

RESEARCH ARTICLE

An Evaluation of Temporal- and Spatial-Based Dynamic Parking Pricing for Commercial Establishments

ELMER R. MAGSINO¹, (Member, IEEE), GERALD P. ARADA¹, (Member, IEEE),
AND CATHERINE MANUELA L. RAMOS²

¹Department of Electronics and Computer Engineering, Gokongwei College of Engineering, De La Salle University, Manila, Philippines

²Department of Manufacturing Engineering and Management, Gokongwei College of Engineering, De La Salle University, Manila, Philippines

Corresponding author: Elmer R. Magsino (elmer.magsino@dlsu.edu.ph)

ABSTRACT All smart parking management systems (SPMS) have incorporated the dynamic pricing into its features and capabilities. The collection of parking fees on a corresponding spot has been dependent on either its time- or space-value, with most SPMS utilizing temporal-based parking fee collection. However, little to no study has been conducted to assess or evaluate these pricing schemes according to its friendliness and economics towards both parkers and business operators. In this work, we evaluate two current temporal- and three proposed spatiotemporal-based dynamic parking pricing methods by computing their social optimum range and economic effects to both users and parking management entities. Our extensive analysis utilizing both empirical mobility traces and driver parking duration behavior provide important insights in the current pricing setups and present necessary adjustments in improving parking fee collection that contribute to societal benefits.

INDEX TERMS Dynamic parking pricing, fixed, linear, min-max, adaptive, complementary rate pricing.

I. INTRODUCTION

While the number of vehicles on the road increases exponentially, transportation infrastructures such as roads, highways, and parking spaces remain relatively constant and are becoming scarce. As the ratio of vehicles to infrastructures is getting larger, managing transportation structures becomes imminent, e.g., optimized traffic flow in highways [1], reduced or minimized road accidents [2], and optimized usage of parking lots [3]. In efficiently managing car garages, one way of reducing congestion and maximizing space usage is the imposition of tariffs and collectible fees from vehicles. When using vacant and available parking lots, appropriate and dynamic pricing fees are applied to discriminate parkers and allow congestion control. For example, commercial establishments offer self-service, valet, and online reservation parking [4]. In the collection of appropriate parking dues, some previous studies included the walking distance covered, reservation,

and estimated time of arrival in their parking payment [5] and cruising time and parking limitations [6].

With the advent of sensor electronics, wireless technologies, and cloud computing, there has been an abundance of published smart parking management systems (SPMS) aimed in pollution reduction and user convenience in their smart parking management system [7]. Most of all, SPMS should maximize profit and optimize vacant space usage [8]. In maximizing parking revenues, dynamic pricing has been implemented that considers both the temporal and spatial values of a parking slot, such as peak and off-peak hours, and street and covered parking areas [9].

While these SPMS provide optimal solution to their respective objectives, pricing has always been biased towards business operators, which, understandably be the case since they can dictate the price of their own properties. However, there is no existing study yet that evaluates and analyzes the various parking price friendliness to parking users, or how can it be sustainable to the parkers. Empirically, land properties appreciate in value, therefore, parking fees will definitely increase as time goes on. Given this land appreciation,

The associate editor coordinating the review of this manuscript and approving it for publication was Ajit Khosla¹.

we evaluate these dynamic parking pricing schemes and provide decision-making criteria that will allow users to avail or not to avail the parking space any time of the day, and even decide based on a monthly basis what will be their chosen car garage for work or leisure. In this work, we define the parking price as the payment of a user for the time duration in the parking facility. The time duration includes the following activities, namely, 1) upon entry at the garage toll booth, 2) searching for a parking space, 3) parking appropriately, 4) attending to the day's business, 5) returning to the vehicle, and 6) leaving the parking premises. We disregard the total travel time from origin to a parking slot and the online reservation system.

Under the premise that the number of parking spaces are fixed and depleting, we extend the analysis of our earlier work [10] by categorizing dynamic parking pricing methods according to its time and space-time dependence values, thereby, assessing five dynamic parking methods. To make the evaluation realistic and extensive, we employ various parking duration behaviors based on empirical mobility traces, survey, and long-duration parking scenarios. We then compared each pricing method based on various performance metrics. The framework of our evaluation is shown in Figure 1.

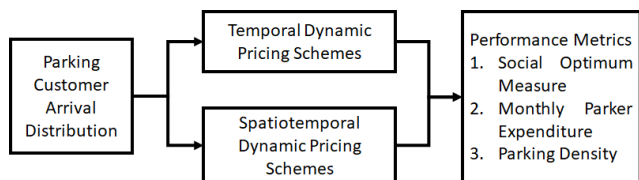


FIGURE 1. Framework for the assessment of various temporal and spatiotemporal dynamic parking schemes.

Since we do not present any ‘smart’ features, this work is fitted for parking businesses and commercial centers unwilling to upgrade their car park infrastructures and simply rely on optimal fee collection that is beneficial also to parkers. The major contributions of this paper are enumerated below.

- 1) We evaluate two existing parking pricing schemes and propose three alternative techniques that consider time and space values of an available parking space. These five schemes do not need to introduce any large capital expenditures to modify their existing parking business. In order to gauge the effects of these prices on both users and businesses, the social optimum range for each pricing is calculated, and the bias of the average earning is checked. For a given set of parking rate constants, if the observed social optimum is less than the average, then we conclude that the established parking rate is parker-friendly, otherwise, business-friendly.
- 2) Through an online survey, we present a lognormal distribution of the parking duration behavior from 246 respondents. To the best of our knowledge, this is the first research work to provide an empirical

parking duration behavior from commercial establishment users that can serve as a benchmark for further understanding and studying parking duration behavior.

- 3) Extensive simulations employing empirical mobility traces and parking duration have been implemented to compare and evaluate the proposed pricing schemes. We also incorporated a synthetic human behavior of long-duration parking to foresee its effects to business and user.

The paper is outlined as follows: Section II discusses the published works related to dynamic pricing involved in parking management. We also state here that while these papers discussed dynamic pricing, there is no literature that compares the friendliness of such methods to the users. To allow realistic vehicular parking traces, we utilized the taxi GPS traces in Section III. In Section IV, we present the dynamic parking pricing schemes that will be evaluated in this study. We also present here two alternative pricing based on spatial and temporal values. To provide a common ground of comparison, we derived the social optimum range for each parking pricing scheme. This is presented in Section V. We then present the results of our extensive simulations in Section VI. Finally, we conclude our work in Section VII.

