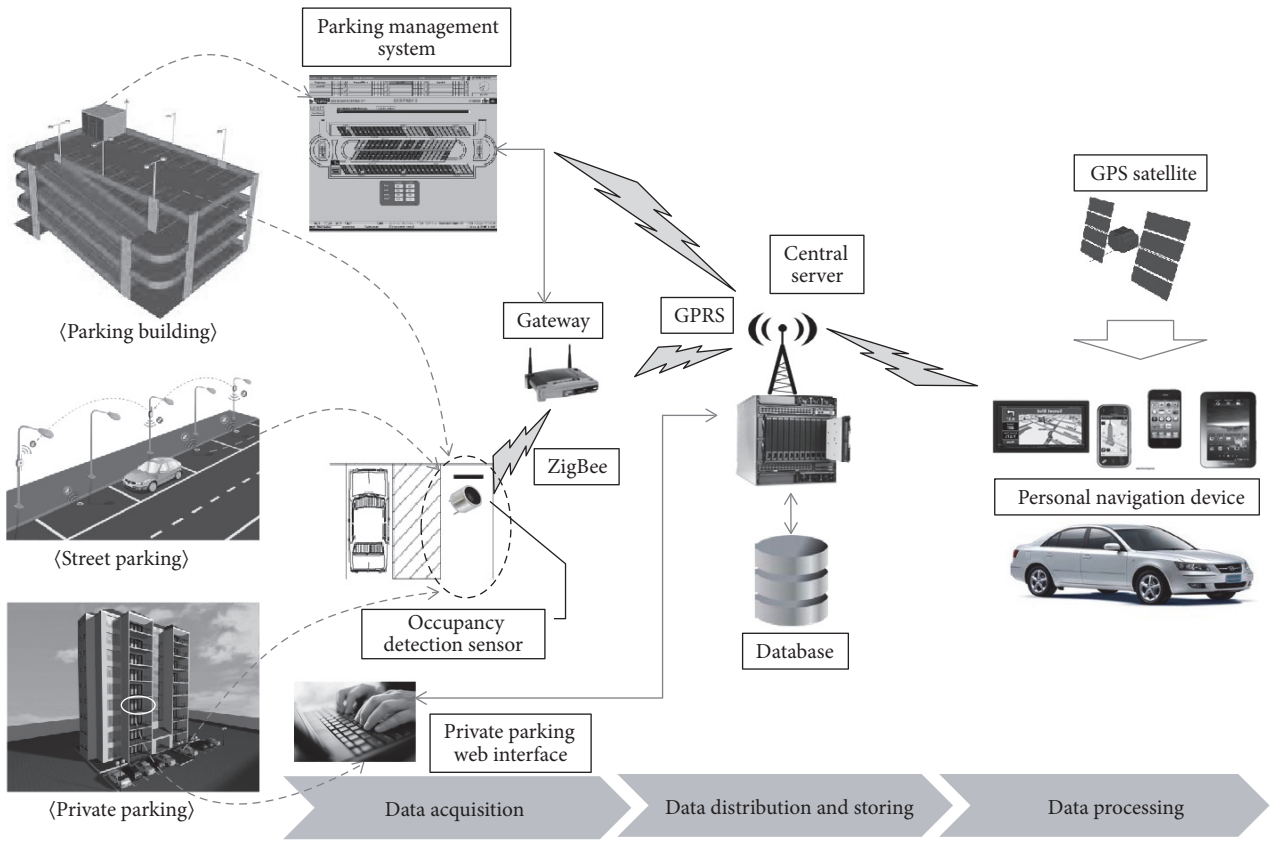


Figure 1: Overall system architecture of the proposed intelligent parking guidance system.

capacity is efficiently utilized. The proposed method in this paper is based on this concept, which uses the parking choice model to assess and compare parking spots. This will be explained in the following subsections.

4.1. Parking Choice Model. According to the previous studies on finding the best parking [16, 23, 24], parking choice can be made by the utility comparison among parking. Therefore, the utility of parking is represented as a generalized cost function that consists of several factors affecting the behavior of parking selection. Various works [28–31] mentioned the factors related to parking behavior such as walking distance to destination, driving and waiting time, parking cost, and service level of parking, safety, and optimal traffic flow. Some of them are chosen from the previous works and some factors are newly defined in the proposed utility function. In this paper, the utility function is also adopted as a decision-making criterion in the assessment and selection of parking. Two kinds of utility function, called the *utility function for reservation* and the *utility function for suggestion,* are proposed, which are defined in authors' previous work [32], and modified in order to be suitable for a megacity environment. Since the reservation causes additional costs to keep a parking spot vacant, time related factors are included in the first utility function. On the other hand, the second utility function focuses on the possibility of finding a vacant parking spot when the driver arrives at the guided parking. Common factors (i.e., parking cost and traffic congestion) affecting parking selection are included in both utility functions. Since drivers have different preferences in parking choice, the importance of considered factors in the utility function is moderated by the weights on each factor. The parking spots are assessed and compared by the utility function, and the one with the lowest value of utility function is selected. The detailed considering factors and formulations of the utility functions are explained in the following subsections. When the parking guidance is requested, the utilities of available parking spaces are calculated using these two functions so that the parking spaces can be compared and the best parking can be recognized.

4.1.1. Utility Function for Reservation. In crowded urban areas, it is difficult to guarantee that there is a vacant parking when the driver arrives at the guided parking. If the driver fails to find a vacant parking spot when he/she arrives, the driver will have to wander to find another spot, which wastes fuel and time and annoys drivers. To avoid this situation, the real-time reservation option of the proposed system could secure a parking spot until he/she arrives. Since the reservation option requires additional costs to keep the parking spot vacant until the driver arrives, many factors in the utility function are related to time and cost. The driving duration from the current location of the car to the parking spot is important, so this is included in this utility function

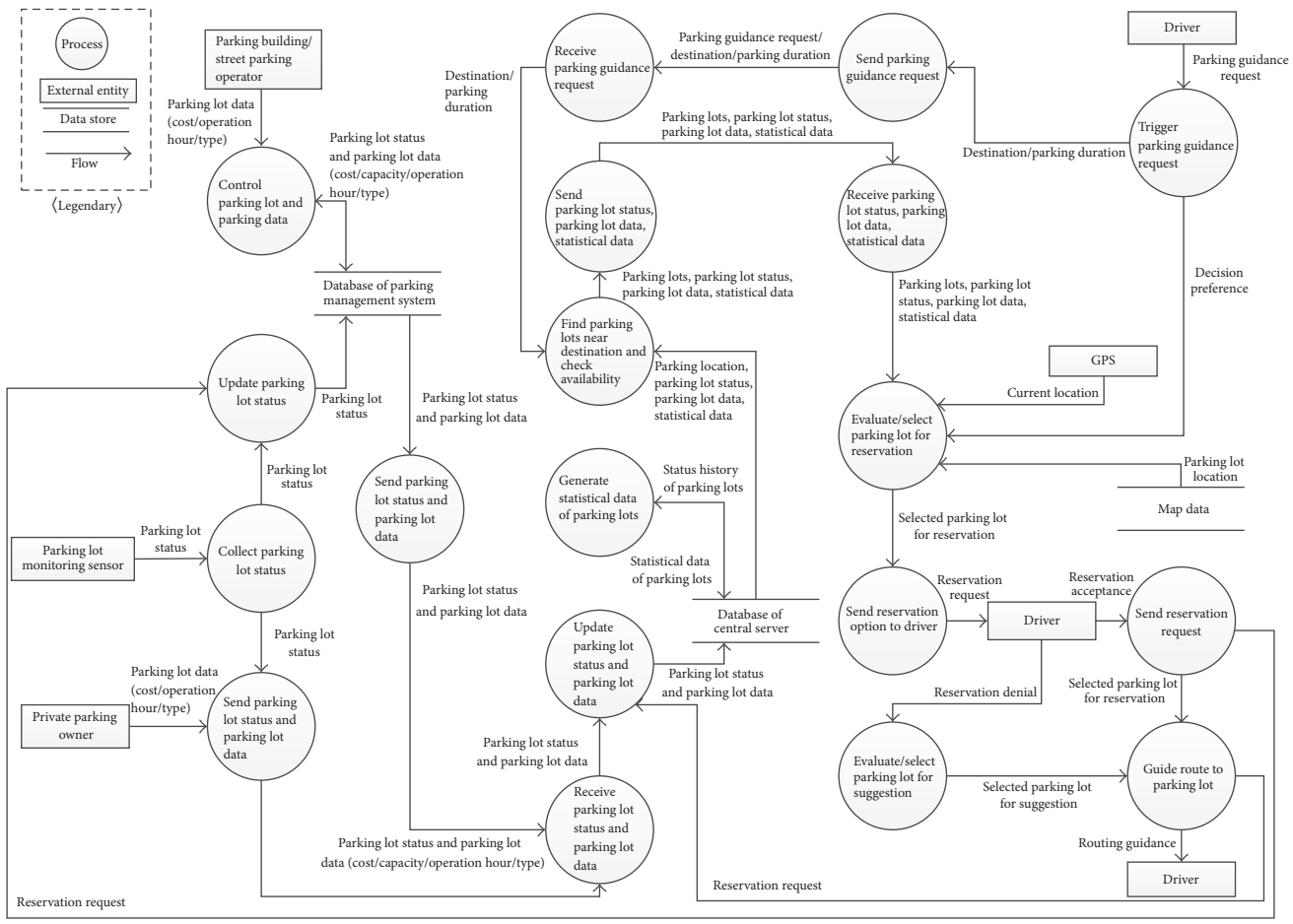


Figure 2: Process and data flow of the intelligent parking guidance system.

as one of decision factors. The walking distance from the parking spot to the destination, parking cost, and traffic congestion created by the guidance system itself are also considered as decision factors in parking choice. The defined utility function including all these factors is formulated as

$$U_r\left(T_d, D_w, P, C\right) = \alpha_1 T_d + \alpha_2 D_w + \alpha_3 P + \alpha_4 C, \qquad (1)$$

where

U_r is the utility function for reservation,

T_d is the driving duration from current location of car to parking spot,

D_w is the walking distance from parking spot to destination,

P is the parking cost,

C is the traffic congestion by guidance itself,

α is the weights of each factor.

To calculate the utility, the information of each factor is needed and it comes from the navigation software and the central server. The driving duration, T_d, is the estimated travel time to arrive at the specified parking from the current location of the requesting car. Since the personal navigation device includes navigation software, the driving distance can be calculated, and the driving duration is estimated by the navigation software. The walking distance can be also calculated in the same way. The information regarding parking cost is stored in the database of the central server and transferred to the personal navigation device when parking guidance is requested. The traffic congestion is defined to avoid parking where too many cars are heading. Hence, the traffic congestion is measured by the number of cars heading to the parking and a high value of traffic congestion prevents the selection of the congested parking spot. When the parking request is sent to the central server, the required information is transmitted to the personal navigation device and the utility of each parking spot is calculated. The lower the value of the utility function the parking has, the higher the priority and chance to be selected.

4.1.2. Utility Function for Suggestion. Unlike the *utility function for reservation*, this utility function focuses more on the uncertainty that the driver fails to park when he/she arrives at the guided parking. Since the parking suggestion is provided without reservation, the currently available parking spot can become occupied by other cars during the time spent driving

to the parking. Hence, it is important to suggest parking which has a high possibility of availability when the driver arrives. To do this, the following factor is defined, which is called the degree of availability (3). This factor estimates the possibility of finding a vacant space, considering the arrival rate of the car and the currently available number of vacant parking spots. To measure the arrival rate of a car, the mean time between arrivals, MTBA, is defined as in (2) at first.

$$\text{MTBA} = \frac{\text{sum of time spans between arrivals}}{\text{number of arrivals}}. \quad (2)$$

The MTBA represents how frequently cars arrive at the parking spot. Using the MTBA, the expected number of arriving cars to each parking spot during the driving duration of the requesting car toward the parking can be estimated. Then, the degree of availability, A, is calculated by the following equation:

$$A = \frac{T_d/\text{MTBA}}{n}. \quad (3)$$

In (3), n indicates the number of vacant parking spots in the parking facility. As the number of vacant parking spots and the MTBA increase (i.e., a plenty of vacant parking spots exist and less cars will arrive), the value of the degree of availability decreases, which means that it is more likely to find a vacant parking spot when a driver arrives. Hence, this factor can increase the possibility of finding a vacant parking spot based on the historical usage and current status.

Since the developing system will be implemented into a megacity that covers a large area in a highly congested environment, frequent parking failures cause other problems, as well as unreliability and annoyance. A car that fails to find vacant parking needs to move to another parking spot or wait. Frequent parking failure worsens the overall performance, especially regarding the total travel distance of all requesting cars. If there are other available parking spots near the guided parking spot which is unavailable, the requesting car can find another parking spot with a short additional driving distance. Unlike our previous work (Shin and Jun 2014), in this paper a new factor is introduced in the utility function. To reduce redundant driving distance caused by parking failure, regional possibility, S_p, to find vacant parking spots nearly is defined as (4). By this equation, the possibility of finding the next vacant parking spot nearby can be improved, so that unnecessary long distance driving to another parking spot can be eliminated.

$$S_p = \sum \left(D_p \times A\right). \quad (4)$$

In (4), D_p represents the distance between the considered parking and the surrounding parking. For each surrounding parking place, the distance is multiplied by the degree of availability, and the calculated value is summed with all surrounding parking spots. The considered parking with a low value of regional possibility has a high possibility of finding the next vacant parking nearby. Considering all the factors affecting a parking choice without a reservation, the *utility function for suggestion* is defined as the following equation.

$$\begin{aligned} U_s\left(T_d', D_w, P, C, A, S_p\right) \\ = \beta_1 T_d + \beta_2 D_w + \beta_3 P + \beta_4 C + \beta_5 A + \beta_6 S_p, \end{aligned} \quad (5)$$

where

U_s is the utility function for suggestion,

T_d' is the driving distance from current location of car to parking spot,

D_w is the walking distance from parking spot to destination,

P is the parking cost,

C is the traffic congestion by guidance itself,

A is the degree of availability,

S_p is the regional possibility,

β is the weights of each factor.

Using (5), the utility of each parking spot to be suggested without reservation is calculated and compared with each other. The parking spot having the lowest value is selected and suggested to the drivers as the best parking.

4.2. Procedure for Parking Guidance. Parking guidance is conducted by the following steps.

Step 0 (Collect Parking Spot Status and Parking Information). The status change and related data of each parking spot of parking buildings, street parking, and private parking are stored and traced within the database of the central server.

Step 1 (Trigger Parking Guidance). Parking guidance is triggered by the driver's request through the personal navigation device. In the personal navigation device, a software module with a user interface to handle the driver's request is installed, and the driver can push a button to request parking guidance. After initiating the parking guidance, the destination, weight of each factor, and expected parking period should be inputted together by the driver. Then, the current location is obtained by GPS and the inputted data is transferred to the central server.

Step 2 (Find Available Parking). When the central server receives the parking guidance request, it searches the available parking spots near the destination from the stored database. This searching is done by considering the parking location from the destination, available hours of private parking, and current occupation status.

Step 3 (Return Available Parking). The found parking in the second step is sent back to the personal navigation device. The GPS location of each parking spot, current occupation status, and related parking information that is required to calculate the utility function is also transferred to the personal navigation device.

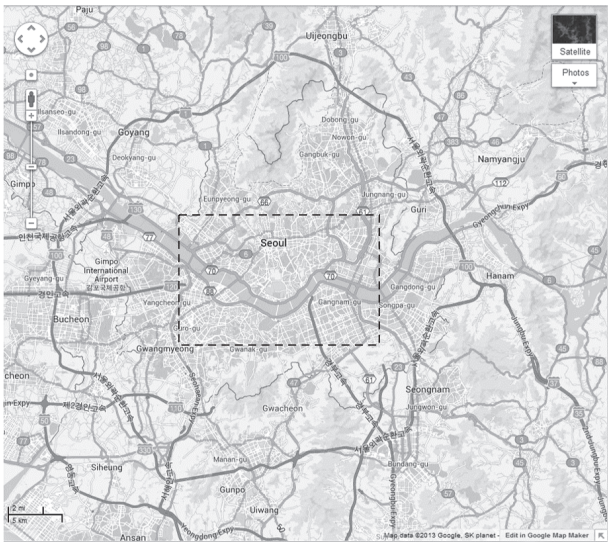


Figure 3: The downtown area of a big city used in the simulation experiment.

Step 4 (Calculate Utility Function for Reservation). To find the best parking for reservation, the *utility function for reservation* is calculated using the transferred data from the central server by (1). The calculated values of parking are sorted and the spot with the lowest value is provided to the driver on the screen of the personal navigation device. The driver can decide whether he/she reserves the provided parking or not. In the case that the reservation is requested, the reservation request is sent to the central server and the parking spot is reserved until the driver arrives.