II. REVIEW OF RELATED LITERATURE

In this section, we provide a brief literature review of papers discussing how parking management systems determine their pricing method. In these previous studies, it is accepted that the number of available spaces that can be used by parkers are always static and scarce, thus, there is a need to dynamically allocate these fixed resources. It is in this line that most research papers have focused their work and based their pricing policies.

In [11], a demand-driven dynamic parking pricing has been studied on the street parking slots in Beijing. The pricing scheme was based on traffic performance and current parking demand. Ref. [12] included additional charges in collecting parking fees such as, vehicle type and miscellaneous. The work presented seven dynamic pricing schemes but were only differentiated by its introduced price adjustment and occupancy rates. On the other hand, pricing schemes in [13] are based on linear and exponential reservation demands, and not on walk-in customers, aimed at maximizing revenues and minimizing cruising cost.

Three pricing schemes, based on space occupancy, were assessed in [14], where the proposed new scheme focused on price variation based on peak periods. This was also the criterion employed in [15] in developing their reactive and proactive pricing schemes. In [16] and [17], a bidding process took place when the number of parkers was more than the number of available parking slots. The maximum revenue was chosen from these requesting parkers. Similar to this process was found in [18], except that parking owners were the ones proposing time-differentiated parking fee rates to surrounding customers. In [19], parking fees were

based on the cumulative effect of many factors, such as distance-to-slot, remaining free slots, traffic density, and parking duration. This was also the case considered in [20]. Instead of these factors, [21], determined their parking fees based on the parking status and utilization rate of member establishments. Accordingly, the price can increase or decrease depending on the parking system losses.

The parking pricing fees in [22] implemented a linear rate collection for both autonomous and regular vehicles by considering both parking duration and location. In another work, [23], the parking fees were recalculated daily based on the parker's travel information and focused more on driver benefits rather than establishment revenue. Different from these research works, the pricing policy in [24] was based on a regional distribution of parking lots and fine-grained durations. The policy changes saw an increase in the normal parking fees being paid by the user. In [25], a study was also conducted on the effects of the pricing changes and was used to develop a Gaussian model for locations with similar demands. Finally, [26] incorporated game theory in obtaining its parking fee with government agencies, drivers, and parking firms as the players involved.

Machine learning was used in determining occupancy-based parking prices for various parking lots in Seattle. Compared to two benchmarks, this pricing method provided the largest city revenue [27], [28].

We differentiate our work from these papers in three ways. Firstly, we focus only on the evaluation of current parking pricing schemes implemented by business entities, excluding the infrastructures. We evaluate the parker friendliness of the fees from each scheme based on its social optimum range, which is lower- and upper-bounded by the optimal user parking fee rate and maximum earning per user, respectively. We also suggest new dynamic schemes that consider both the spatial and temporal values of the available parking spaces while at the same time can be considered user-friendly.

Secondly, we only focus on the scenario when a vehicle is already entering the chosen parking garage, thereby, neglecting the cruising, network traffic congestion problems, and online reservations, effectively, eliminating accurate modeling of these activities. Also, we provide the parking duration behavior probability distribution of mall goers based on an online survey.

Lastly, most efficient parking system covers the period from reservation to the arrival, i.e., a full system analysis of the parking scenario. This entails a lot of back- and front-end re-designing of an existing parking system, plus, the accurate modeling of the traffic flow from an origin to its parking destination. However, our evaluation does not entail any changes in the parking infrastructure of a business center, because they can only change their parking fee structure on the fly, while just placing a billboard informing the users how their dynamic parking pricing schemes works. Our work also excludes the need to accurately model the various traffic conditions surrounding a parking lot.

III. MOBILITY DATASET

In evaluating the current and proposed dynamic pricing schemes, we utilize empirical mobility taxi datasets roaming an urban city from [29] to mimic vehicles looking for a parking space, while at the same time, disregard traffic modeling. The parking buildings are set to be located at the intersections, for simplicity of evaluation, but can easily be adjusted once participating parking businesses have been identified. This method of assuming parking locations is applicable to places where empirical parking data from commercial establishments and buildings are inaccessible or difficult to obtain, e.g., in the Philippines.

The Beijing City taxi mobility traces are arranged per taxi ID and sampled every 10 seconds for seven days. A taxi ID has many trajectories, τ_{ID} , composed of GPS coordinate points, λ_e , such that $\tau_{ID} = (\lambda_S, \lambda_2, \dots, \lambda_e, \dots, \lambda_E)$. λ_S and λ_E are denoted as the start and end points, respectively, $\lambda_e \in \mathbb{R}^2$ is a tuple $\{lat, lon\}$ where *lat* and *lon* are the latitude and longitude coordinates of the taxi's instantaneous position, respectively [30].

In Figure 2, a parking business, $P_n, n \in \{1, 2, \dots, N\}$, has Ω_n maximum available slots, where a vehicle can select a space that can be leased with an hourly rate. At time $t = kT_S, k = 0, 1, \dots, \kappa$, there are m nearby (within R_r of P_n) vehicles, V_m , looking for a possible parking space with reasonable fees. The parking business displays its available number of vacant slots and its dynamic pricing.

Upon entry, time T_{entry} starts, and based on the dynamic pricing scheme, the vehicle is allotted a free space. For spatiotemporal methods, available parking slots are categorized into regular and special spaces. Regular categories are those with equal probability, regardless of its proximity to mall entrance/exit, elevators, PWD spots, and other important landmarks. However, regular spaces can be classified into indoor or outdoor (street) parking. The rest is classified under special categories where the location matters and it adds value to the dynamic price. The parking duration ends, T_{exit} , when the vehicle is already exiting the parking center. Effectively, the parking duration, $PD, PD = T_{exit} - T_{entry}$.

One may argue that the traces utilized in this study are those with no parking intentions, however, employing these mobility traces will help understand, and even predict, the worst case scenario when there are many vehicles looking for a possible parking space. Therefore, by allowing these vehicular movements to mimic parking vehicles is justified, more specifically, in comparing and evaluating the different applied and proposed dynamic parking pricing schemes given a huge amount of customers.

IV. DYNAMIC PARKING PRICING SCHEMES

In this section, we evaluate temporal- and spatiotemporal-based dynamic parking pricing schemes, $F_{xx}(m)$, considering temporal and spatial values of a car garage up for lease by a vehicle V_m . The proposed parking fees take into account salient variables and features of an available parking space, e.g., land value, entry time, demand value, unique services,

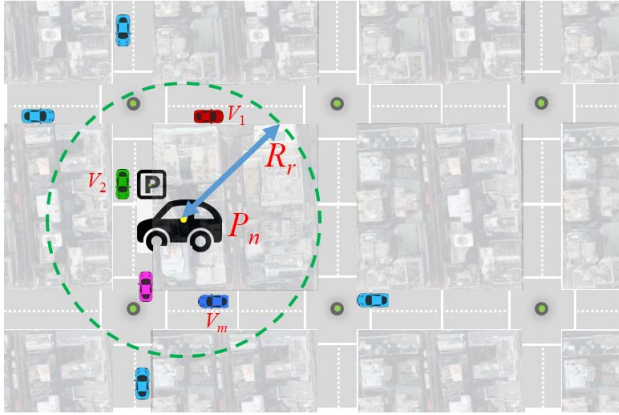


FIGURE 2. Parking building with four nearby vehicles looking for viable vacant and available parking spaces.

etc. Considering these variables allows a commercial establishment to promote its parking services to its targeted customers.

A. TEMPORAL-BASED DYNAMIC PARKING PRICING

We discuss here three parking pricing schemes which are based only on the parking duration.

1) FIXED RATE PRICING

The fee employing the fixed rate parking pricing for vehicle m , $F_{FR}(m)$, has a constant parking fee throughout the day, regardless of parking duration, $0 \leq PD \leq 24$, and serves as a benchmark for most studies [13], [14], [15], [16], [19], [27], [31]. Fixed price is dictated by (1).

$$F_{FR}(m) = K \quad (1)$$

Note that the fixed rate pricing can be derived from the Egalitarian cost-sharing theory [32] in (2), where C_{max} and C_{min} are the average maximum and minimum amount among the prices nominated by M users, respectively. $C(P_n)$ is defined as the minimum cost to retrieve capital and operating expenses of a parking lot P_n .

$$C(m) = \frac{C(P_n) + M[C_{max} - C_{min}]}{M} = K \quad (2)$$

2) LINEAR RATE PRICING

The fee utilizing the linear rate parking pricing [13], [33] for user m , $F_{LR}(m)$, is an adjusted fixed rate pricing and is governed by (3).

$$F_{LR}(m) = K + K_{adj}\Delta t_{LR} \quad (3)$$

In (3), a user has to pay a fixed parking fee, denoted by K , for a certain parking duration threshold, T_{def} , and then is charged with an additional amount depending on the exceeded duration of the parking vehicle, denoted by $\Delta t_{LR} = \text{ceil}[PD - T_{def}] > 0$. $0 < K_{adj} \leq K$. We also assume that $K = \beta K_{adj}$, where β is a constant of proportionality. The operation ‘ceil’ gets the next upper time value in hours.

In linear rate pricing, parking users are advised to park only for a certain duration to provide other incoming vehicles available parking slots and avoid the additional penalty equal to $K_{adj}\Delta t_{LR}$.

Note that when $T_{def} = 24$ hours, $\Delta t_{LR} = 0$, effectively, $F_{LR}(m) = F_{FR}(m)$.

3) MIN-MAX RATE PRICING

The fee using min-max [10] rate parking pricing for user m , $F_{MM}(m)$, is described by (4), where charged fees, K_h , are based on parking duration value, T_h , $h \in \{1, \dots, h, \dots, H\}$. $T_{min} < \dots < T_h < \dots < T_H$ and $K_{min} < \dots < K_h < \dots < K_{max}$.

$$F_{MM}(m) = \begin{cases} K_{min}, & 1 < PD \leq T_{min} \\ \vdots & \vdots \\ K_h, & T_{h-1} < PD \leq T_h \\ \vdots & \vdots \\ K_{max}, & T_{H-1} < PD \leq 24 \end{cases} \quad (4)$$

Lemma 1: The Min-Max Rate Pricing is a proposed intermediate pricing scheme between the Fixed and Linear Rate Pricing techniques, i.e., $F_{FR}(m) \leq F_{MM}(m) \leq F_{LR}(m)$.

Proof: If $T_{min} = \dots = T_h = \dots = T_H = 24$ and $K_{min} = \dots = K_h = \dots = K_{max} = K$, then $F_{MM}(m) = F_{FR}(m)$.

If $T_{min} = T_{def}$ and $K_{min} = K$, then the lower bounds of Linear and Min-Max Rate Pricing schemes are equal, i.e., $F_{LRlower}(m) = F_{MMlower}(m)$.

When $T_h > T_{min}$, for $T_h < PD \leq T_{h-1}$, $K_h = K \left[\frac{1+(T_h-T_{h-1})}{\beta} \right]$, then $F_{LR}(m) = F_{MM}(m)$. \square

B. SPATIOTEMPORAL-BASED DYNAMIC PARKING PRICING

Two spatiotemporal dynamic parking pricing schemes are presented in this subsection. The parking duration is still a vital component of the proposed pricing methods, however, the spatial value of the parking slot has now been considered.

1) ADAPTIVE RATE PRICING

The adaptive rate parking pricing for user m , $F_{AR}(m)$, allows parking price movement based on both temporal and spatial conditions. It is shown in (5).

$$F_{AR}(m) = \frac{K_{space}}{PD} \Delta y \sum_{j=1}^J T_j \quad (5)$$

where $T_j > 0$ assigns the parking slot premium value at the j^{th} time interval the car entered, stayed, and left the parking premise. T_j assigns the temporal weight of the vacant parking slot and considers peak and off-peak scenarios.

On the other hand, $\Delta y = \Delta y_K - \frac{\Omega_n - |PS_{nocc}|_{entry}}{\Omega_n + 1}$ is the normalized occupancy of the parking lot, upon vehicle entry, and it can be defined as the spatial value of the parking slot. If $|PS_{nocc}|_{entry}$ (the number of occupied parking spaces upon

entry) approaches Ω_n , the parking slot should be valued at a higher price, else, vehicles will be charged less. $\Delta y_K \geq 1$ increases the parking lot's spatial value.

In adaptive rate pricing, parking users can avail of the parking slot at a lower cost especially, during off-peak hours. One may argue that the adaptive rate pricing is not realistic, however, for businesses entirely operating as a parking space provider and open 24/7, then, this dynamic pricing scheme encourages car owners to use their parking amenities at a rate adapting to the spatiotemporal parking conditions. Also, business centers located on prime spots will benefit more on this scheme because their land value is given an appropriate weight, while at the same time, their target market are already identified.