Step 5 (Calculate Utility Function for Suggestion). In the case that the driver does not want to use the reservation option, the *utility function for suggestion* is calculated using (5). Like *Step 4*, the parking spot with the lowest value is suggested as the best parking for the driver and displayed on the screen of the personal navigation device.

Step 6 (Update Parking Spot Status). As soon as the guided car succeeds in parking, the parking spot status is changed. The monitoring sensor checks parking spot status and updates the current status to the central server. If the driver fails to park, he/she can request further parking guidance.

5. Simulation Experiment

This study has performed a simulation-based experiment to verify the proposed methodology and evaluates its effectiveness. The simulation has been coded and performed by MATLAB.

5.1. Simulation Setup and Assumptions. For the simulation-based experiment, the following city is targeted: around 10 million people with 7 million registered cars are living in this city (see Figure 3), and another 10 million with 4 million registered cars are within a 50 km distance from the city; 24% of more than 3.1 million daily commuters use their cars; the number of registered private cars is up to 2.4 million; there are about 270,000 available parking spaces; the average parking fee in the downtown area is about 5 US dollars per hour; the dotted area on the map of Figure 3 indicates the downtown of the city that covers a central area of 20.84 km × 11.4 km of the entire rectangular city area (47.2 km × 36.5 km); and the primary destinations of drivers and all parking are assumed to be located only in the downtown area, while parking guidance requests occur randomly throughout the entire map area. For a realistic simulation, we have set multiple parking guidance requests to occur at the same time, and the availability of parking spots in the city to change in every simulation.

To rank-order the parking facilities and find the best one using the utility function, it is required to estimate the driving distance and duration from the location where the driver requests parking guidance to parking facilities and from parking facilities to his/her destination. Note that in a real PGIS system, the distance and the duration can be calculated by the GPS navigation software in a personal navigation device. In the simulation, however, it is time consuming to calculate the exact driving distance and duration for every parking guidance request. Hence, the driving/walking distance and duration are estimated statistically, based on the sample data. To do this, 200 pairs of GPS locations are randomly generated and the straight distances between all the pairs are calculated. The real driving/walking distances between all the pairs of GPS locations are calculated by GPS navigation software. The differences between the straight distance and real driving/walking distance of all the pairs are calculated and the probability distribution of these differences is developed. The estimation of driving/walking distance from the straight distance of a pair of GPS location is done by adding a random generation based on the probability distribution to the straight distance. The driving/walking duration is estimated by the linear regression model, formulated using the driving/walking distances and their driving/walking durations by GPS navigation software.

5.2. Performance Measurement of the Proposed Parking Guidance Methodology. The performance of the proposed parking guidance methodology is evaluated with respect to the following six performance criteria:

(i) *Average Driving Distance*. This criterion represents the averaged driving distance per car from the initial positions of the cars to the guided parking facilities. The average driving distance could be estimated by letting the total driving distances of all cars divided by the number of cars. The lower value of this measure is preferable from the viewpoint of reducing energy waste, pollution, and other harmful effects.

(ii) *Average Walking Distance*. The average walking distance is equal to the total walking distance of all the drivers from the arrived parking facilities to their destinations divided by the number of drivers.

(iii) *Average Level of Congestion*. The traffic congestion caused by the parking guidance itself is assessed by this measure. As more cars are heading to the same

parking facility, the traffic near the parking facility will be congested. Hence, it is more desirable to disperse cars to different parking facilities. To measure the average level of congestion per parking spot, the distribution of cars heading to each parking is calculated at each simulation time and the mean of all distributions during a simulation period is defined as the average level of congestion. The lower level of this measure indicates that cars are evenly assigned to each parking spot, which can reduce traffic congestion.

(iv) *Average Occupancy Rate of Parking Spots*. From the viewpoint of the utilization of parking resources, it is beneficial to increase the occupancy rate of all available parking spots in the city. The occupancy rate is defined as the ratio of parking spots occupied during the simulation versus the total number of parking spots in the city.

(v) *Average Parking Failure Rate*. The recommended parking facility may happen to be fully occupied when a driver arrives there. As the number of drivers who get parking guidance support but fail to find vacant parking space increases, the levels of satisfaction of and reliability for drivers decrease. Moreover, parking failure causes additional driving to another parking spot, and eventually, drivers may no longer want to use the proposed system. To prevent this, it is important to measure and reduce the parking failure rate. The level of parking failure is calculated by the sum of all parking failures divided by the number of all parking facilities and by the simulation period.

(vi) *Average Requesting Number*. In some cases, it is difficult to find available parking spots. The car which fails to find a vacant parking spot needs to find another parking and request parking guidance again. This measure shows how many times a driver requests parking guidance, on average, until he/she succeeds to park. The requesting number of all cars is summed and divided by the number of cars. To prevent driver's frustration, the average requesting number should be reduced.

5.3. Simulation Parameters. The performance measures can be affected by the setting of the weight of each factor in the utility function. Hence, it is important to decide how much weight is given to each factor. In this experiment, the authors assume two preference types: (1) weights of factors are decided by each driver (more individual preference) and (2) weights of factors are decided by the central server (central control). In both different preference types, the weight of each factor is decided manually by humans so that the simplified preference levels, such as low (1), medium (2), and high (3), are used in the simulation. The predefined preference types of weight factors in the case of central control and their meanings are described in Table 1. To compare the performance improvement, the preference named "base preference" is defined, and this assumes that all cars are heading to the nearest public parking to their destinations in a straightforward way, without the help of any parking guidance system.

To check the effectiveness of the proposed parking guidance methodology, different experiments according to parking request demands and parking resources supply are tested (see Table 2). "Experiment I" focuses on the effect of variations of the parking request demands. To change the demand level, the maximum number of parking requesting cars (N) per simulation time is set to three levels (N = 500, 1000, and 2000 cars). The parking request is generated as a uniform random distribution between zero and the maximum number of parking requesting cars (N) at each simulation time, so that the number "N" regulates the level of parking request demands. To vary parking supply and study its effect, "Experiment II" was designed. In "Experiment II," parking supply is defined as three degrees according to the number of available parking spots, location congestion of parking, and initial occupation status of parking facilities. The first case assumes a congested situation, so the initial occupancy rate of parking facilities is set to a high level in the range of 80~100%, which represents a parking supply shortage. To maximize the congestion effect and check how the downtown area affects performance measures, the area of downtown is squeezed compared to other cases. The second case has the same area as the first case of "Experiment I" but is highly occupied at the beginning of the simulation to reduce parking supply. The last one doubles the supply of public parking and private parking, which means that the parking supply is expanded.

In the simulation, the data related to a parking facility (i.e., location, cost, capacity, and initial occupation rate) is randomly generated according to the parameter values (see Table 2). The total simulation period is defined as 240 units of time in order to reduce the calculation burden. To consider cars not using the proposed system on the road, the unexpected occupation of public parking spots by these cars is defined as a random number between zero and three cars per simulation time. The number of freed parking spots per parking facility is also randomly generated in the same way as the unexpected occupation. Since the target city is too big to consider all parking areas, and it is meaningless to consider parking far away from the destination, the searching area to find parking is confined to a 2 km radius. Regarding the driver's behavior, the reservation acceptance probability is defined as 50%, which means that there is a 50% probability that a driver will accept the reservation option. When a driver fails to find a vacant parking spot with the guided parking, the driver can either request further parking guidance or give up using parking guidance. This is defined as the rerequesting probability and it is set to 80%, which means that there is about an 80% probability a driver will request further parking guidance. Table 2 summarizes the setting value of simulation parameters.

5.4. Results and Analysis. Table 3 shows the result of "Experiment I."

As explained, the base preference chooses the nearest parking to the destination without any guidance, so no private parking is used in this case. Without the help of the parking

Table 1: Weight factor configuration.

Preference type	*Utility function for reservation*		*Utility function for suggestion*		Description
	Weight factor	Value	Weight factor	Value	
Base preference	$(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$	(0, 3, 0, 0)	$(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6)$	(0, 3, 0, 0, 0, 0)	Drivers choose the nearest parking to destinations without parking guidance
Weighted personally by each driver (individual preference)					
I	$(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$	(U(1–3) for all weight factors)	$(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6)$	(U(1–3) for all weight factors)	Random weight on each factor by each driver
Weighted identically by system for all drivers (central control)					
II	$(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$	(2, 2, 2, 2)	$(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6)$	(2, 2, 2, 2, 2, 2)	Equal weights of all factors
III	$(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$	(1, 3, 1, 1)	$(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6)$	(1, 3, 1, 1, 1, 1)	Strong emphasis on the walking distance from parking to destination
IV	$(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$	(3, 1, 1, 1)	$(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6)$	(3, 1, 1, 1, 1, 1)	Strong emphasis on the driving distance/duration from current location to parking
V	$(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$	(1, 1, 3, 1)	$(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6)$	(1, 1, 3, 1, 1, 1)	Strong emphasis on reducing parking cost
VI	$(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$	(1, 1, 1, 3)	$(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6)$	(1, 1, 1, 3, 1, 1)	Strong emphasis on the avoidance of traffic congestion
VII	$(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$	(1, 1, 1, 1)	$(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6)$	(1, 1, 1, 1, 3, 1)	Strong emphasis on the degree of availability to reduce parking failure
VIII	$(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$	(1, 1, 1, 1)	$(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6)$	(1, 1, 1, 1, 1, 3)	Strong emphasis on regional possibility of reducing parking failure

Table 2: Parameters and setting value.

	Parameter	Parameter setting value		
		Case 1	Case 2	Case 3
Experiment I (demand variation)	The number of generated parking requesting cars (N) (cars/unit time)	0~500	0~1000	0~2000
	The number of public parking areas (parking facilities)	200	200	200
	The maximum number of generated private parking areas (parking spots/unit time)	0~30	0~30	0~30
	Capacity of public parking facility (parking spots)	0~100	0~100	0~100
	Initial occupancy rate of public parking (%)	0~100	0~100	0~100
Experiment II (supply variation)	The number of generated parking requesting cars (N) (cars/unit time)	0~500	0~500	0~500
	The number of public parking areas (parking facilities)	200	200	400
	The maximum number of generated private parking areas (parking spots/unit time)	0~30	0~30	0~60
	Capacity of public parking facility (parking spots)	0~100	0~100	0~100
	Initial occupancy rate of public parking (%)	80~100	80~100	80~100
	Modified downtown area	Small	Normal	Normal
Common parameters of experiment I/II	Simulation period (unit time)		240	
	Parking searching radius (km)		2	
	Unexpectedly occupied parking spots in parking facility (parking spot/unit time per parking)		0~3	
	The number of leaving cars from parking building (parking spot/unit time per parking)		0~3	
	Parking cost (unit cost)		1.2~1.8	
	Reservation acceptance probability (%)		50	
	Rerequesting probability when parking fails (%)		80	

Table 3: Parking guidance performance depending on demand variation.

Number of generated parking requesting cars (N)	Preference	Average driving distance (km/car)	Average walking distance (km/driver)	Average level of congestion (car/parking/unit time)	Average occupancy rate of parking spots		Average parking failure rate (car/parking/unit time)	Average requesting number (max number of requests)	Number of guided requests with reservation	Number of guided requests without reservation
					Public parking (%)	Private parking (%)				
Case I-1 $N = 500$ (3803 parking spots/61845 cars)	Base preference	22.9605	0.72174	27.6702	80.4988	0	0.025043	1.2327 (8)	0	80128
	I	21.5506 (↓6%)	0.98291 (↑36%)	22.7688 (↓18%)	89.8438 (↑12%)	24.9924	0.011089 (↓56%)	1.1347 (7) (↓8%)	26771	43109
	II	21.4676	1.00060	22.5077	89.8472	**25.4711***	0.011221	1.1371 (7)	26765	43223
	III	21.7281	**0.90458***	23.3576	90.1835	24.7503	0.011370	1.1389 (8)	26640	43457
	IV	**21.1605***	1.00780	22.3043	90.1450	24.5330	0.011482	1.1385 (8)	26789	43433
	V	21.6975	0.98089	24.7918	89.2112	24.5422	0.012658	1.1515 (7)	27477	43577
	VI	21.5371	0.98867	**22.2014***	89.6899	24.9919	0.011002	1.1335 (7)	26814	43006
	VII	21.6270	1.02280	22.6633	89.1475	24.9718	0.011636	1.1422 (7)	26727	43555
	VIII	21.7081	0.96744	23.3832	**90.4098***	24.6744	**0.010694***	**1.1239 (6)***	26950	42639
Case I-2 $N = 1000$ (3803 parking spots/123690 cars)	Base preference	24.6585	0.50886	60.5467	84.5796	0	0.104270	1.2549 (10)	0	199860
	I	22.7156 (↓8%)	0.81393 (↑60%)	49.7275 (↓18%)	95.3087 (↑13%)	29.7477	0.070314 (↓33%)	1.2474 (12) (↓1%)	27101	148084
	II	22.6351	0.80623	49.4764	95.2266	29.9682	0.071097	1.2545 (10)	27325	148425
	III	22.8763	**0.73988***	50.9695	95.4472	29.7705	0.067334	1.2334 (11)	27965	145066
	IV	**22.1031***	0.83583	49.0828	95.5196	29.7831	0.071135	1.2469 (10)	27067	148729
	V	22.9482	0.79219	54.6269	95.2399	29.7430	0.074098	1.2669 (11)	30917	147012
	VI	22.6140	0.82576	**48.1356***	95.2445	29.9037	0.069554	1.2495 (11)	26865	147773
	VII	23.0624	0.85870	48.5179	94.9319	**30.4838***	0.083321	1.2894 (11)	25863	158816
	VIII	22.8299	0.80001	51.3338	**95.5811***	29.5631	**0.060780***	**1.2047 (10)***	28747	139505
Case I-3 $N = 2000$ (3803 parking spots/247374 cars)	Base preference	26.4823	0.28565	131.9973	88.0935	0	0.32702	1.1249 (8)	0	485902
	I	24.9567 (↓6%)	0.45939 (↑61%)	113.4958 (↓14%)	98.1017 (↑11%)	35.7630	0.31971 (↓2%)	1.2098 (13) (↓8%)	22837	457770
	II	24.8592	0.45077	113.0066	98.0833	35.8187	0.32751	1.2173 (12)	22575	463709
	III	25.0646	**0.41912***	116.0776	98.1397	35.5323	0.30324	1.1960 (13)	23267	445322
	IV	**24.0608***	0.46474	112.8768	98.1253	35.3169	0.32213	1.2082 (11)	22223	460117
	V	25.0589	0.45520	126.5023	98.0938	35.7421	0.31832	1.2997 (14)	24719	454887
	VI	24.8704	0.46062	109.7411	98.0430	35.8383	0.32518	1.2010 (13)	22395	462192
	VII	25.7938	0.47779	**108.9119***	97.9611	**36.2550***	0.37879	1.2492 (17)	21808	501777
	VIII	24.9187	0.45932	118.0292	**98.1527***	35.3867	**0.27071**	**1.1739 (11)**	23954	420854

*The bold shows the best performance among preferences (I–VIII).
The percentage written under each performance of preference I shows the relative increase/decrease compared to the base preference.

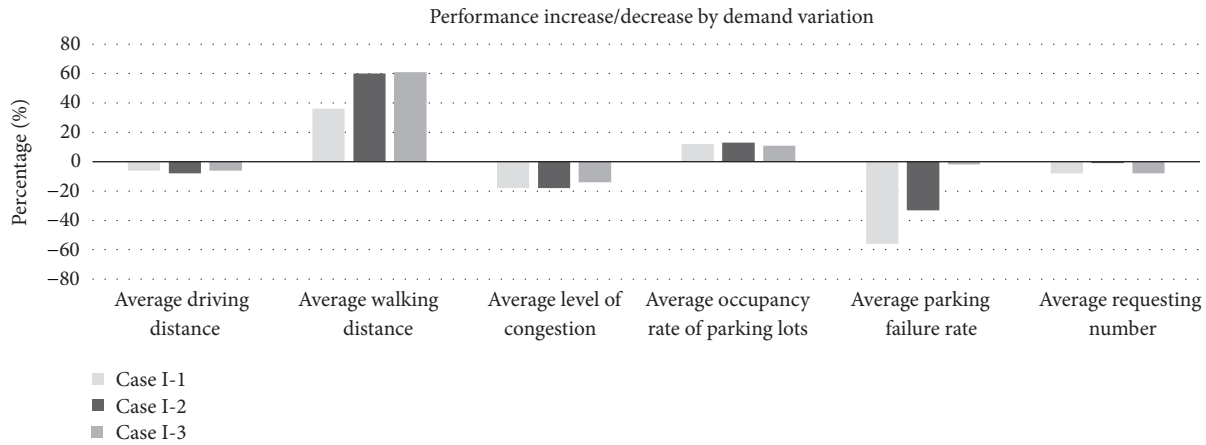


Figure 4: Performance increase and decrease by demand variation.

guidance system, it is difficult for a driver to find private parking which is dynamically available. The reservation under the base preference is also impossible without the parking guidance system, so there is no trial record of reservations, as shown in the 10th column (number of guided requests with reservation) of Table 3. Due to its characteristics of parking choice, the base preference shows the best performance of the average walking distance compared to other preferences. However, other performance measures of the base preference show worse results than those of other preferences, which means that the applications of the proposed methodology can be a possible solution to the parking problem.