2) COMPLEMENTARY RATE PRICING

The complementary rate pricing in (6) is the linear combination of the spatiotemporal values characterizing the parking slot.

$$F_{SR}(m) = \sum_{\epsilon=1}^{\epsilon} a_{\epsilon}(t)F_{\epsilon}(t) + \sum_{\gamma=1}^{\Gamma} b_{\gamma}(s)F_{\gamma}(s) \quad (6)$$

where $a_{\epsilon}(t)$ and $b_{\gamma}(s)$ are time- and space-dependent coefficients of the time- and space-defining functions $F_{\epsilon}(t)$ and $F_{\gamma}(s)$, respectively. $F_{\epsilon}(t)$ can be any of the previous dynamic parking pricing schemes, while $F_{\gamma}(s)$ includes slot classification (multi-level/regular, PWD slots, street, etc.), occupancy rate, and proximity in determining its parking fee.

For simplicity, we let $a_{\epsilon}(t)$ and $b_{\gamma}(s)$ be constants within the range $[0, 1]$ and $b_{\gamma}(s) = 1 - a_{\epsilon}(t)$, thus, called complementary rate pricing. Also, we let $F_{\epsilon}(t) = F_{MM}(m) = K_{CR}$. We define $F_{\gamma}(s)$ below in (7), where Λ 's and Ω 's are the associated parking land dues (similar to real estate property tax) and maximum vacancies in each classification, respectively. The coefficient α denotes which car park category will the vehicle be parked.

$$\begin{aligned} F_{\gamma}(s) &= \alpha_{Ind} \Lambda_{Ind} \frac{|PS_{n_{Ind}}|_{entry} + 1}{\Omega_{Ind} + 1} \\ &+ \alpha_{PWD} \Lambda_{PWD} \frac{|PS_{n_{PWD}}|_{entry} + 1}{\Omega_{PWD} + 1} \\ &+ \alpha_{St} \Lambda_{St} \frac{|PS_{n_{St}}|_{entry} + 1}{\Omega_{St} + 1} \\ \text{s.t. } &\alpha_{Ind}, \alpha_{PWD}, \alpha_{St} \in \{0, 1\} \\ \text{s.t. } &\alpha_{Ind} + \alpha_{PWD} + \alpha_{St} = 1 \end{aligned} \quad (7)$$

Unlike the Adaptive Rate Pricing, the Complementary Rate Pricing can easily favor time-based or space-based values by making either coefficient, $a_{\epsilon}(t)$ or $b_{\gamma}(s)$, one or zero.

C. PARKING FEE ADJUSTMENT DUE TO ONLINE RESERVATION

If parking businesses will employ online reservations, then, the presented schemes can be easily adjusted to have additional reservation fee that can be simply specified by (8)

below.

$$F_{res}(m) = K_{res} \delta T \quad (8)$$

where $K_{res} > K$ for having the convenience of a reserved parking slot and δT as the time difference between arrival and reservation, normally dictated by the reservist. In practice, this is automatically deductible from the parker. Any excess charges will just be subtracted from the actual parking payment upon checkout.

V. USER AND BUSINESS SOCIAL OPTIMUM MEASURES

We define the user and business social optimum range, S_{xx} , in (9), for a parking pricing scheme as the ratio of parking charges and duration to gauge business profitability and monetary impact to users. $xx \in \{FR, LR, MM, AR, CR\}$, denotes the parking pricing scheme for fixed, linear, min-max, adaptive, and complementary rate pricing, respectively.

$$S_{xx_{lower}} \leq S_{xx} = \frac{F_{xx}}{E[PD]} \leq S_{xx_{upper}} \quad (9)$$

where F_{xx} is the parking pricing scheme, $E[\bullet]$ is the expectation operator, $S_{xx_{lower}}$, and $S_{xx_{upper}}$ are the lower and upper bounds, respectively.

For user m , S_{xx} can be defined as the parking pricing impact, i.e., effective parking fee rate. This value should be minimized to denote the value of their money for the service rendered, i.e., lease of a parking space. On the other hand, for businesses, S , means how much can they effectively profit per parker m multiplied by the total available parking slots Ω_n . The limits of S_{xx} are determined by getting the minimum and maximum values of (9) in each of the dynamic parking pricing schemes.

In general, we assume that a parking business is operational 24 hours a day and the parker is charged on an hourly rate. Note that a fraction of an hour is already considered as one hour. Also, we do not consider parking durations with overlapping days.

In Fixed Rate Pricing, the social optimum range, S_{FR} is given below in (10). As an example, the $S_{xx_{lower}}$ is computed by dividing K with the maximum allowable $PD = 24$ hours, while $S_{xx_{higher}}$ is obtained by dividing K by $PD = 1$ hour.

$$\frac{K}{24} \leq S_{FR} \leq K \quad (10)$$

For Linear Rate Pricing, assuming that K is only applicable for the first $\Delta t_{LR} = 3$ hours and $K_{adj} = \frac{K}{\beta}$, $\beta > 3$, is charged for each succeeding hour or a fraction of it, we have (11). From simulations, $1 \leq \beta \leq 3$, the Linear rate pricing scheme becomes unreasonable and less competitive.

$$K \frac{\beta + 21}{24\beta} \leq S_{LR} \leq K \quad (11)$$

For Min-Max Rate Pricing, S_{MM} for both user and business is given in (12), where the assumption $K_{max} < 24K_{min}$ should hold. Also, since $K_{min} < K_h < K_{max}$ and

$1 < T_{min} < T_h < 24$, the lower and upper bounds are determined from the limits of $F_{MM}(m)$.

$$\frac{K_{max}}{24} \leq S_{MM} \leq K_{min} \quad (12)$$

For Adaptive Rate Pricing, since the spatial and temporal values of a parking lot are directly related, thus, the lower and upper bounds of S_{AR} for both user and business is given in (13) below.

$$\frac{S_{AR_l}}{24} \leq S_{AR} \leq S_{AR_h} \quad (13)$$

where $S_{AR_l} = K_{space} \left(\Delta y_k - \frac{\Omega_n}{\Omega_n+1} \right) T_{j,min}$ and $S_{AR_h} = K_{space} \left(\Delta y_k - \frac{1}{\Omega_n+1} \right) T_{j,max}$.

For Complementary Rate Pricing, S_{CR} is given in (14) below, where the lower bound is the least value between the temporal and spatial parking lot values, while the upper bound is given by the maximum combination of these spatiotemporal parking lot value.

$$\frac{K_{CR} + \frac{\Lambda_{St}}{\Omega_{St}+1}}{24} \leq S_{CR} \leq K_{CR} + \Lambda_{PWD} \quad (14)$$

For each S_{xx} in the five parking pricings, the lower bound is always the preferred rate of parking users, while the upper bound is the ideal case for the business establishment.

To evaluate and compare the five parking pricing schemes, we calculate Y_{xx} as the average daily revenue. We then compare Y_{xx} to the mean of each S_{xx} , denoted as $S_{xx,ave}$, and derive our observation, $S_{xx,obs}$ in (15). If $S_{xx,obs}$ equates to *User*, the pricing scheme S_{xx} is more parker-friendly, else, business-oriented.

$$S_{xx,obs} = \begin{cases} User, & Y_{xx} < S_{xx,ave} \\ Busi, & Y_{xx} > S_{xx,ave} \end{cases} \quad (15)$$

VI. EXTENSIVE SIMULATION RESULTS AND DISCUSSION

In this section, we present our extensive simulation results using empirical mobility traces from Beijing City where the characteristics are described in Table 1.

TABLE 1. Simulation and dataset attributes/parameters.

Simulation Attribute/Parameter	Value
Total area (in \approx km ²)	50
Number of Parking Buildings	40
Number of parking slots per building, Ω_n	1000
Parking Building Radius (meters)	500
Sampling time of GPS traces (mins)	10

We use the GPS coordinates of nearby taxis to act like vehicles that will be utilizing the parking space of a commercial building found at locations depicted in Figure 3 [34].

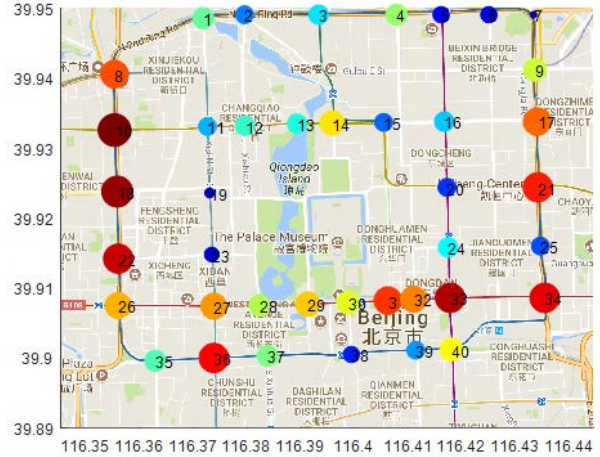


FIGURE 3. Locations of the 40 assumed parking buildings in Beijing City. Colored circles represent the average number of taxis passing the building per hour. The larger and the darker the circle is, the more passing taxis.

A. ASSUMPTIONS IN PRICING CONSTANTS

Table 2 shows the various price constants used in each of the parking pricing schemes presented in this work guided by the House Bill 7725 in the Philippines [35]. The first two rows are allotted for the Fixed and Linear Pricing rate schemes. The third and fourth rows are constants for the Min-Max pricing. The fifth and sixth rows belong to the Adaptive Pricing. The last two rows are for the Complementary Rate pricing, where we also set $a_\epsilon(t) = b_\gamma(s) = 0.5$, for simplicity.

TABLE 2. Spatiotemporal Pricing Constants.

Row	Dynamic Pricing Constants	Value
1	K, K_{adj} (in PhP)	50, 10
2	Δt_{LR} (in hr)	3
3	K_{min}, K_2, K_{max} (in PhP)	50, 75, 100
4	T_{min}, T_2, T_{max} (in hr)	8, 16, 24
5	K_{space} (in PhP)	50
6	Δy_k	2
7	$\Lambda_{Ind}, \Lambda_{PWD}, \Lambda_{St}$ (in PhP)	25, 37.5, 12.5
8	K_{CR} (in PhP)	25

The values of T_j (for the Adaptive Rate Pricing) are assumed and shown in Table 3. Later on, T_j can be derived from empirical situations and is highly dependent on the establishment. In our example, we placed the highest premium on the 10:00 AM – 2:00 PM time interval since these are rush/peak hours when people tend to meet up for lunch and meetings. Note that an exact value for these assumptions can be derived per each parking building. If $T_j = 1$ for all time intervals, then $F_{AR}(m)$ charges the parker based on the spatial value of the parking slot only.

Note that the constant values selected here are chosen such that the discrepancies between temporal and spatiotemporal pricing schemes do not have a big discrepancy. In reality, however, premium establishments can charge their customers a fee equivalent to the parking lot’s high value and demand

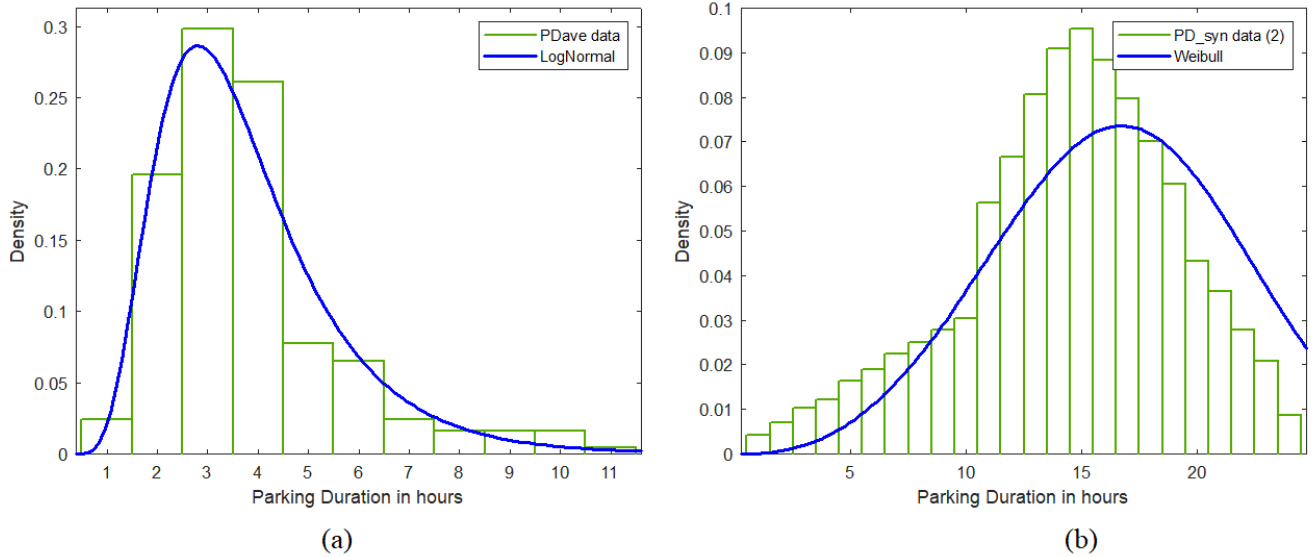


FIGURE 4. (a) Average parking duration obtained from 246 respondents (bar graph) and fitted lognormal probability distribution to best characterize the respondents’ answers (blue curve) (b) Synthetic parking duration portraying long-duration parkers (bar graph) and fitted Weibull distribution.