As described in Table 1, preference I puts arbitrary weights on each factor by each driver, and all of the performance measures, except the average walking distance and average requesting number for all cases in "Experiment I," show a better performance than those of the base preference, regardless of parking request demand variation. Even though the average walking distance increases, the additional distance for drivers to walk does not exceed 300 m on average, which seems not to be critical hindrance to use the guided parking. It is assumed in preferences II–VIII that the weight of each factor is configured by the central server identically for all drivers.

Since the important balance among weights of factors can be adjusted depending on the objective of a parking guidance policy, the authors define several types of preferences, as shown in Table 1 (see preferences II–VIII). In most preferences II–VIII, the total travel distance that includes both driving distance and walking distance becomes less than that of the base preference. For example, by using the intelligent parking guidance, about 600,000 km of driving distance (i.e., the case I-3) can be reduced totally, which means that a huge amount of energy can be saved. Preference IV shows quite good performance on the average driving distance, since the highest weight is put on the factor related to driving distance and duration. The parking spot with a shorter driving distance and less duration from a requesting car has the higher priority than other available parking spots in this preference. Hence, it is likely that the closer parking spot from the current location of the car is selected and provided to drivers. Preference II puts more emphasis on walking distance, so this preference shows a good performance of the average walking distance. However, unlike the base preference, the nearest parking spot from the destination is not always selected, since the proposed methodology considers other factors concurrently in the assessment. Therefore, even though the strongest emphasis is given to the factor related to walking distance, the average walking distance of preference II cannot beat that of the base preference.

Regarding the average level of congestion, preference VI shows a good performance since the number of cars heading to each parking spot is more emphasized in this preference. A parking spot with high congestion is strongly avoided so that the average level of congestion can be reduced. From the viewpoint of parking management of a city, it is important to maximize the utilization of spatial resources. The average occupancy rate of parking spots indicates how well the parking spot is utilized. Since there is no factor directly related to utilization, it seems that there is no dominant preference for utilization increase. However, it seems that the factor "regional possibility" has a tendency to improve the parking utilization. According to the last two columns in Table 3, the number of guided cars using reservations does not increase much, contrary to the expanding guidance by suggestion. It is because the number of parking spots is confined, so the expansion of available parking spots for reservation is limited. The number of reservation options seems to be dependent on the number of available parking spots. To provide more opportunities for reservations, an increase of available parking spots will be helpful.

Figure 4 shows the increase or decrease of performance measures compared to those of the base preference according to demand variation. According to Figure 4, three performance measures (average driving distance, average level of congestion, and average occupancy rate of parking spots) show little improvement over those of the base preference. On the contrary, the improvement of the averaged parking failure rate dramatically worsens as the demand (N) increases.

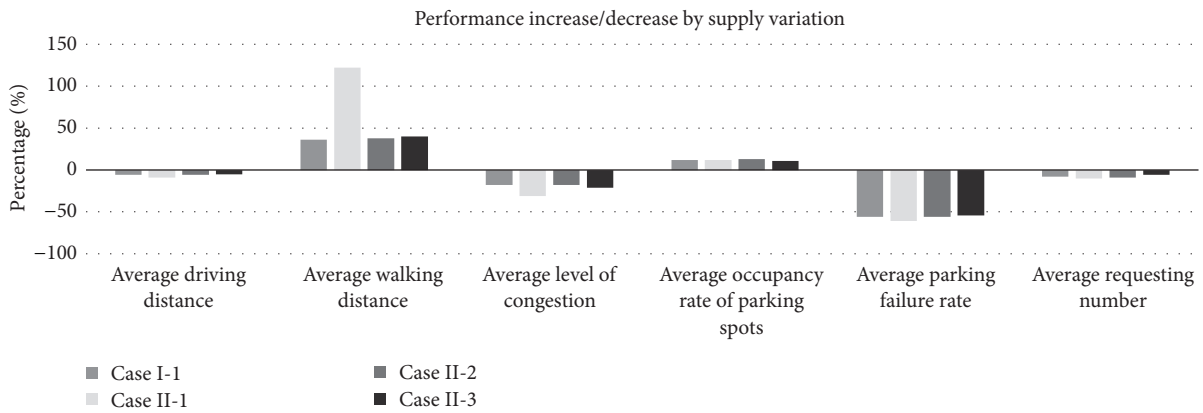


Figure 5: Performance increase and decrease by supply variation.

As shown in the column of public parking utilization, the number of vacant parking spaces decreases as the demand (N) increases, so the effect of guidance to reduce parking failure is diminishing. In the case of another performance measure, the averaged walking distance also worsens (larger) as the demand (N) increases. Like the average parking failure rate, the increased number of demands (N) makes it difficult for a driver to find a vacant parking spot near the destination, so drivers must walk further to get to their destinations.

The result of "Experiment II" is described in Table 4.

As shown in Table 4, similar to the result of "Experiment I," the performance measures of all preferences (I–VIII), except the average walking distance, show better results than those of the base preference. This means that the proposed parking guidance methodology is also effective regardless of supply variation within the simulation. The best scored performance measure by preferences is similar to "Experiment I." However, the average parking failure rate in case II-1 shows the best performance with preference VI, which indicates that the regional factor does not have much impact on reducing parking failure in the case of the squeezed downtown area. The factor "regional possibility" seems to be effective on the large area, so it is expected to be used in reducing parking failure in a megacity environment. On the other hand, the average level of congestion and average parking failure rate are improved quite a lot compared to those of the base preference. Preferences III and IV are designed to improve the averaged driving distance and the averaged walking distance, so the best performances are scored by these preferences. However, unlike "Experiment I," preference VI does not always guarantee the best performance of the average level of congestion. In the case that there are many available vacant parking spots, the factor for traffic congestion cannot dominate other factors. Therefore, the traffic congestion of case II-3 scores the best performance with preference IV.

The performance increase and decrease compared to the base preference depending on supply variation are depicted in Figure 5. This increase or decrease of performance measures compared to the base preference seems to not be much affected by supply variation, since there is no factor considering supply directly.

Regarding two preference types (individual and central), the best performance of each measure is obtained by the centrally controlled parking guidance, depending on the preferences. However, other performance measures are sacrificed for the best measure on each preference. Figure 6 depicts how much the performance of individual preference differs from the best performance obtained from central control (preferences II–VIII). According to Figure 6, the performance increase/decrease does not exceed 20%, except the average walking distance of case I-2. Even though the individually defined preference on parking choice factors does not score the best performance, it is better than the base preference, so the proposed methodology will be beneficial to parking management of city.

To prove the effectiveness of the proposed methodology, the statistical analysis is carried out using two sample t-tests with the level of significance at 5%. The performance measures of preference I are compared with those of the base preference. In total, 30 different sets of the first case of "Experiment I" are generated and tested. The analysis result of the t-test is described in Table 5 and shows that the performance measures, except the averaged walking distance, are improved compared to those of the base preference. All the P values of the performance measures are less than 0.05, which means that the improvement of performance measures, except the averaged walking distance, is accepted statistically.

The proposed methodology includes private parking in the parking management of a city. To analyze the utilization of private parking, Figure 7 is plotted. The used data in this figure is the first case of "Experiment I."

In Figure 7(a), the black line represents the available period of private parking and the gray line is the occupied period. According to the simulation test, the utilization of private parking is lower than that of public parking. Since the parking spot is selected by the utility function, the normalized mean value of each factor in the utility function during simulation is calculated and drawn in Figures 7(b) and 7(c) for public parking and private parking, respectively. In Figures 7(b) and 7(c), the overall utility of private parking is lower than that of public parking, which means that private parking

Table 4: Parking guidance performance depending on supply variation.

Case (N = 500)	Preference	Average driving distance (km/car)	Average walking distance (km/driver)	Average level of congestion (car/parking/unit time)	Average occupancy rate of parking spots		Average parking failure rate (car/parking/unit time)	Average requesting number (max number of requests)	Number of guided requests with reservation	Number of guided requests without reservation
					Public parking (%)	Private parking (%)				
Case II-1 Smaller area of city center Congested situation (3803 parking spots/61845 cars)	Base preference	21.6332	0.35187	25.6694	94.1055	0	0.026187	1.2746 (9)	0	80938
	I	19.5915 (↓9%)	0.78156 (↑122%)	17.8303 (↓31%)	97.4196 (↑4%)	31.2051 (—)	0.010198 (↓61%)	1.1425 (6) (↓10%)	33870	35391
	II	19.5360	0.75635	17.5453	97.3725	**31.5946***	0.010062	1.1410 (6)	33866	35296
	III	19.9355	**0.56967***	19.7374	97.6051	30.2565	0.009528	**1.1342*** **(6)**	33593	35204
	IV	**18.9900***	0.90549	16.0418	**97.6682***	30.7745	0.010261	1.1403 (8)	33691	35638
	V	19.7273	0.79276	20.1168	96.9211	30.7973	0.013251	1.1839 (8)	35171	36301
	VI	19.5391	0.77311	**17.2064***	97.2644	31.5568	**0.009945***	1.1408 (8)	33911	35187
	VII	19.6603	0.84388	17.4606	96.9932	31.4301	0.010497	1.1472 (7)	34092	35390
	VIII	19.5973	0.76175	17.8334	97.3322	31.5509	0.010005	1.1400 (6)	33870	35279
Case II-2 Normal area of city center Congested situation (3803 parking spots/61845 cars)	Base preference	23.0837	0.71475	27.8862	93.7890	0	0.026844	1.2587	0	81411
	I	21.5854 (↓6%)	0.98517 (↑38%)	22.7865 (↓18%)	97.3508 (↑4%)	24.9837 (—)	0.011691 (↓56%)	1.1429 (↓9%)	26366	43956
	II	21.5306	0.97899	22.6756	97.3115	25.0311	0.011769	1.1459	26168	44211
	III	21.7374	**0.90594***	23.3329	97.3520	24.6874	0.011711	1.1422	26308	44057
	IV	**21.1697***	1.00820	22.2663	**97.4146***	24.6696	0.011872	1.1459	26268	44219
	V	21.7382	0.97780	24.7694	97.0914	24.7457	0.013220	1.1595	26813	44669
	VI	21.5284	0.99654	**22.1451***	97.3713	**25.2128***	0.011342	1.1431	26496	43616
	VII	21.6357	1.02540	22.3054	97.1988	25.0922	0.012179	1.1515	26258	44424
	VIII	21.7373	0.96680	23.3953	97.3151	24.7822	**0.011032***	**1.1313***	26363	43491
Case II-3 Normal area of city center Increased parking (7612 parking spots/61845 cars)	Base preference	22.0005	0.66235	12.8652	91.0065	0	0.0052893	1.1375	0	69860
	I	20.9720 (↓5%)	0.92681 (↑40%)	10.1891 (↓21%)	93.5620 (↑3%)	22.4560 (—)	0.0024331 (↓54%)	1.0729 (↓6%)	32519	33236
	II	20.9215	0.91611	10.1013	93.4981	23.0983	0.0025196	1.0742	32588	33246
	III	21.2007	**0.79048***	10.6312	93.7910	21.6959	0.0023422	1.0690	32755	32818
	IV	**20.4944***	0.99019	**9.6568***	**93.8086***	22.0150	0.0025229	1.0717	32617	33202
	V	21.0366	0.93361	11.6132	92.2926	21.5380	0.0028037	1.0831	32930	33346
	VI	20.9475	0.93321	9.8819	93.3371	**23.2097***	0.0023691	1.0700	32474	33141
	VII	21.0110	0.96073	10.0913	93.1367	23.0383	0.0024561	1.0728	32699	33037
	VIII	21.0401	0.91965	10.3102	93.6266	22.7484	**0.0023373***	**1.0686***	32639	32951

*The bold shows the best performance among preferences (I–VIII).
The percentage written under each performance of preference I shows the relative increase/decrease compared to the base preference.

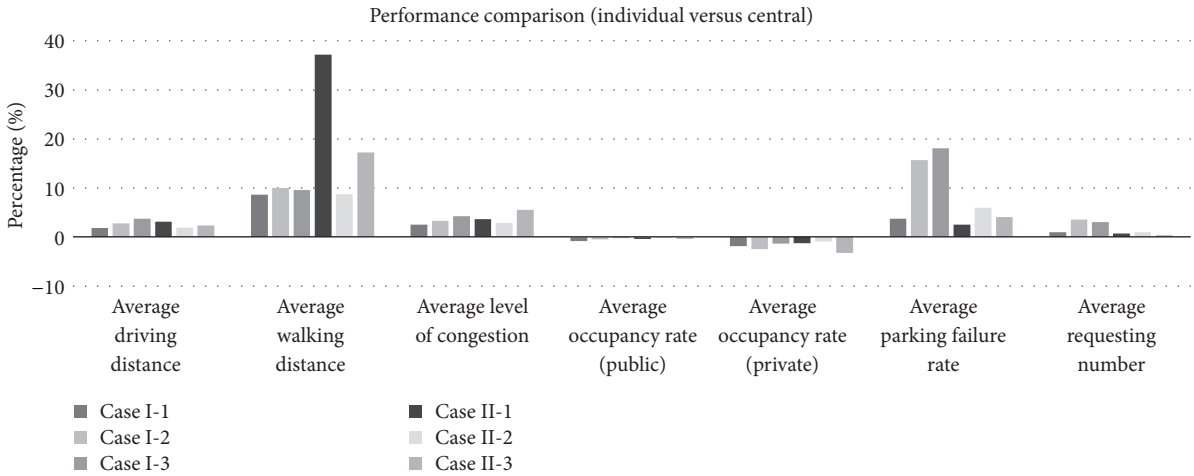
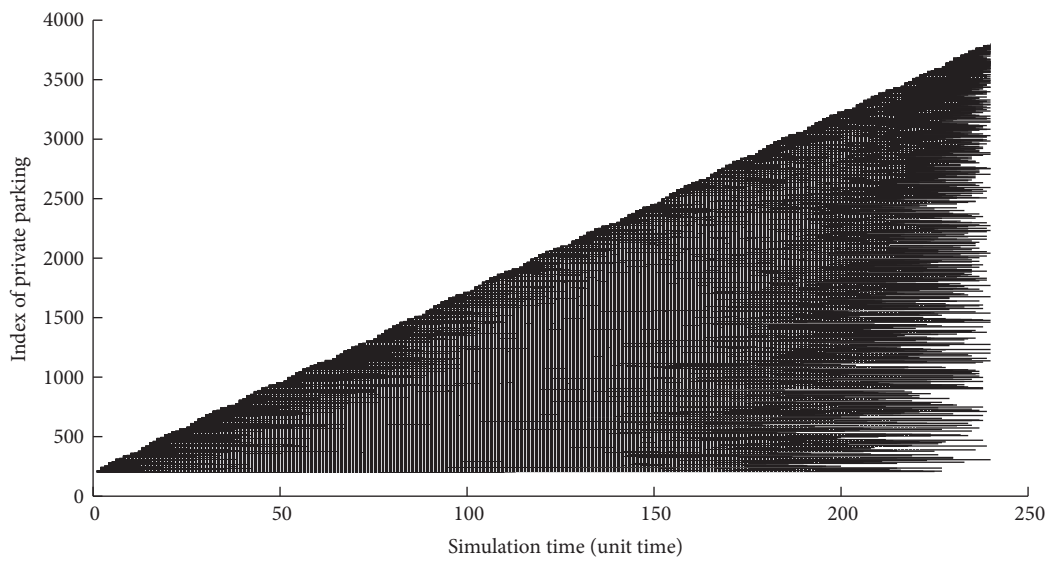
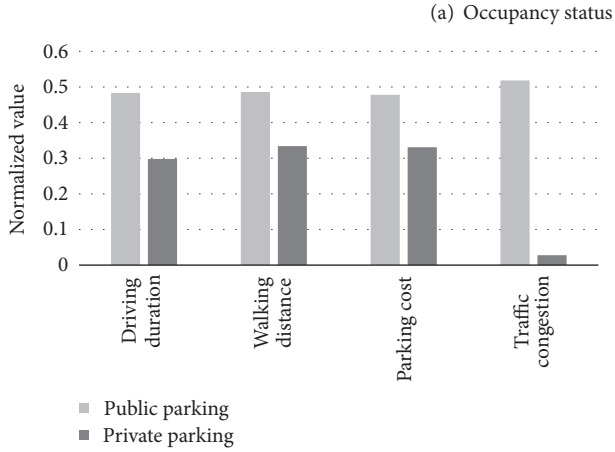


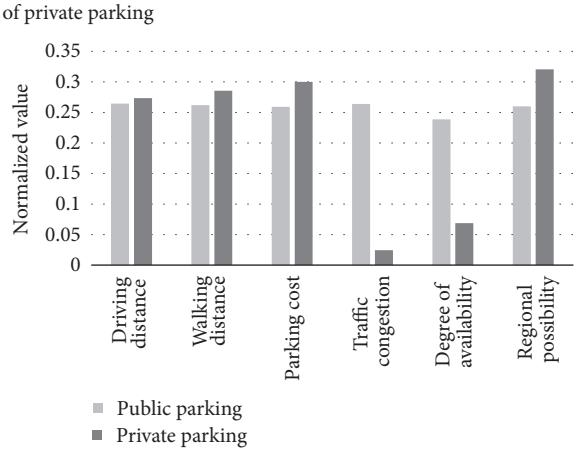
Figure 6: Performance increase and decrease by supply variation.