TABLE 3. T_j values for various daily time intervals.

j^{th} Time Interval	T_j
00:00 – 04:00	0.25
04:00 – 07:00	0.5
07:00 – 10:00	1
10:00 – 15:00	1.5
15:00 – 20:00	1
20:00 – 24:00	0.25

availability. Also, commercial establishments will also consider the surrounding competition to attract customers.

B. PARKING DURATION CHARACTERIZATION

We present three scenarios on the parking duration behavior of people leaving their cars on commercial malls/establishments. These are enumerated below.

- 1) We employ the parking duration behavior from an online survey we conducted to determine the people’s experience on how long they leave their vehicles at the parking lots when visiting a commercial establishment (during pre-pandemic time). The survey only asked one question, i.e., how long is your average parking duration (in hours) inside malls or commercial places? There are 246 respondents and their activities done during their visits are not questioned. The shortest and longest time period of parking are one and eleven hours, respectively. A lognormal distribution with mean 3.7915 hours and a variance of 3.2107 hours is used to best fit the data. This probability distribution choice is based on [36]. Empirical and fitted results are shown in Figure 4(a). Generally, this scenario captures the short parking duration exhibited by parkers.
- 2) We characterize the amount of time a vehicle is parked by using the uniform distribution over a period of

24 hours. In this experiment, we observe the effect of equally distributed short and long parking durations.

- 3) To simulate the situation where long-duration parkers are using the car garages, a Weibull distribution with scale value of 18.4009 and shape value of 3.5211 fitted over a set of synthetic parking duration samples is simulated. This is shown in Figure 4(b).

C. COMPARING THE VARIOUS SPATIOTEMPORAL PARKING PRICING SCHEMES

We performed a set of extensive simulations composed of 1000 runs for each parking duration scenario over the seven-day mobility dataset. We limit our cost evaluation to those given values in Table 2 only.

1) PARKING BEHAVIOR ANALYSIS

Given the three parking duration characteristics and with a sampling time of 10 minutes, the average cumulative distributions parked and unparked (those who do not have any available parking slot upon arrival) vehicles are shown in Figure 5. We note that as sampling time is decreased, these numbers increase as there are more available vehicular GPS traces to consider.

Given an allotted $\Omega_n = 1000$ available slots for each commercial building, for a short-duration parking behavior, the number of unparked vehicles is negligible since they will have available spaces to leave their cars, as shown in Figure 5(a). However, when the duration of a parked car is increased, the establishments are overwhelmed by incoming vehicles, starting at 11:00 AM, since there are already parked vehicles with no intention of vacating their spaces. This is exhibited by Figure 5(b) and Figure 5(c). This scenario is exemplified by office employees leaving their vehicles parked in an establishment near their work places. From the standpoint of

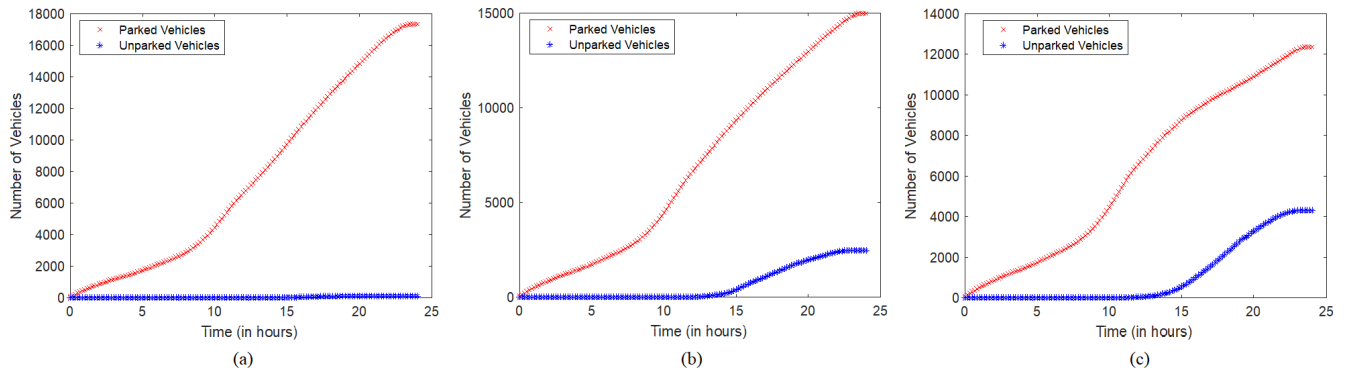


FIGURE 5. Average cumulative distribution of parked and unparked vehicles with parking duration characterized by (a) Empirical (lognormal), (b) Uniform, and (c) Weibull distributions.

a commercial establishment, unparked vehicles are already considered as lost customers, therefore, translating to financial losses. Parking managers can mitigate these lost profits by increasing the number of available parking slots, which in some cases, convert other free spaces to parking spots. On the other hand, parkers who cannot find a vacant slot in its desired parking building will either do any of these two things: 1) stay in queue and wait for future available slots while their engines are still turned ON, and 2) look for a nearby car garage with available space.

From Figure 5, shorter and longer parking durations favor the business and parker, respectively. Shorter duration allows more vehicles to park and the flow of parking fees is faster when compared to vehicles with longer parking duration. On the other hand, parkers following the Weibull model pays a relatively lower parking fee on a daily basis, but the effects can be seen when tallied every month.

2) AVERAGE COLLECTED PARKING FEES

The range and average of collected parking fee rates obtained from the five schemes for the 40 identified parking buildings are shown in Figure 6 for empirical parking durations, Figure 7 for uniformly distributed length of vehicles staying in a parking lot, and Figure 8 for long-staying vehicles in car garages. The black dashed line in each plot represents the average effective parking rate, $S_{xx_{ave}}$.

The Fixed rate pricing is generally the cheapest for parkers and less revenue-generating for an establishment. Also, this is the simplest method to implement for businesses and easiest to remember for a parking customer. However, the Fixed rate becomes expensive when there is an unreasonable price hike of K . An example of this can be seen in [37].

As can be seen from Figures 6–8, the linear rate dynamic parking pricing scheme is the most expensive of all current and proposed pricing schemes. Normally, the parking establishments employing this method are those near offices, since the turnout of parking vehicles is much slower and those establishments with limited slots. The parking fees become more expensive when Δt_{LR} and K_{adj} are decreased (since

there will be more time interval adjustments) and increased, respectively [37].

The Min-Max pricing offers the intermediate price between the Fixed and Linear rate dynamic pricing schemes. From its definition in (4), short-, mid-, and long-duration parkers can easily be discriminated by various fixed pricing rates, K_h . The more fixed prices involved in Min-Max is, the better it is to understand the parking behaviors of customers. From the extensive simulation results, the Min-Max Rate dynamic pricing method allows a compromise for both businesses and users.

The Adaptive Rate pricing offers a relatively low price offering to nearby parkers. This is so because the time interval value T_j has values less than one. However, the adaptive rate can easily be more expensive when the spatial value, Δy_K , or the temporal value, T_j , is increased unjustifiably. This variable is left to the parking managers to place the appropriate values that will not discourage its customers.

Finally, the Complementary rate pricing is advantageous to establishments that offers special types of parking lots and services, e.g., valet or PWD assistance. These supports are charged based on service rendered by the driver taking over the vehicle and/or the premium (e.g., security) location where the car is parked. The coefficients $a_\epsilon(t)$ and $b_\gamma(s)$ can easily be adjusted accordingly too to provide which of the time-value or space-value is prioritized. Compared to the other four pricing schemes, a customer must be well-informed about the convenience this pricing scheme is offering.

D. SOCIAL OPTIMUM MEASURE

Given the values in Tables 2 and 3, the social optimum value range, S_{xx} for each of the dynamic pricing is shown in Table 4 below. The midpoint of S_{xx} , $S_{xx_{ave}}$, is also given in the fourth column.

We evaluate the user- or business-friendliness of each dynamic parking pricing scheme. Recall that if the average is near the lower S_{xx} , then the pricing model is user-friendly, otherwise, it is business-friendly.

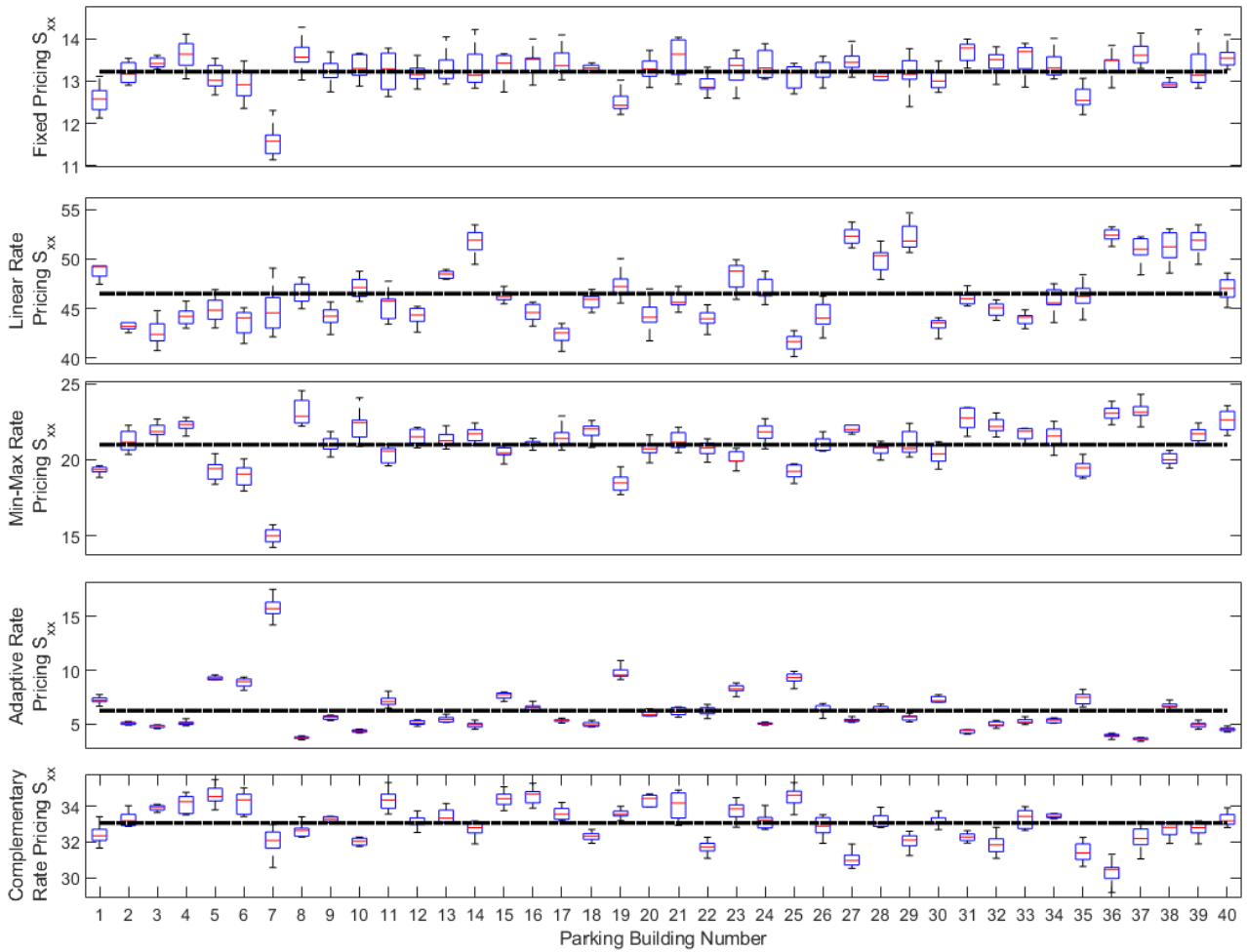


FIGURE 6. Average collected parking fees having empirical parking duration characterized by a lognormal distribution.

TABLE 4. Social optimum range for each dynamic parking pricing scheme.

Dynamic Pricing	$S_{xx_{lower}}$	$S_{xx_{upper}}$	$S_{xx_{ave}}$
Fixed	2.0833	50	26.0417
Linear	10.8333	50	30.4167
Min-Max	4.1667	50	27.0833
Adaptive	0.5214	149.9251	75.2232
Complementary	1.0422	62.5	31.7711

The observations for each of the spatiotemporal dynamic pricing schemes under various parking duration model are shown in Table 5. Clearly, Fixed and Linear parking pricing methods, the highly-utilized schemes, are inclined to users and business establishments, respectively. Min-Max and Adaptive rates are also user-inclined while the complementary is a mix.

Let us analyze the various pricing schemes by looking at the lognormal distribution, i.e., empirical parking duration model.

In general, the Fixed rate pricing is really customer-friendly and encourages its customers to avail its facility since only

one value needs to be paid. The parker does not need to worry about its time and the varying cost. In most commercial establishments, e.g., malls and restaurants, that are located within the vicinity of each other, this kind of parking pricing is implemented.