(a) Occupancy status of private parking



(b) Mean of each factor of the utility function for reservation



(c) Mean of each factor of the utility function for suggestion

Figure 7: Utilization of private parking.

Table 5: Two-sample t-test.

	Averaged driving distance (km)	Averaged walking distance (km)	Averaged congestion (car)	Averaged parking utilization		Averaged failed car (car)	Averaged requesting number (max number of requests)
				Public parking (%)	Private parking (%)		
Base preference							
Mean	22.5005	0.6512	25.5778	76.7635	(—)	0.0193	1.1604 (6.3226)
Standard deviation	0.0443	0.0103	0.5546	1.1304	(—)	0.0007	0.0043 (0.5408)
Preference I							
Mean	21.4121	0.9051	21.1283	87.2624	41.0770	0.0098	1.1157 (7.5484)
Standard deviation	0.0259	0.0155	0.3149	0.8406	0.3575	0.0004	0.0032 (1.0905)
T	118.109	−76.0936	38.846	−41.4975	(—)	64.8038	46.4647 (−5.6069)
P	$9.196E-73$	$2.2006E-61$	$3.1263E-44$	$6.8432E-46$	(—)	$3.00E-57$	$9.4806E-49$ ($5.51E-07$)

has a higher chance to be selected for reservation. However, public parking is more frequently provided in spite of its worse utility. This is because the available period of private parking restricts its selection. To increase the utilization of private parking, it seems desirable to put an advantage to the private parking which has a matched available period.

From the simulation test, it is verified that the proposed methodology improves both a driver's benefits and parking management of a city from various points of view. Compared to the conventional way for drivers to choose parking, the proposed methodology reduces driving distance from current car location to parking, relieves traffic congestion by guidance itself, increases utilization of parking resources including both public and private, and provides convenience to secure a parking space by reservation. Moreover, the proposed methodology makes it possible for private parking to participate in the parking management of a city and to respond to dynamic parking demands.

6. Conclusion and Discussion

In this paper, we have proposed a novel intelligent parking guidance methodology for a megacity, which includes both public parking facilities and private parking. To assess and select the best parking, two kinds of parking utility functions are formulated and used. The first parking utility function is designed to provide reservation options to secure a parking spot until the driver arrives at the guided parking. This utility function focuses on the cost perspective factors that are required to preserve a parking spot as vacant. Hence, the temporal and monetary cost factors, such as driving duration and parking cost, are included in this utility function. The other function aims to provide the best parking space without a reservation. Since there is no guarantee for vacant parking when the driver arrives, this utility function considers the possibility of finding an empty parking space so that two factors, such as the degree of availability and the regional possibility, are defined and included. Other factors affecting parking choice behavior are also included in both utility functions so as to enhance the driver's satisfaction and the public benefits. In addition, the defined utility functions are also designed to avoid traffic congestion caused by guidance itself. Unlike conventional parking guidance, the proposed methodology is designed to consider private parking as an available parking resource, as well as public parking facilities. During the simulation, private parking is dynamically joined in the parking management of a city and successfully provided to drivers. In spite of the effectiveness of the utility functions to assess and select parking, to decide a proper amount of weight for each factor still remains as a problem. An optimal weight configuration can be varied depending on the parking environment and operation strategy of the system. A proper methodology to find optimal weight configuration needs to be studied in the future.

The proposed methodology is tested using a computational simulation so as to verify the proposed system and analyze its effectiveness using an exemplary case of the megacity. Depending on the results of the simulation test, the proposed methodology proves its usefulness. Compared to the straightforward parking choice generally conducted by most drivers, most of the performance measures are significantly improved. The driving distance to parking and the traffic congestion by guidance become diminished. Moreover, the parking failure rate is also reduced when using the proposed methodology. From the viewpoint of the city, the utilization of parking resources increases quite a lot. While the walking distance in the proposed methodology is increased over the conventional parking method, this increase seems to be negligible considering the benefits of the other performance measures. In addition, two kinds of management policies (individual preference and central control) are studied by the simulation, and it is shown that the centrally controlled parking has the best performance at the cost of other performance measures. However, individual preference scores better than the base preference, which proves both parking guidance policies can be beneficial to the parking management of a city.

In spite of the verification of the usefulness of the proposed methodology, there still remain many challenging issues on further research and implementation. First, it is needed to reduce repeated parking failure of a driver. According to the simulation test, some cars are analyzed to

fail to find vacant parking spot repeatedly whenever they arrive at the guided parking. Too many parking failures for a driver will degrade the reliability of the proposed system, which may hinder drivers from using the presented smart parking guidance system. Second, the utilization of private parking keeps low level, which may make the owners of private parking hesitate to participate in the parking management of a city. To maximize the spatial resources, more private parking is desirable and the utilization of it should be increased. To do this, a new factor or procedure to give the higher priority on private parking can be considered. In this study, the effectiveness of using utility function is well described, but it is still needed to modify many parameters according to real parking environment. These issues should be studied and improved in future work, for developing better parking guidance systems with accompanying management policies. Third, in the studied developing system, the parking selection is performed by the information that is collected at the moment of parking guidance request. Hence, each requesting car uses the different information which changes as time goes. Due to this characteristic, the suggested parking spot cannot be altered even though the information changes. To cover this limitation, all the requesting cars in the megacity should be traced and the selected parking is reassessed continuously, which is impossible due to computational time and cost. Hence, the available solution to this limitation is that the reassessment of parking selection should be performed discretely during driving to parking spot. However, the decision of reassessment interval or policy needs more study and this will be the further research work.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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Research Article

More Effective Use of Urban Space by Autonomous Double Parking

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The new capabilities of autonomous cars can be used to mitigate to a large extent safety concerns and nuisance traditionally associated with double parking. In this paper double parking for autonomous cars is proposed as a new approach to temporarily increase parking capacity in locations in clear need for extra provision when best alternatives cannot be found. The basic requirements, operation, and procedures of the proposed solution are outlined. A curbside parking has been simulated implementing the suggested double parking operation and important advantages have been identified for drivers, the environment, and the city. Double parking can increase over 50% the parking capacity of a given area. Autonomous car owners would (at least) double their probabilities of finding parking compared to traditional drivers, saving cruising time and emissions. However, significant work and technological advances are still needed in order to make this feasible in the near future.

1. Introduction

Most cities have areas where the provision of parking supply is unable to meet peak period demand. Consequently, many drivers are forced to seek an alternative parking location near their destination, creating environmental and economic impact in terms of increased traffic congestion, air pollution, and time delay for individuals who are searching [1–4]. A good case in point is an article published in 2010 by the Washington Post [5] stating that finding a vacant space in a 15-block business district in Los Angeles takes on average 3.3 minutes, involving 950.000 excess miles traveled and 47.000 gallons of gas wasted and 730 tons of carbon dioxide every day. In general terms, the magnitude of the problem is hard to ascertain as few cities have recorded evidences of the number of vehicles searching for parking. Shoup [6] reviewed 16 different studies in congested downtown areas around the world reporting that on average 30 percent of vehicles were searching for parking, with cruise time ranging from 3,5 to 14 minutes depending on the city which evidences that each municipality is a unique case. Effectively, the spatial organization of a city as defined by [7] (i.e., its spatial distribution of population and trips patterns) along with parking supply can be used as first approach to roughly estimate the level of parking search in specific areas of large cities. A good example of this kind of analysis can be found in [8] where the authors estimated the magnitude of the freight parking problem in New York City on the basis of curb space and trips attracted by commercial establishments per zip code. As the authors state "parking is even more of a challenge in old cities, in which narrow streets and land-use patterns that predate motorized traffic add an additional layer of complexity to the parking problem."

Different views on the parking problem and solutions arise from different actors with normally different interests. Local governments provide on-street parking supply, create regulations and policies, and enforce compliance. According to Mingardo et al. [9], parking policy trends have evolved from predict and provide (e.g., creating restricted parking spaces), to command and control (e.g., pricing parking), and,

(a) (b) (c)

Figure 1: Double parking in Seville (a), Nice (b), and Rome (c).

more recently, to managing demand (e.g., differentiated fees, promotion of remote park and go facilities, and massive use of IT to guide people and save cruising time; see initiatives listed in [4, 8]). Academia has also studied the problem of parking search and parking economics, contributing with analytical or simulation models [1–3, 10–13] and optimizing parking efficiency in scenarios such as curbside [10, 14], campus [15], freight traffic [13], or off-street parking [1, 16]. Private initiatives offer websites and smartphone apps to find parking in advance (e.g., Parkopedia [17], CarPark4you [18]) thus reducing the need for parking search. However, regardless of the measures taken, most drivers in congested large cities would agree that more parking supply is needed in destinations where, simply put, there are not enough parking space. A survey conducted among 374 drivers of commercial vehicles in Midtown Manhattan [8] revealed another undesirable consequence of this situation: illegal parking (e.g., expired/unpaid parking meter, noncompliance with the requirements of parking signs, or double parking). Unlawfully parked vehicles are estimated to cost 20 Million (Euro) every year to Barcelona or 2,5 Million (Euro) to New York according to Morillo and Campos [19].

Double parking is present in some metropolitan areas around the world. Figure 1 shows pictures of on-street double parking on the authors Campus in Seville (a), in a peripheral area in Nice (b), or in a commercial street in Rome (c). Double parking usually exhibits temporal and spatial patterns, happening spontaneously in destinations that attract a large number of people but which have a shortage of parking for peak demand (e.g., school drop-off/pick-up times, concert hall, load/unload, and market). Parking returns to normal state after the event or activity is over. According to the authors experience, in order to avoid major troubles, double parking should operate under the following rules: (a) the road use and traffic flow should be preserved (notice in Figure 1 that streets are usually wide and one-way; thus the remaining lanes are just narrowed) and (b) double parked cars should still let vehicles exit. The latter implies that a double parked car should be pushed away by those that want to exit, which can only be carried out with manual transmission cars left in neutral gear without handbrake and in leveled streets. Undoubtedly, the circumstances in Europe are more prone for double parking than in the USA in regard to either the adoption of manual transmission cars or the metropolitan spatial organization. However, according to the aforementioned survey [8] 10% of drivers of commercial vehicles in central Manhattan declared they double park for a short time period (load/unload) during peak hours presumably without leaving their vehicles completely unattended.

Double parking creates a negative impact in terms of shrinking the remaining road space available for other users, which in turn could slow traffic depending on the street speed limit. If unattended, double parking could also create occasional hazards as a result of maneuvering or cars pushed away from the parking area, unintentional hard collisions, or vehicle damage. Last but not least, it increases the exit time for drivers who find their car blocked, not to mention the physical effort required to push by hand those cars that prevent the exit. The previous reasons justify that double parking is illegal and generally perceived as something negative. However, it still happens every day in the streets of some cities, especially where officers overlook it as long as safety and traffic are not seriously compromised. In the authors' opinion, two possible reasons can be argued in support for permissiveness: (a) to preserve local economy and (b) simply in recognition that some destinations are clearly underprovisioned and drivers lack of reasonable alternatives.

But on the other hand, double parking can temporarily increase the supply in locations where the city cannot offer better solutions during peak hours. This paper proposes *autonomous double parking*, which basically consists of a self-organized double row made by autonomous vehicles which implement a series of capabilities suggested in this work. Our hypothesis is that, with the new capabilities offered by autonomous cars, most of the inconveniences associated with this practice (e.g., safety concerns, nuisance) can be mitigated to a large extent. As such, autonomous double parking could be postulated as a disruptive approach to temporarily increase parking supply in specific destinations where it was duly justified and traffic and safety were not severely compromised, thus reducing the occurrence of parking search. Although increasing parking supply can be controversial in the light of current trends in parking policy, it should be noted that we suggest the use of this practice only after a case-based thoughtful cost/benefit analysis.

To the best of our knowledge, the use of autonomous cars has been suggested to alleviate parking problems by driving away from the city center to large capacity multistory parking garages [15, 20] but not to create a self-organized double row (which is a more realistic short term goal). This paper takes a first step in suggesting a solution. Nonetheless, the aim is to add value in providing a conceptual foundation for

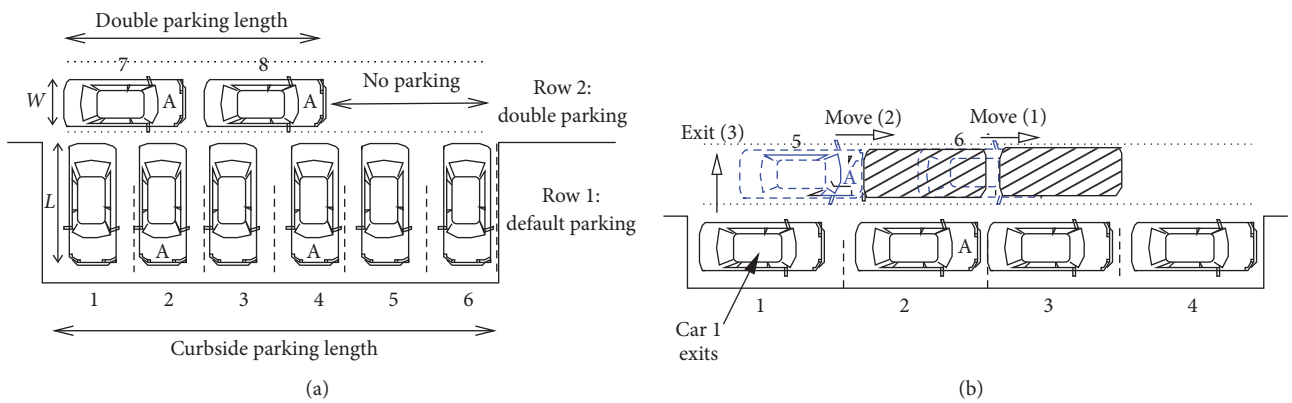


Figure 2: Example of double parking basic operation.

subsequent thorough refinement and development and to illustrate the potential benefits and limitations of this practice.

More specifically, the objective of this paper is twofold:

(i) To layout the operation, requirements, and applicability of autonomous double parking

(ii) To provide a preliminary analysis of performance which quantifies its potential benefits.

2. Autonomous Double Parking: Basic Operation and Procedures

Figure 2(a) illustrates a row of six vehicles (row 1) parked in a 90-degree angle to the curb (i.e., perpendicular parking). A second row (row 2), marked with dotted lines, indicates the space for parallel double parking. Here, the assumption is that row 2 can only be used by autonomous vehicles that implement such capability (marked with "A") whereas row 1 can be used by any type of car. Note that usable length of row 2 should be shorter than row 1 by at least $L+W$ (i.e., the largest length and width among the cars) in the studied scenario to let cars exit/enter row 1.

The basic operation is driven by the following two events:

(i) *Arrival*. Vehicles should park in row 1 if possible. If row 1 is complete, row 2 could be used by autonomous cars. If necessary, cars in row 2 will move to let arriving vehicles park in either row 1 or row 2.

(ii) *Departure*. Parked vehicles can leave anytime. If necessary, cars in row 2 will move to open a gap wide enough to let blocked cars exit from row 1. This is illustrated in the all-parallel parking example in Figure 2(b) where car 1 departure forces cars 6 and 5, respectively, to move forward before the exit.

The previous description is based upon the assumption that autonomous vehicles have the capability to coordinate themselves to create a gap of specific dimensions whenever and wherever is needed. This entails a number of requirements such as: (i) vehicles need to know the parking dimensions and their relative position; (ii) vehicles should be able to sense the distance between themselves and their neighbors in row 2; (iii) a vehicle-to-vehicle (V2V) distributed application has to be executed to convey information and commands to move; and finally (iv) the parking space should be equipped with some technology to provide information about its boundaries to autonomous cars.

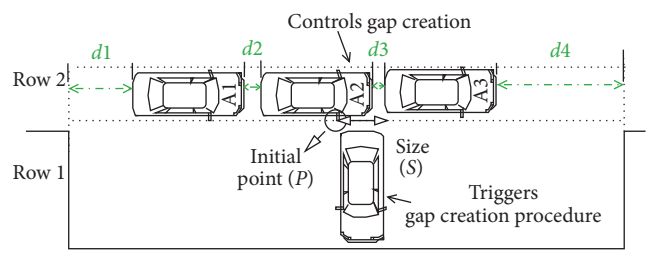


Figure 3: Main elements in gap creation.

A self-organized double row made by autonomous vehicles is advantageous with regard to the manual fashion described in Section 1 in terms of safety and comfort. Collisions or cars unattended out of the parking bounds after being pushed away should be drastically reduced. In addition, without manual pushing, physical effort is no longer required and exit time is reduced.

2.1. Procedure for Gap Creation. This procedure is the nuts and bolts of double parking. To illustrate it, an example of the exit of a blocked car is studied (see Figure 3). It is assumed that one car in row 2 receives the order to open a gap of size (S) at an initial spatial point (P). This car (A2 in Figure 3, also termed root for the remainder of this paper) takes control of the procedure execution until completion. It is also assumed that cars in row 2 cooperate until the operation is terminated, ignoring other calls in the meantime.

Then, car A2 (root) sequentially performs the following three broad steps:

(i) *Collect Information about Cars in Row 2*. It is assumed that each car i in row 2 knows its length (l_i) and width (w_i) and can sense its distance to neighbors or parking boundaries (d_i in Figure 3). Thus, cars in row 2 can

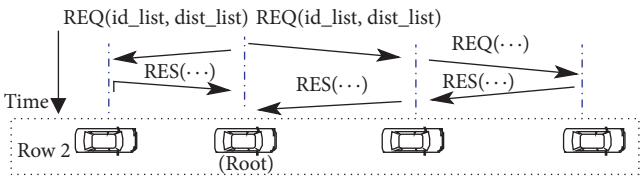


Figure 4: Communication flow for distance vector.

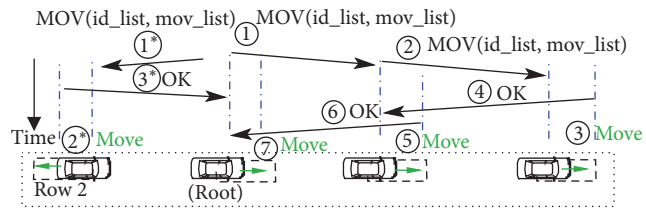


Figure 5: Communication flow for movement execution.

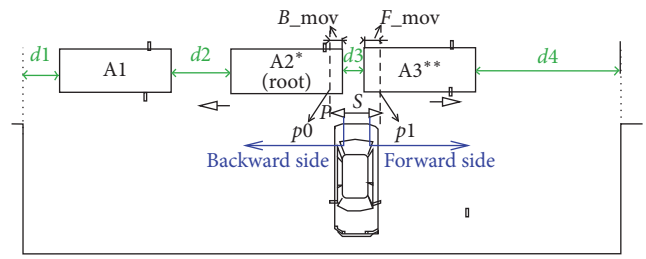


Figure 6: Illustration of key elements in the algorithm.

sense and send this information upon request as illustrated in Figure 4. The root car creates and sends a *Request* message to its neighbors. This message includes a list of car identifications (initially with only one item: the root), a list of intercar distances (initially with the gap from the root car to the next), and a flag indicating whether to go forward or backward. Each car receiving this message adds its own identification and intercar distance (edge cars add their distance to the parking bounds instead) and forwards the message until the accumulated gap amounts to the size S. Then, a new message *(Response)* is created. This message includes the previous information and follows the reverse path, indicating each car's confirmation to be engaged in this operation until completion.

(ii) *Determine Optimal Moves*. The root car executes an algorithm to find out the optimal moves to create a vacant space from P to $P + S$ minimizing the number of cars to move. The output of such algorithm provides the direction (forward or backward) and length of the movement to be performed by each car involved in the operation. Note that cars in row 1 can exit as long as $\sum d_i$ is greater than $\max(w_i) + \max(l_i)$. This constraint is assumed to be met throughout the paper. In the next subsection this algorithm will be elaborated.

(iii) *Order and Verify Movements*. Each car involved in creating the gap receives a request to move according to the algorithm output, starting with the outliers. Figure 5 illustrates the sequence of steps. First, the root car sends the movement vector to its neighbors which, in turn, resend this message. When the message reaches the last car on each side, the movement is executed and an acknowledgement message is sent back to the previous car which in turn performs the same operation. This is repeated until acknowledgments from both sides (the backward side is marked with $*$ in the figure) reach the root car, which is the last one to move. Note that some kind of visual or aural warning should be signaled by autonomous cars before and during their moves in order to warn other users such as pedestrians and pets.

Observe that the time to complete the procedure depends mainly on the number of cars involved in each operation (each car has to move a short distance, usually a fraction of S) which in turn depends on the actual state of the second row and the gap size and position. More specifically, because backward and forward sides can act simultaneously, the time to exit will depend on how many cars are moved on the *slower* side. The completion time will be addressed in the simulations results presented in Section 4.2.

2.2. Design of the Gap Creation Algorithm. To elaborate the algorithm that determines the moves, the scenario in Figure 6 will be used. As default, it is assumed that two cars (A2 and A3 in Figure 6) are always next to point P (i.e., points $p0$ and $p1$ are in between their boundaries). The case where only one car is involved is simpler and can be viewed as a reduction of this example.

The algorithm steps are as follows:

(1) Find out the two cars whose boundaries lie within $p0$ and $p1$ (marked with $*$ and $**$, resp., in Figure 6) and calculate the distance to move forward and backward, respectively, in order to create the gap (B_{mov} and F_{mov}). Initially, the car marked with $*$ should move backward B_{mov} and the car marked with $**$ should move forward F_{mov}.

(2) Check B_{mov} and F_{mov} feasibility. The addition of all intercar distances on the backward side should be greater than B_{mov}. Similarly, adding all intercar distances on the forward side should let moving F_{mov}. If one of these two constraints fails, then only one car will be marked and moved to the opposite side. For example, if $d4$ was 0, car A3** would not be able to move forward. Then, instead of car A2, car A3 would be marked with $*$ and would have to move backward. Consequently, F_{mov} would be 0, and B_{mov} would be recalculated. After this step, B_{mov} and F_{mov} are definite and feasible.

(3) Calculate movements on both sides. The minimum number of cars to let car A2* move a distance of B_{mov} is searched for. This is readily done by adding intercar distances on the backward side starting with $d2$ until

the result is greater than B_{mov}. The same applies to the forward side.

The output of this algorithm is a vector with the direction and distance that each car should move (where null means no movement). Observe that the case where cars are moved only in one direction can be viewed as a case where either B_{mov} or F_{mov} is 0.

2.3. Other Procedures and Communication Flows. It is believed that in practice the following procedures can also be necessary in addition to the one described in Section 2.1:

(i) *Root Selection.* A procedure is needed to determine which one is the root car in case there are various candidates. A number of parameters could be considered for this such as car id, proximity to P.

(ii) *Abort.* There should be a way for aborting an ongoing operation due to irresponsive cars. A broadcast message should ensure that all cars are aware that the operation in progress has been canceled. Alternatives should be found to allow drivers to exit (e.g., an irresponsive car could also be considered as parking boundary without aborting the procedure).

(iii) *Completion.* After receiving the respective confirmations, the root car should broadcast a message informing all cars in row 2 that the operation in progress has successfully finished. Cars are then released from actual engagement.

(iv) *Exit/Arrival Signaling.* Drivers should have the means to signal their arrival/departure. In the case of autonomous cars this could be done through a communication protocol providing information about the car, gap position and size (i.e., P and S), and the operation (e.g., leave). However, nonautonomous cars should have other means to request this (e.g., horn beeping, touching door handler or a smartphone app). In this latter case, the root car would have to sense and infer somehow (maybe with the cooperation of other cars) both P and S. Arrival requests could be denied as a result of insufficient space in row 2.

3. Scenarios of Application

In our view, locations eligible for autonomous double parking should meet two minimum requirements: (1) there is a clear need for extra provision that cannot be better fulfilled otherwise and (2) traffic and safety are not severely compromised because of double parking.

Regarding the first requirement, some patterns or common situations prone to excessive parking search have been identified. In [4] a survey was conducted among local officials from different UK cities. There was consensus in identifying high levels of parking search in the following situations: (i) larger market downtowns with many attractors pulling a large number of visitors for shopping and personal business purposes but unable to provide sufficient parking supply for peak demand and (ii) peripheral urban areas away from the core city center that have a lack in parking facilities. Another situation identified in [8] was (iii) the freight parking problem in large urban areas, especially in old towns. Finally, the authors believe that (iv) off-street parking lots can also be considered for autonomous double parking as both customers and land owner can benefit from extra parking provision. Table 1 summarizes these scenarios.

However, not all locations meet traffic and safety minimum requirements. Among candidate locations, a second step would be to analyze plausibility and political justification. Obviously, the first requirement is that row 1 surroundings are spacious enough to allow double parking without severely impacting traffic congestion or safety. Parking spaces or lane size can be compacted up to a point but should still adhere to minimum standards as set up by national or local authorities.

Among plausible destinations (i.e., those which meet both requirements), a political decision should be made regarding authorization. A case-based cost/benefit analysis should be performed including the trade-off between the disadvantages (e.g., reduced road space, increased nuisance) and advantages (e.g., local economy, reduced parking search). Implications in policy follow from this second analysis. For example, in scenario A or C, keeping safety and congestion under control can be more challenging than in scenario B or D; consequently, enforcing parking time restrictions can be more important.

Parking areas should also be equipped with some technology (e.g., beacons, visual signs, or kind of systems such as those proposed in [20]) to inform at least the parking boundaries. No more complexity is strictly required to be installed in the parking as we rely on a vehicle-to-vehicle (V2V) system. But observe that an alternative vehicle-to-infrastructure (V2I) system can also be developed with the root car being a device installed at the parking facility. Finally, informative signs should be exhibited in the parking space indicating usage and specific rules for autonomous double parking (e.g., car type allowed, time restrictions, and pricing) including warnings and penalties for those impairing this practice.

4. Quantifying Potential Benefits

Clearly, the main benefit of double parking is the increased parking capacity. Assuming the average size of a vehicle is W (width) $\times L$ (length) (which includes extra space for opening doors), a curbside parking of length L_{park} can host up to $\lfloor L_{\text{park}}/W \rfloor$ vehicles in parallel or $\lfloor L_{\text{park}}/L \rfloor$ in serial manner. Adding a second row would provide approximately (ignoring the floor operator) a parking capacity increment (PCI) of

$$\text{PCI} \simeq \frac{W}{L} \cdot \left(1 - \frac{W + L}{L_{\text{park}}}\right) \tag{1}$$

$$\text{PCI} \simeq \left(1 - \frac{2 \cdot L}{L_{\text{park}}}\right) \tag{2}$$

for parallel (1) and serial (2) parking (see Figures 2(a) and 2(b)), respectively. Thus, for very large values of L_{park} and assuming that W is about half of L (coarse grained), the

Table 1: Potential scenarios of application.

Scenario type	Typical location	Benefit	Temporal pattern
A, attractive	Downtown street with attractors (school, market, bars, etc.)	Business, visitors	During attractions
B, residential	Peripheral streets underprovisioned	Residents	E.g., during night
C, freight	Center, market	Business	Load/unload
D, off-street	Business parking lot	Business, customers	—

asymptotic capacity increment would be 50% for parallel parking and 100% in the case of serial parking.

However, this extra capacity might not be fully used as a result of various reasons such as insufficient autonomous cars or the own parking occupation dynamics. In this section, these factors are evaluated through a series of simulations. The operation described in Section 2.2 has been implemented in MATLAB®. Then, a curbside parking is simulated where arriving cars can or cannot be autonomous with probabilities P_{auto} and $1 - P_{\text{auto}}$, respectively. Like in most works [1, 14], we assume that the parking occupation can be modeled as a birth and death stochastic process, with cars arriving, parking (if possible), and leaving after a certain random time. Two scenarios that differ in the parameters of the distributions used are simulated so that both transient and steady-state dynamics can be analyzed. Other studies addressing in more detail curbside parking occupancy dynamics can be found (e.g., [1, 10]). Our aim is nonetheless to illustrate and quantify the costs and benefits of our proposal and not to provide an in-depth study of parking occupation, which is left for further study.

4.1. Simulation Scenarios. The first scenario consists of a curbside parking of length 200 m where perpendicular parking is done in row 1 and parallel parking is allowed in row 2 such as in Figure 2(a). The main parameters of the simulation are as follows:

(i) Cars arriving: 204

(ii) Cars arrival: Poisson process with mean rate 204 cars per hour

(iii) Parking duration: exponential distribution (mean time 45 min)

(iv) Car length (l): uniform distribution between 4,5 m and 6 m (includes space needed to exit)

(v) Car width (w): uniform distribution between 2,9 m and 3,1 m (includes space needed to open the doors).

From the previous data one can estimate the average capacity of rows 1 and 2 to be 66 and 36, respectively (so the overall parking capacity is 102). This scenario is focused on transient dynamics (fill-up and depletion of the parking), so a mean arrival rate of 204 cars ($2 \times$ capacity) in one hour with an average parking duration of 45 min should be sufficient to fill up the parking depending on the share of autonomous cars. The simulation ends when the last car exits from the parking.

The second scenario is similar to the first one in terms of parking and car sizes (i.e., the same parking capacity). However, the following parameters are different:

(i) Cars arriving: 765

(ii) Cars arrival: Poisson process with mean rate 306 cars per hour

(iii) Parking duration: exponential distribution (mean time 5 hours).

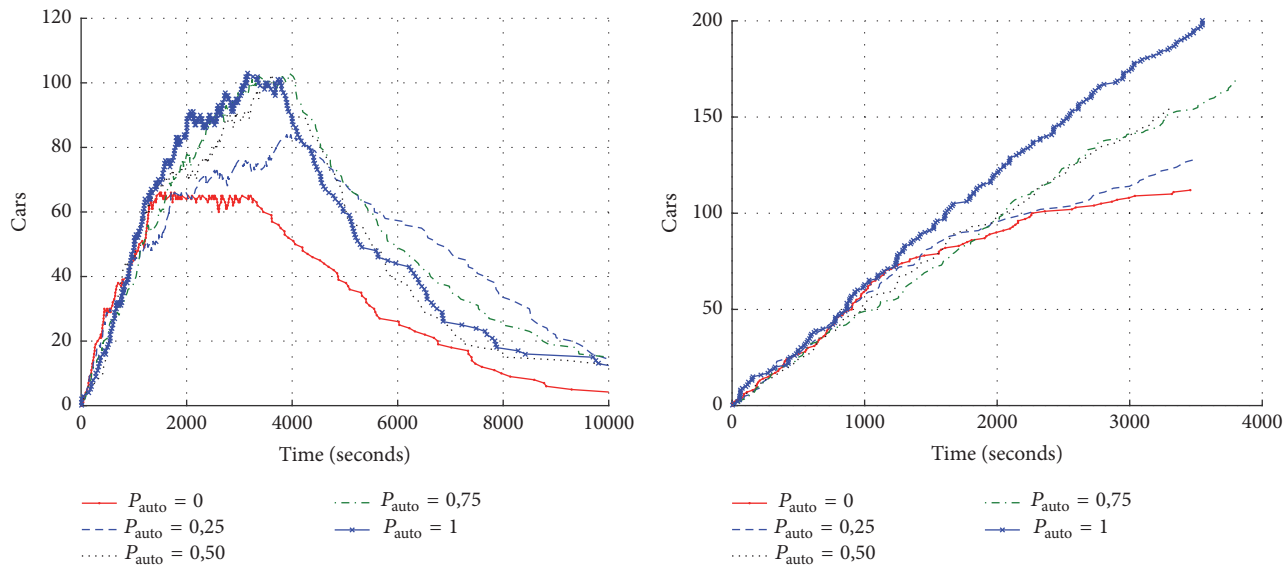
Most cars will arrive on average over the first 150 min at a rate three times the capacity, and parking duration is 5 hours on average. Consequently, it is expected that the parking exhibits full occupancy over an extended period of time. This will let us examine the steady-state situation when fewer vacancies are taken as a result of long term parking.

4.2. Results. Before introducing the main results it is worth examining the parking occupation dynamics through the study of one simulation of the first scenario with different values of P_{auto}. Figure 7(a) provides the evolution of the number of parked vehicles over the first 10^4 seconds of the simulation. Figure 7(b) provides its cumulative value. Fluctuations in the series of Figure 7(a) can be attributed to exits followed by arrivals. We can distinguish four different phases in the occupation dynamics. The first one corresponds to the occupation of row 1 at a rate proportional to the arrival rate (which is independent of P_{auto}). The next phase starts after row 1 is full. In this second phase row 2 is occupied at a rate approximately proportional to the arrival of autonomous cars (i.e., arrival rate $\times P_{\text{auto}}$). A third phase can be observed when the parking is full and fluctuations occur as a result of scarce vacancies amid new arrivals (this can be observed for $P_{\text{auto}} = 0$ or 1 in Figure 7(a)). The last phase starts when the occupancy monotonically decays as there are more cars exiting than arriving. It can also be observed in Figure 7(b) that the number of successful parking attempts tends to increase with P_{auto} which can be traced back to more arrivals to row 2.

Figure 7 represents just one simulation run and has illustrative purposes. Nonetheless, the results presented in the remainder of this section will average the output from 100 simulation runs, providing a level of statistical significance of $\alpha = 0{,}05$. The statistics collected in the simulations are as follows:

(a) *Parking Successful.* Percentage of successful parking attempts

(b) *Row 1 Use.* Number of cars parked in row 1



(a) Parking occupation

(b) Cumulative number of parked cars

Figure 7: Dynamics of the parking occupation in terms of (a) number of cars during the simulation and (b) its cumulative value.

(c) *Row 2 Use.* Number of cars parked in row 2

(d) *Operations.* Number of gap creation operations

(e) *Starts.* Times that a car in row 2 has moved on average as a result of gap creations

(f) *Distance.* Overall distance (in meters) moved on average by a car in row 2 as a result of gap creations

(g) *Autonomous.* Percentage of autonomous cars successfully parked

(h) *Nonautonomous.* Percentage of nonautonomous cars successfully parked.

Table 2 shows the results obtained for the first scenario: 204 cars arriving at a rate of 204 cars/hour to a parking with 102 spaces (66 in row 1).

Row (a) in Table 2 shows that the probability of a driver finding parking rises from ~62% to 91,5% when all cars can double park. However, rows (b) and (c) show that this improvement is experienced only by drivers of autonomous cars, who have over 99% probability of finding parking when $P_{auto} \leq 0{,}5$ (g). The average number of vehicles that used the second row ranges from 4,6 (12,7% of row 2 capacity) to 59,2 (164% of row 2 capacity) for $P_{auto} = 1$. Consequently, double parking has increased up to 46% the number of vehicles that used the facility in this simulation study.

Owners of autonomous cars have saved cruising time because of the right to exclusive use of row 2. However, a cost has to be paid in terms of autonomous moves due to gap creations and waiting time to exit. In this respect, row (d) shows that the number of gap creation operations increases with row 2 occupancy, ranging from 12,5 ($P_{auto} = 0{,}1$) to 87,3 ($P_{auto} = 1$) operations over a period of 45 min (average parking duration). However, these operations do not implicate all cars in row 2. Combining rows (c), (d), and (g) one can estimate that each operation implicates between 2,42 ($P_{auto} = 0{,}1$) and 7,66 ($P_{auto} = 1$) vehicles on average. Considering that cars can be moved either backward or forward and that this can be performed simultaneously, the waiting time to exit entails the movement of 2–4 cars on average. Regarding the economic cost, an average double parked car will end up starting between 6,6 and 15,6 times, driving a cumulative distance between 17,5 and 42,2 meters.

In the second scenario 765 cars arrive at an average rate of 306 cars/hour over an extended period (150 min on average). Now, the parking duration is 5 hours on average. This suggests that the occupation rate will be faster and also that once the parking is full, more cars will not find a space with respect to the first scenario. This is confirmed in Table 3, where row (a) shows that more than 80% of the arriving cars cannot find vacancies in the facility. Now the probability of a driver finding parking rises from 12,5% to 19,1% when all cars are allowed to double park.

Row 2 average usage ranged from 47,7 to 51,1 vehicles (142% of row 1 capacity). Autonomous double parking has increased up to 53,9% the number of vehicles that used the facility in the simulation. However, using the duration and arrival rate, we can go further in this reasoning. On average, after 2,5 hours, only half of the parking will have exited (as the average parking duration is 5 hours); then, dividing the number of cars that have used the parking (approximately 150) between the number of vacant spaces created from the beginning of the simulation (approximately 1,5 times its capacity, 153), it can be seen that the parking occupation consistently reaches the 98%. This result suggests that, effectively, the facility reaches full occupancy fast and remains saturated afterwards. Precisely, this fact also explains why, unlike the first scenario, the occupation in row 2 does not exhibit large variations with P_{auto}.

The number of gap operations remains approximately constant around 73. Since the average parking duration is 5

Table 2: Results, first scenario, 204 vehicles.

P_{auto}	0	0,1	0,2	0,3	0,4	0,5	0,75	1
(a) Parked	61,9%	64,6%	67,6%	72,3%	75,1%	77,8%	84,5%	91,5%
(b) Row 1 cars	126,2	127,1	127,5	129,6	127,7	127,2	127,3	127,5
(c) Row 2 cars	0,0	4,6	10,4	17,8	25,6	31,5	45,0	59,2
(d) Operations	0	12,5	24,2	40,2	54,1	63,4	80,3	87,3
(e) Starts	0,0	6,6	10,1	13,4	15,6	15,6	15,2	11,3
(f) Distance	0,0	17,5	24,9	30,8	35,5	35,7	42,2	33,1
(g) Autonomous	0,0%	99,6%	99,5%	99,4%	99,6%	99,1%	93,9%	91,5%
(h) Nonautonomous	61,8%	60,7%	59,9%	60,6%	58,5%	56,9%	55,7%	0,0

Table 3: Results, second scenario, 765 vehicles.

P_{auto}	0	0,1	0,2	0,3	0,4	0,5	0,75	1
(a) Parked	12,5%	18,6%	18,9%	19,0%	19,3%	19,1%	19,1%	19,1%
(b) Row 1 cars	94,9	94,0	93,6	94,9	95,6	94,7	94,5	94,8
(c) Row 2 cars	0,0	47,7	50,9	50,4	51,6	51,2	51,5	51,1
(d) Operations	0,0	69,7	73,2	73,5	74,8	72,8	73,8	73,2
(e) Starts	0,0	12,2	12,1	12,8	12,0	12,1	11,9	11,8
(f) Distance	0,0	34,6	38,8	44,7	41,9	44,9	44,7	46,6
(g) Autonomous	0,0	74,8%	45,7%	34,6%	29,3%	25,9%	21,4%	19,1%
(h) Nonautonomous	12,4%	12,3%	12,2%	12,3%	12,6%	12,2%	12,3%	0,0

hours, this is about one every four minutes. An operation involves about 8,2 vehicles on average, more than in the first scenario. This is traced back to the fact that row 2 is full for most of the simulation and, hence, space is more fragmented. Finally, an average double parked car ends up starting about 12 times as a result of gap creations, driving a cumulative distance between 34,6 and 46,6 meters. Again, differences with the first scenario can be attributable to the fact that cars are involved in more moves on average.

4.3. Discussion of Results. After analyzing the results from the two scenarios, the following points can be made:

(i) *Driver's Perspective.* Owners of autonomous cars will always find parking in the first two stages of the parking dynamics. In the two studied scenarios drivers of autonomous cars have at least twice more chances of finding parking than drivers of nonautonomous cars. In the first scenario, the probability of finding parking for a driver of an autonomous car is greater than 99%. Even with $P_{auto} = 0{,}1$ (which is more realistic in the short term), autonomous car drivers would have a considerable advantage in both scenarios. The cost of this advantage does not seem to be burdensome in terms of time to exit (i.e., waiting for 8 cars to move in the worst case) when compared with cruising somewhere else.

(ii) *Environment's Perspective.* Moving autonomous cars during gap creations can be seen as a cost. In our worst case scenario a car is moved 15,6 times on average (in 45 minutes) as a result of gap creations to perform very short movements, adding up to 46 meters. At any rate, failing to park implies cruising somewhere else which is likely a worse option in terms of emissions according to results shown in [10]. It is worth noticing that modern autonomous cars are expected to exhibit high standards of efficiency and emissions.

(iii) *City's Perspective.* In the studied scenarios, the addition of row 2 has increased the capacity of the parking facility about 50%, and its use has also increased over 45%. This extra capacity can be potentially extended to justified locations, encouraging a wider adoption of autonomous cars. This is aligned with modern approaches in parking policy as described by Mingardo et al. [9]: proactive management, improving the quality of life, and making massive use of IT to avoid unnecessary cruising.

5. Open Issues and Future Directions

This paper takes just a first step in suggesting a solution. Significant efforts have yet to be made by many actors to make double parking feasible. The following research directions or problems can be identified:

(i) *Application Protocol.* A standard vehicle-to-vehicle double parking protocol has yet to be developed and adopted by the industry. Current communication standards for Intelligent Transportation System (ITS) such as CALM [21] or WAVE [22] should provide support for this.

(ii) *Perception and Cognition.* More accurate (i.e., more than GPS) and reliable sensing of distance, self-localization, gap dimensions, obstacles (e.g., pedestrian position and velocity), and so forth has to be possible to implement the suggested solution. Artificial vision

and multisensor fusing are promising approaches in this field [23]. However, as stated in [24], "today's sensors are capable of collecting detailed data of a car's surrounding environment, but machine cognition and situational awareness are still in their infancy."

(iii) *Modeling and Simulation*. More complete simulations with finer models and calibrated with parameters extracted from real cases should be performed. Variations of the suggested operation could also be explored in order to improve the performance (e.g., simultaneous versus sequential movement, minimizing the distance instead of the number of cars).

(iv) *Problematic Situations*. Problems might occur when either autonomous cars do not cooperate or drivers of nonautonomous cars park in row 2. Potential problematic situations and its consequences should be carefully studied and remedies suggested to guarantee that cars parked in row 1 can always exit.

(v) *Regulations and Policy*. A case-based analysis should determine whether autonomous double parking is the best option for each location. A deeper study of the benefits and disadvantages of this practice (including sustainability) is needed in order to identify the constraints of the space of acceptable solutions. Existing restrictions (spatial, temporal) or parking pricing should be analyzed in the light of double parking. For instance, it might be helpful to apply a harder time restriction to double parked cars in order to achieve a higher turnover or make it free in order to foment its use.

6. Conclusions and Further Work

Autonomous double parking is a new idea which has the potential to benefit drivers, cities, and the environment under the right circumstances, which should be determined by a case-based cost/benefit analysis. Autonomous vehicles equipped with the suggested capabilities can save cruising time and emissions thanks to the increment of the parking capacity in locations in need for extra provision or by off-street parking owners. Indirectly, people are encouraged to buy more efficient cars, helping also in developing smart cities and benefiting the car industry. However, important technological advances and research are still needed to make autonomous double parking feasible down the road. Developing a widely adopted standard protocol and improving the sensing capabilities of present vehicles will be key in the success of this proposal.

We are presently working on creating simulations that use parameters calibrated with real cases on each scenario defined in Section 3 and more complete models (e.g., accounting for the traffic flow into and out of the parking area) which should provide richer results.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Research Article

Modelling the Effects of Parking Charge and Supply Policy Using System Dynamics Method

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Reasonable parking charge and supply policy are essential for the regular operation of the traffic in city center. This paper develops an evaluation model for parking policies using system dynamics. A quantitative study is conducted to examine the effects of parking charge and supply policy on traffic speed. The model, which is composed of three interrelated subsystems, first summarizes the travel cost of each travel mode and then calibrates the travel choice model through the travel mode subsystem. Finally, the subsystem that evaluates the state of traffic forecasts future car speed based on bureau of public roads (BPR) function and generates new travel cost until the entire model reaches a steady state. The accuracy of the model is verified in Hangzhou Wulin business district. The related error of predicted speed is only 2.2%. The results indicate that the regular pattern of traffic speed and parking charge can be illustrated using the proposed model based on system dynamics, and the model infers that reducing the parking supply in core area will increase its congestion level and, under certain parking supply conditions, there exists an interval of possible pricing at which the service reaches a level that is fairly stable.

1. Introduction

Parking policy is a direct and effective approach in traffic demand management [1]. It affects parking demand and travel state and helps ease parking difficulty and traffic in the central area of a city. However, predicting the actual benefits of the implementation of this policy is challenging. Thus, we should determine whether the new parking policy is more appropriate and effective than the currently implemented policy. Therefore, this study aims to analyze the influence of parking charge and supply policy on travel mode choice and road network state and to establish the relationship among parking policy, travel mode choice, and road network state.

Parking policy is implemented in two mechanisms: by changing the level or structure of parking charges and by altering the supply of parking spaces [2]. Reasonable parking charge and supply help alleviate parking and driving difficulties in the city center. The structure of urban traffic is a consequence of the cost of the different travel choices. Strict parking policy with high charge and low supply can reduce the volume of cars in the central area on one hand, but the parking search time will be prolonged for its low parking supply. This condition results in partial traffic congestion and entails high charges. On the contrary, flexible policy with low charge and high supply can increase the volume of cars that enter the central area and may also increase traffic congestion.

Parking policy has been extensively investigated in terms of its influence on various aspects and numerous advantages. The effects of parking policy not only on parking demand but also on the whole traffic system have also been widely explored.

Parking charge and supply policy are considered as two essential factors that affect parking behavior. Different parking policies, trip structure, public transit, traffic facilities, and other factors can influence parking demand distribution [2, 3]. As the two main forms of parking policy, parking charge and supply policy significantly affect parking choice [4–6].

The effects of parking charge and supply policy on traffic congestion have also been evaluated. Parking charge and

supply are considered the second most effective tool to alleviate traffic congestion, and they are easier to be carried out compared with congestion charging [7, 8]. Arnott and Rowse [9] and Cutter and Franco [10], respectively, established the relationship model of parking and traffic congestion. Cruising time is also crucial when parking management and traffic condition are optimized on the basis of parking policy [11, 12] because cruising time is a relevant factor of traffic congestion [13]. These models reveal the relationship between parking policy and traffic congestion in different aspects, but road network state should be further evaluated on the basis of parking policy.

Traditional four-stage modes or dynamic microsimulation models are costly and unsuitable for this study because parking policy implementation is a complicated process. Conversely, system dynamics [14, 15] is an approach to understand the nonlinear behavior of complex systems, and it is employed in public and private sectors for policy analysis and design. With its special advantages, a model with system dynamics is established to determine the complexity of parking policy and accept its dynamic characteristics. Bernardino and Hoofd [16] developed a model by applying system dynamics to assess the effectiveness of parking policy in predicting traffic congestion and speed, but this model has failed to quantify travel cost. The types of policies are mainly associated with parking price, whereas parking supply is rarely considered. Therefore, the present study explores the actual state of traffic in terms of the effects of parking charge and supply by using a discrete choice model. Our results will provide a scientific basis for traffic management.

Different parking policies directly influence travel cost, which possibly affects the choice of travel mode and travel structure. Also, travel mode choice contributes to the condition of road network state, which also influences travel cost accordingly. Therefore, travel cost is related to travel mode choice and road network state. This study aims to evaluate the influence of parking policy on road network by identifying the relationship among the three factors.

Travel cost is a decisive factor of trip decision and directly influences the choice of travel behavior. Since the 1970s, travel costs have been quantified in monetary terms [17]. On a microperspective, studies on travel cost aim to evaluate the traveler's choice of travel mode. Travel time and travel cost are considered, and travel cost is calculated by using travel time values based on random utility theory in a travel mode choice model [18]. In addition to studies on the travel cost of one trip, research on travel cost quantification based on a trip chain has been performed [19].

Since the early 1960s, factors influencing the changes in modes [2], especially between car and public transport modes, have been investigated. The main models include discriminant model [20], probit model [21], and logit model [5, 22]. The effects of policy or other factors on the choice of travel behavior have also been analyzed on the basis of a logit model.

Travel mode directly affects the traffic flow on a road network and the state of the road network [23]. Changes in the travel mode choice can effectively alleviate regional traffic, and parking policy is an effective method to alter the travel mode choice [24].

Therefore, this paper proposes a method to estimate the travel mode choice based on travel cost as influenced by parking policy. The travel cost of various travel modes is selected as basic variables, and travel mode choice is subjected to multivariate logit model analysis. A prediction method is also established to estimate the average speed of road network based on the current network speed, which greatly minimizes the difficulty in investigating the condition of network model calibration and evaluation. The proposed method can determine the dynamic travel cost, identify the travel choice for network speed prediction, and provide a scientific basis for parking demand management.

The major contributions of this study are described as follows:

(1) An evaluation model of the combined effects of parking charge and supply policy is proposed. The model contains three subsystems to calculate travel cost, make a travel choice based on travel mode, and evaluate the traffic state under parking policy.

(2) The travel cost of each travel mode is chosen as the basic variable because travel cost is the basis for travel choice analysis, and the essential difference among various carriers is travel cost that includes direct and indirect costs.

(3) This paper presents a method to predict the future road network speed after the new parking policy is implemented on the basis of the current traffic state. The model can continuously determine dynamic variables, such as travel cost and travel mode distribution, to predict road network speed, which provides a scientific basis for parking demand management.

This paper is organized as follows. Section 2 describes the structure of the three subsystems in the evaluation model in detail. Section 3 verifies and discusses the effectiveness of the proposed method based on future parking policy simulation. Section 4 presents the conclusions.

2. Model Development

2.1. Parking Charge and Supply Policy Evaluation Model. This model aims to study the state of traffic under the influence of parking charge and supply policy in a certain district. Usually, alleviating traffic congestion in the city center, especially in the center business district (CBD), is the purpose of related policies. So, the center business district is chosen as the study area.

The effects on the traffic of the parking policy are complicated process, and the affected objects are potential parking lot users. The four-stage model is not suitable to analyze the effects of policy on the traffic system. But system dynamics make it possible to understand the complicated process. For its special advantages, a model using system dynamics that can capture the complexity of parking policy while accepting its dynamic characteristics is built in this paper.

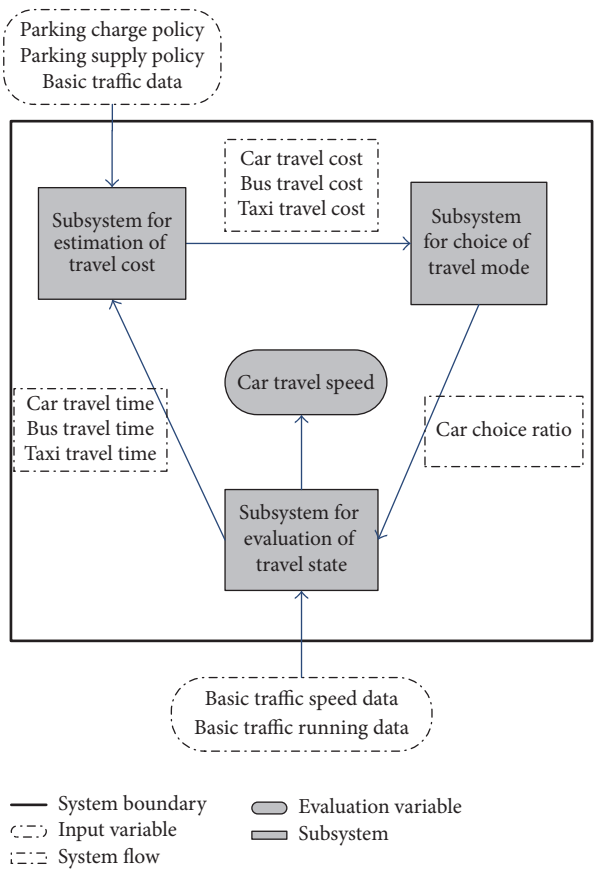

Figure 1: Evaluation model of the combined effects of parking charge and supply policy.

For the convenience of research, several assumptions are made in the evaluation model as follows:

(1) The total travel demand in the study area is fixed, but the choice of travel modes is flexible.

(2) There is no bus lane or rail transit in the study area; public transportation only contains bus transit.

(3) The travel speeds of cars and buses interact with each other and are treated as the same.

The model is composed of three subsystems, namely, subsystem for estimation of travel cost, subsystem for choice of travel mode, and subsystem for evaluation of traffic state. The structural diagram of evaluation model is shown in Figure 1.

The variables of the model, like the traffic speed, parking supply ratio, time value, and others, are chosen as the average value. According to the structural diagram of evaluation model in Figure 1, the variables in the model can be classified into input variables, flow variables, and output variables. The input variables include three parts. Firstly, parking policy variables such as parking charge and parking supply are necessary to evaluate the effects of parking policy. Secondly, three travel modes, which are car, bus, and taxi, are considered in the travel mode choice subsystem according to Figure 1. And to estimate the travel cost, fuel price, taxi fee, average time value, and some other variables connected to the cost need to be considered. Lastly, to evaluate the travel state, traffic characteristic variables such as free-flow speed and initial bus speed should be taken into consideration. The flow variables of the model include the travel cost of different travel modes, car's travel time, and congestion level. The output variable that measures the service level of traffic is the travel speed of cars.

A typical trip can be classified into two types, namely, commuting trip (going to work, school, or home) and extra trip (going to shops, entertainment centers, or restaurants). The parking place for a commuting trip is usually the parking lot annexed to the companies or villages. The parking fee for this kind of trip is free or paid monthly and is not significantly affected by policies. Therefore, the presented model focuses on extra parking behavior.

2.2. Subsystems of the Model

2.2.1. Subsystem for Estimation of Travel Cost. Travel cost is the basis of analysis in making travel choices. The subsystem for estimating travel cost aims to turn the indirect cost of each travel mode into money. This subsystem combines the travel cost of each travel mode with direct cost.

The fee for traffic instruments is only trip consumption that can be directly felt by travelers. The subsystem for estimating travel cost can provide a quantitative index that enables travelers to evaluate the quality of travel mode.

Direct cost is the direct money expenses on one trip, including the fee for traffic instrument, parking fee, and oil consumption. Indirect cost includes time cost, comfort cost, and time reliability cost. Time cost means the maximum return that a traveler can obtain from the time lost on one trip. Time reliability cost is the cost of time reserved by travelers because they cannot predict an accurate travel time on one trip. Comfort cost includes the cover of vehicles, the degree of congestion, and other factors that have a direct relationship with the current high vehicle ownership in large cities.

Residents can choose from several modes of travel, such as cars, buses, taxis, and subway, but this study does not calculate all kinds of travel cost in the model. Only four main types of vehicles are used: cars, taxis, nonmotor vehicles, and buses. Only cars, taxis, and buses are affected by the state of traffic. Traffic congestion increases these three travel choices and raises their travel cost, but it does not affect nonroad travel choices such as the subway. So, the travel cost subsystem calculates the travel cost of cars, taxis, and buses only. The diagram of estimating car travel cost subsystem is displayed in Figure 2.

In Figure 2, to calculate the car travel cost, several main parts, including parking cost, parking search time cost, travel time cost, fuel cost, and car reliability cost, are taken into consideration. Similarly, when it comes to bus travel cost, bus travel time cost, bus ticket, walking, and waiting time cost, bus reliability cost and bus congestion cost are considered. For taxi travel cost, taxi travel time cost, waiting time cost, taxi fee, and taxi reliability cost are considered.

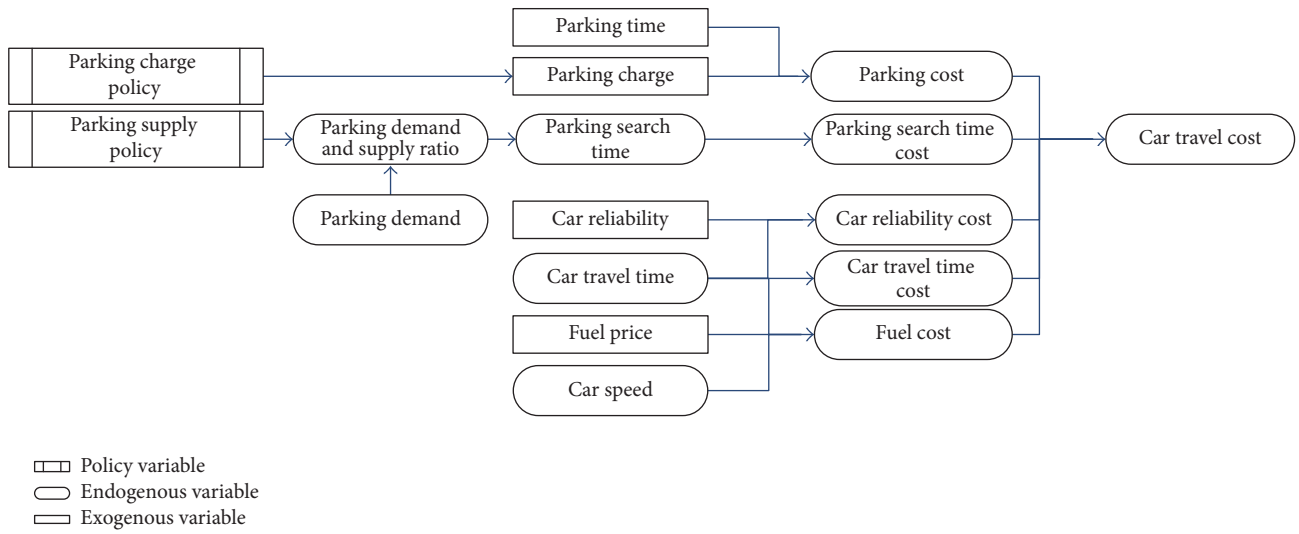

Figure 2: Subsystem for estimating car travel cost.

The main parameters of the subsystem that estimates time cost are described as follows.

(1) Time Value. According to the World Bank [25], the travel time value p_v of adults in extra trip is 0.3 times the hourly wage. Parking search time, walking time, and waiting time value can be treated as 1.5 times the value of travel time. The rate of car load is denoted by C_f, travel time of road a at moment t is t_a, and the standard deviation of travel time is σ. Congestion cost T_{cc} [26] and reliability cost T_r [19] are denoted as

$$T_{cc} = \begin{cases} 0 & 0 \le C_f \le 0.8 \\ \sum_a t_a 0.55 \left(C_f - 0.8\right) e^{-0.74(C_f-0.8)^2 p_v} & C_f > 0.8, \end{cases} \quad (1)$$

$$T_r = 1.77 p_v \sigma.$$

(2) Fuel Cost. If the car average speed is denoted by v, fuel price is P_f, and total time on one trip is T; then fuel cost T_f [27] is

$$T_f = \begin{cases} \left(5.143 - 0.077v + 0.001v^2\right) \times P_f \times T & \text{normal} \\ \left(5.917 - 0.127v + 0.002v^2\right) \times P_f \times T & \text{peak}. \end{cases} \quad (2)$$

2.2.2. Subsystem for Choice of Travel Mode. The function of the subsystem for travel mode choice is to calculate the ratio of car choice to the travel cost of each travel mode in an extra trip using the logit model.

Logit function is used to predict the travel choice distribution in the model. The logit model does not require a simulation method. This model is used widely in the predicting travel mode choice. The research objects of this study are car, taxi, bus, and other travel modes. The diagram of this subsystem is displayed in Figure 3

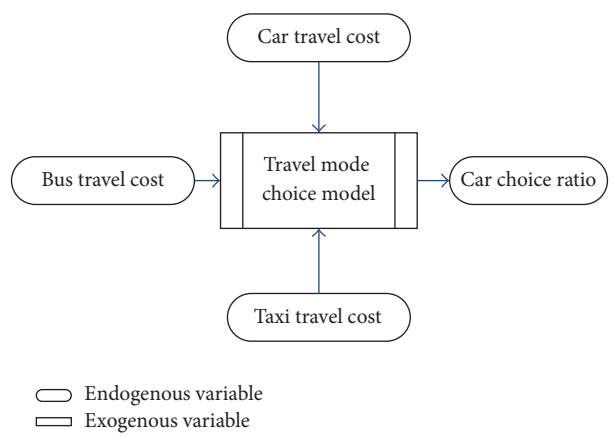

Figure 3: Subsystem for the choice of travel mode.

We take residents who have travel demands in a district as a collective. The basis for the travel mode choice i of each person in the collective is the maximum mode utility U_i. The factors that affect U_i include parking price and bus service level. The influencing factors can be divided into travel cost factor V_i and random factor ε_i. Utility function U_i is

$$U_i = V_i + \varepsilon_i. \quad (3)$$

The logit model assumes that random factor ε_i obeys the Gumbel distribution. Thus, the probability of travel mode choice i is

$$P_i = \frac{e^{U_i}}{\sum_{j \in S} e^{U_j}}. \quad (4)$$

The effects of travel costs on travelers are different considering the developing levels of different cities. Thus, the influence

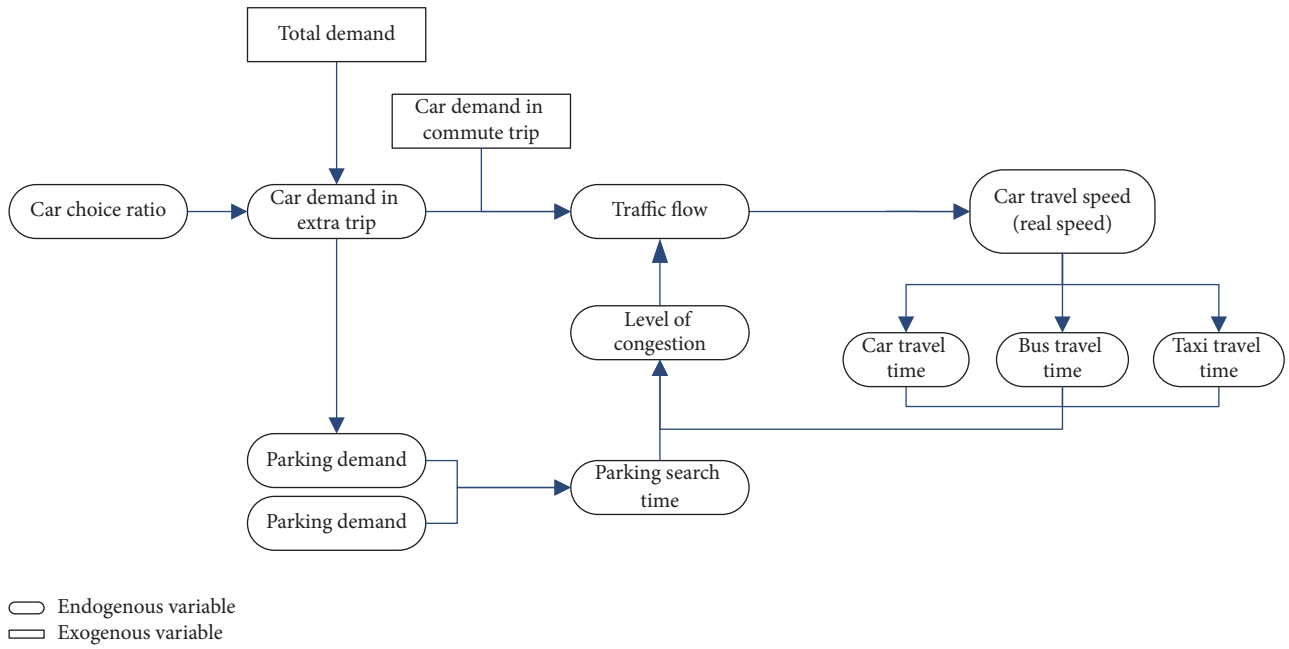

Figure 4: Subsystem for evaluating the state of traffic.

coefficient η_i is the corresponding parameter for travel mode i, and C_i represents the total travel cost of travel mode i. Then, the travel cost factor V_i can be denoted as

$$V_i = \eta_i C_i. \tag{5}$$

Car choice ratio in an extra trip after the new parking policy can be calculated according to the current travel mode distribution and the new parking policy.

2.2.3. Subsystem for Evaluation of Traffic State. The function of the subsystem for evaluating the state of traffic is to forecast a car's travel speed using the car choice ratio. The detailed process of evaluating traffic state subsystem is shown in Figure 4.

The main relationships in the subsystem for evaluating the state of traffic are as follows.

(1) Relationship between Car Choice Ratio and Car Travel Speed. Data on traffic demand and capacity of the road network of Hangzhou have no current records, and accurate values are difficult to obtain. Nevertheless, an existing real-time system can record the average travel speed in the Hangzhou road network, and the data are more complete. A series of unchanged data, such as total demand in commute trip and capacity of road network, can be reduced by comparing the state of traffic. Future car travel time after changes in charge policy can be predicted by the change in travel choice ratio and the current travel speed of car. Parking search time has been seen as an important part when analyzing the traffic congestion. In the next part, the effects of parking search time on traffic congestion are discussed and parking search time is taken into the model. The relationship between travel mode distribution and travel speed is illustrated in Figure 5.

This study focuses on the evaluation of parking charge policy for public parking lots. This policy mainly affects extra trips. The effect of the policy on commuting trips is small. Thus, only the changes in traffic demand for extra trips are considered in later calculations. The traffic demand of one commuting trip is considered constant.

The average speed of the Hangzhou Traffic Congestion Index System is selected as the measured speed in this article. Assuming that the current total number of cars in a region is N, the measured speed is V, the total length of road network in the region is L, and the average flow in a region can be written as

$$Q = \frac{N \times V}{L}. \tag{6}$$

According to the model for road resistance function (BPR function) of the American Federal Highway Administration, the relation between traffic flow and average travel time can be written as

$$\frac{1}{V} = \frac{1}{V_0}\left[1 + \alpha\left(\frac{Q}{C}\right)^{\beta}\right], \tag{7}$$

where V_0 is the free-flow speed, C is the actual capacity in the region, and α and β are the model parameters. According to the American Federal Highway Administration, α and β are the parameters in BPR function and have default values of $\alpha = 0.15$ and $\beta = 4.0$. The ratio of the congestion degree between the current situation and the situation after the parking charge policy changes in a region can be written as follows:

$$\frac{Q/C}{Q_x/C} = \frac{Q}{Q_x} = \sqrt[\beta]{\frac{V_0/V - 1}{V_0/V_x - 1}} = \frac{N \times V}{N_x \times V_x}, \tag{8}$$

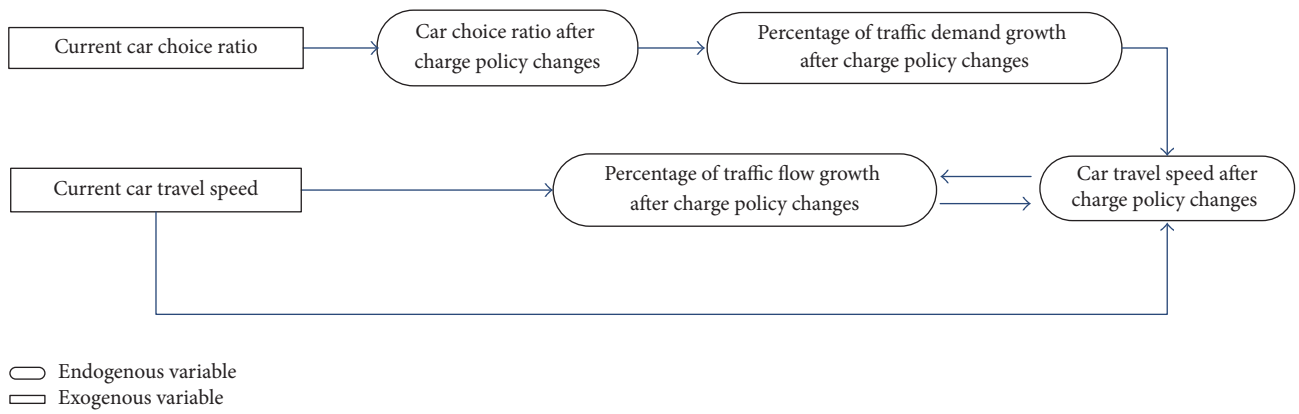

Figure 5: Relation between travel mode distribution and travel speed.

where Q_x, N_x, and V_x are the traffic flow, total number of cars, and average travel speed, respectively, under the condition of changes in parking charges. Measured speed V_x after changes in the policy for parking charges can be calculated as

$$\frac{{N_x}^{\beta}\left(V_0 - V\right)}{N^{\beta}V^{\beta}}{V_x}^{\beta+1} + V \times V_x - V_0 \times V = 0. \quad (9)$$

So, (9) is a multidegree univariate polynomial equation about V_x. If the total number of cars before and after the charge policy changes, the current travel speed, and a series parameter are determined, travel speed V_x after the charge policy changes can be solved using the Matlab program.

(2) Effect of Parking Search Time on Traffic Congestion. When parking facilities become saturated, search circuits and cruising flows increase traffic congestion when vehicles search for parking space on the road. Assuming that parking search time is T_s and car travel time on one trip is T, then the total number of cars N_s that have been added to the number of searching cars on the road is

$$N_s = N\left(1 + \frac{T_s}{T}\right). \quad (10)$$

Parking search time and the ratio of parking supply and demand have an exponential relationship [16] as shown in Figure 6.

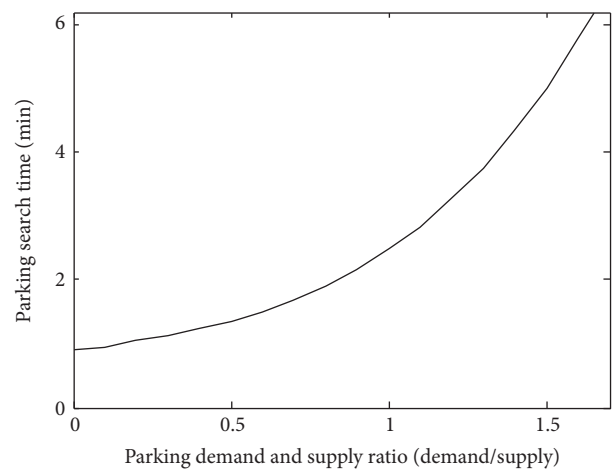

Figure 6: Relation between parking search time and parking demand and supply ratio.

3. Case Analysis

To verify the accuracy of the suggested model and to evaluate future policy, this article takes Wulin CBD in Hangzhou as the study area. The area of Wulin CBD is approximately 18.8 km^2 and the population is about 0.65 million. The road networks data are the average in Wulin CBD. Data are collected from the Hangzhou Bureau of Statistics and parking survey information. Parking fee data are obtained from the Hangzhou Price Bureau.

3.1. Parameter Calibration

(1) Travel Cost of Different Travel Modes. The average wage of a Hangzhou on-the-job worker in 2014 is 9794.5 \$, the hourly wage is 4.63 \$/h, and the corresponding time value is 1.41 \$/h. The travel cost of three types of travel mode is calculated in Table 1.

v is the average speed in the area (km/h), T is the total time for this travel mode on one trip (h), P_c is the parking fee (\$/h), T_p is the total parking time on one trip (h), and T_s is the parking search time (h). $\lceil\rceil$ is always rounded down to the nearest whole unit.

(2) Parameters of Travel Mode Choice. According to some relevant documents from the Hangzhou Price Bureau, parking fee in the core zone was 0.92 \$/h before the new parking policy took effect. After the implementation of new parking policy, parking fee for the first hour has increased to 1.54 \$ and the follow-up time is 1.95 \$/h. According to the data of the Hangzhou Comprehensive Transportation Research Center, the average travel distance in Hangzhou is 8.19 km, average parking time is 2.17 h, average travel speed in the core zone

Table 1: Travel cost of all types of travel mode.

Travel mode	Travel cost (dollars)
Car	Off-peak: $(5.143 - 0.077v + 0.001v^2)1.01T + P_cT_p + 1.41T + 0.25T + 2.12T_s$ Peak: $(5.917 - 0.127v + 0.002v^2)1.01T + P_cT_p + 1.41T + 0.25T + 2.12T_s$ Fuel cost + parking cost + travel time cost + reliability cost + parking search time cost
Bus	Off-peak: $0.30 + 1.41T + 2.12 \times (7.3 + 5.9)/60 + 2.12 \times 10.4/60 + 0.33T + 1.01T$ Peak: $0.30 + 1.41T + 2.12 \times (7.3 + 5.9)/60 + 2.12 \times 10.4/60 + 0.33T + 0.91T$ Bus fare + travel time cost + walking cost + waiting time cost + comfort cost + reliability cost
Taxi	$\lceil 3.45 + (T - 0.56)/26 \rceil + 1.41T + 2.12 \times 5/60 + 0.25T$ Taxi fare + travel time cost + waiting time cost + reliability cost

Table 2: Distribution of extra and commute trips.

	Car	Bus	Taxi
Extra trip proportion	26.44%	19.10%	1.26%
Commute trip proportion	11.01%	21.53%	1.05%

Table 3: Coefficient of travel cost of all types of travel mode.

	Car	Bus	Taxi
Travel cost influence coefficient	−0.1061	−0.4921	−0.1133
Constant term		0.8787	

before the new policy implementation is 18.83 km/h, parking demand and supply ratio is 1.05, and extra trip proportion is 20%. The distribution of the different travel mode choices is shown in Table 2.

In order to investigate the sensitivity to parking charge increasing of travelers, a questionnaire focused on extra parking behavior is designed in this study. We used the investigation method combining RP survey and SP survey [28]. RP survey mainly contains the traveler's travel choice, travel distance, reasons for parking choice, and so forth. And SP survey investigates the preferences of travelers under the hypothesis that parking charge increases in different levels.

The survey issued a total of 350 questionnaires; for the reason that this study focused on extra parking behavior, a total of 200 valid samples were recovered. Based on the 200 questionnaires obtained from the survey on parking behavior, 10.5% of vehicle drivers choose other ways to travel when the parking fee increased to 2.31 \$/h, and the percentage increases to 22.5% when the parking fee increased to 3.08 \$/h

Through the travel cost estimation subsystem, we can obtain that the car travel cost is 7.50 \$ at peak hours when the parking fee in the core zone was 0.92 \$/h, and it rises to 9.20 \$ after the implementation of the new parking policy. Also, if the parking fee increases to 2.31 \$/h, the car travel cost is 10.51 \$.

Using the logit model in the travel mode choice subsystem, we can obtain the following two equations:

$$\frac{\exp(7.5\eta_c)}{\exp(7.5\eta_c + C)} = 26.44\%,$$
$$\frac{\exp(10.51\eta_c)/\exp(10.51\eta_c + C)}{\exp(9.2\eta_c)/\exp(9.2\eta_c + C)} = 1\text{–}10.5\%, \quad (11)$$

where C is a constant which represents the travel costs of other travel modes except cars, such as bus and taxi. By calculating (11), we can obtain that $\eta_c = -0.1061$ and $C = 1.2445$. So, car travel cost influence coefficient is −0.1061. Similarly, the coefficient of other travel costs is calculated in Table 3.

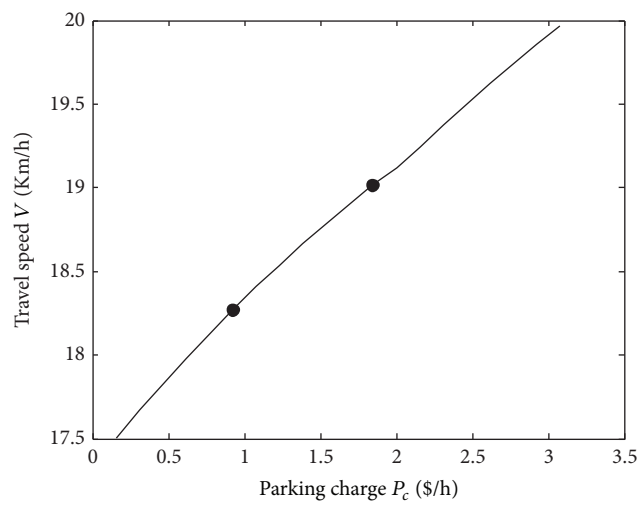

Figure 7: Relation between parking charge and travel speed.

3.2. Model Validation. The new parking policy in Hangzhou was implemented on 25 August 2014. The road network data before and after the policy implementation can be used to detect the accuracy of the suggested model. According to the data from the Hangzhou Comprehensive Transportation Research Center, the average travel speed in the core zone before the implementation of the new policy is 18.83 km/h (based on three consecutive Tuesday mornings peak data in May 2014). The average speed after the implementation of the new policy is 19.16 km/h (based on three consecutive Tuesday mornings peak data in October 2014). To calibrate the parameters α and β in the BPR function, the measured traffic flow data in the study area are used to fit the BPR function. After function fitting, the parameters α and β are chosen as 0.5 and 4.0, respectively.

The current travel speed in the Hangzhou core zone was used as basic data. The relation between parking charge and travel speed is simulated in Figure 7.

Table 4: Simulation of effect of different policies.

Parking policies	Current situation	Decreasing supply (−20%) Charge unchanged	Increasing supply (+20%) Charge unchanged	Supply unchanged Increasing charge to 3.07 $/h
Travel speed (km/h)	19.16	18.80	19.54	20.31
Parking search time (min)	2.66	3.59	2.15	1.99

According to the model, the average travel speed before the implementation of the new policy is 18.39 km/h. Back-stepping was performed and showed a relative error of 2.2% compared with the actual travel speed.

3.3. Future Parking Policy Simulation and Discussion. Policy simulation predicts the possible influence of the parking policy on the road network after the implementation of the new policy according to the actual situation and development direction of Hangzhou. According to the current version, the total number of vehicles in Hangzhou will continue to increase for a long period in the future. Therefore, parking policy in the core zone should focus on improving the level of network service. Increasing the parking supply or lowering the parking fees increases parking demand, thus increasing the congestion degree in the core area. On the other hand, increasing the parking supply will reduce parking search time on the road. So the effect on the level of network service remains uncertain.

Parking policy can be divided into three categories: decreasing supply, increasing supply, and increasing parking charge. The effects of different policies after the policy implementation are evaluated though travel speed. The simulation travel speed under several specific policies is shown in Table 4, and the relationship between parking charge, parking supply, and travel speed is illustrated in Figure 8.

According to the results of the simulation, we can see the following from the table and the figure:

(1) Decreasing supply on the basis of current situation will reduce the number of vehicles in core area, but the parking problems will be more prominent. Also, parking search time on the street will be longer which will increase congestion and the average travel speed will decline.

(2) Increasing supply on the basis of current situation will attract more vehicles in core area, but for the reason of its convenience of parking and less parking search time, the network average travel speed has a small rise. However, this policy is difficult to achieve for the land use restrictions in core zone.

(3) When parking supply continues to increase, the traffic system travel speed will show a trend of slow decline after reaching an extreme value. This result is not difficult to imagine for the attraction of a large number of vehicles into the core area due to the less travel cost.

(4) Changes in parking fees allow the emphasis on the use of pricing which is critical in obtaining the best performance of the traffic system. In this model, the losses in average travel speed incurred by not applying a price will reach 16%. A curious outcome is that the performance achieved is better with very high prices than with a zero price alternative.

(5) An interesting finding is that, under certain parking supply conditions, there is an interval of possible pricing at which the travel speed reaches a level that is fairly stable. In the traffic system well illustrated by this model, politicians would rather keep prices at high levels in order to optimize the city traffic system service level, but under public acceptability constraints they would rather keep prices at low levels of this interval, which may ignore the other possible targets, such as reducing air pollution or releasing of public space.

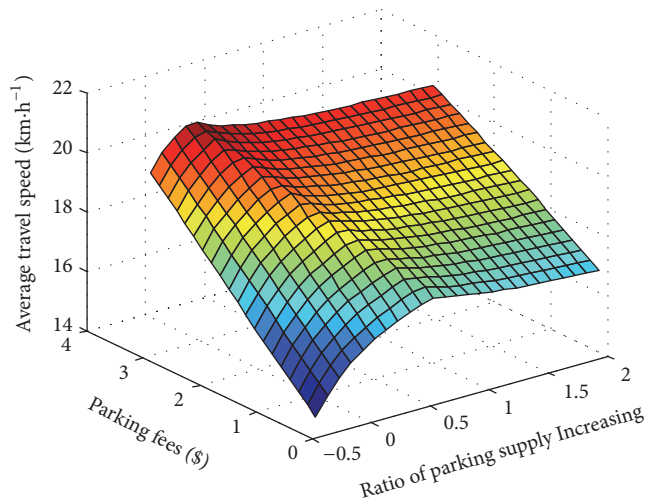

Figure 8: The relation between parking charge, parking supply, and travel speed.

4. Conclusion

With the emergence of new technological possibilities and political considerations, the present use of parking-based policy instruments as a response to urban problems of road congestion has been paid more and more attention. Because the parking policy is an instrument to manage the urban road demand, it is necessary to consider the aggregate traffic flow behavior. However, due to the complexity of the traffic system, it is difficult to directly estimate the effect of the implementation of the parking policy. Therefore, it is

necessary to make use of the method of system dynamics to simulate and predict the effect of policy implementation.

This paper aims to build a simulation model that can be used to evaluate the effects of different parking policies. This article verifies the model using the basic data of a road network before and after implementation of parking policy in Hangzhou. This study simulates the effects of different parking policies on the simulation results obtained with different objectives. The maximum average speed can be obtained with a price for parking. Decreasing supply on the basis of current situation will increase the parking search time, which will cause traffic congestion. And increasing parking supply will produce limited benefits.

This study focuses on the average travel speed in a certain area and does not forecast some parameters of a specific road. The case of application parameterized and successfully calibrated the model with available local data, but the efficiency of parking supply policy has not been confirmed by the actual data, and the parameters affecting the parking search time should be more specific in future studies.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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