On the other hand, the Linear rate pricing is mostly utilized by commercial establishments which are near offices. Understandably, since there is a lower vehicular parking arrival, getting the target revenue is difficult to achieve under this circumstance, thus, implementing this method instead of the fixed pricing.

The Min-Max pricing is between the Fixed and Linear rate methods. It addresses both the short- and long-duration parkers by having their respective parking fees. However, under the empirical distribution, the Min-Max behaves like the Fixed rate pricing.

In the simulations, $0 < T_j < \infty$ and those off-peak hours have weights less than one. However, setting $T_j > 1$ can easily turn the Adaptive rate pricing business-friendly. Also, setting $\Delta y_K > 2$ will automatically increase the parking fee that will make it lean towards the business side.

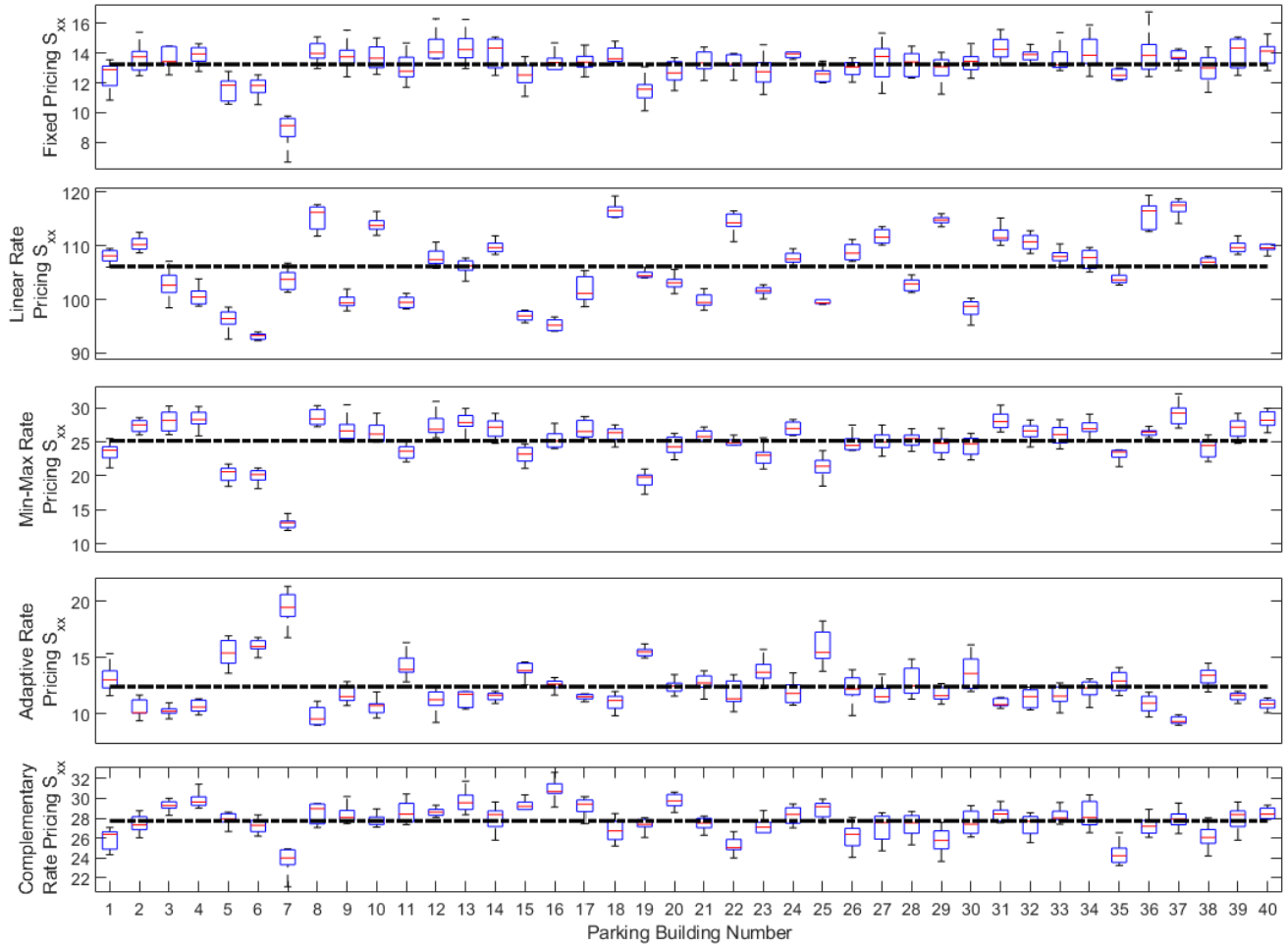


FIGURE 7. Average collected parking fees having uniform distribution, i.e., short and long parking duration have equal probability to happen.

TABLE 5. User and Business inclinations derived from social optimum average.

Dynamic Parking Pricing	Unif	$S_{xx_{obs}}$	LogNrm	$S_{xx_{obs}}$	Weibull	$S_{xx_{obs}}$
Fixed	13.24654	User	13.2271	User	2.831178	User
Linear	106.1628	Business	46.5012	Business	122.2224	Business
Min-Max	25.17451	User	20.9932	User	4.59865	User
Adaptive	12.42436	User	6.2602	User	12.80545	User
Complementary	27.72755	User	33.0582	Business	15.69163	User

Lastly, in the proposed Complementary pricing here, the scheme is a business-oriented method because the spatial value has added services such as type of parking slot, introduction of valet assistance to name a few. Although these provide convenience to the users, an additional cost is shouldered by them. Also, the temporal value can also be easily changed to Linear rate where Δt_{LR} can be adjusted accordingly.

E. PARKING ESTABLISHMENTS WITH DIFFERENT VEHICULAR PARKING DENSITY

Let us look at parking buildings (PB) 7 and 34 which have the lowest and highest average number of vehicles in its vicinity, respectively. Surprisingly, in our simulation, PB7

has the lower number of parking vehicles, but utilizing the appropriate pricing method can yield a better parking revenue when compared to PB34, i.e., implementing the Adaptive rate parking pricing. One reason here is that the parking vehicles happened during the time interval from 10:00 AM to 3:00 PM where $T_j = 1.5$. Given this finding, the Adaptive rate pricing can be utilized by establishments with the majority of its customers using their facility during peak hours. From Figure 9 below, we can see the monthly consumer rental for each of the pricing scheme. Therefore, depending on the location of the commercial establishment, any of these studied dynamic pricing schemes can be implemented in order to address target parking revenue. However, one difficult thing, is explaining

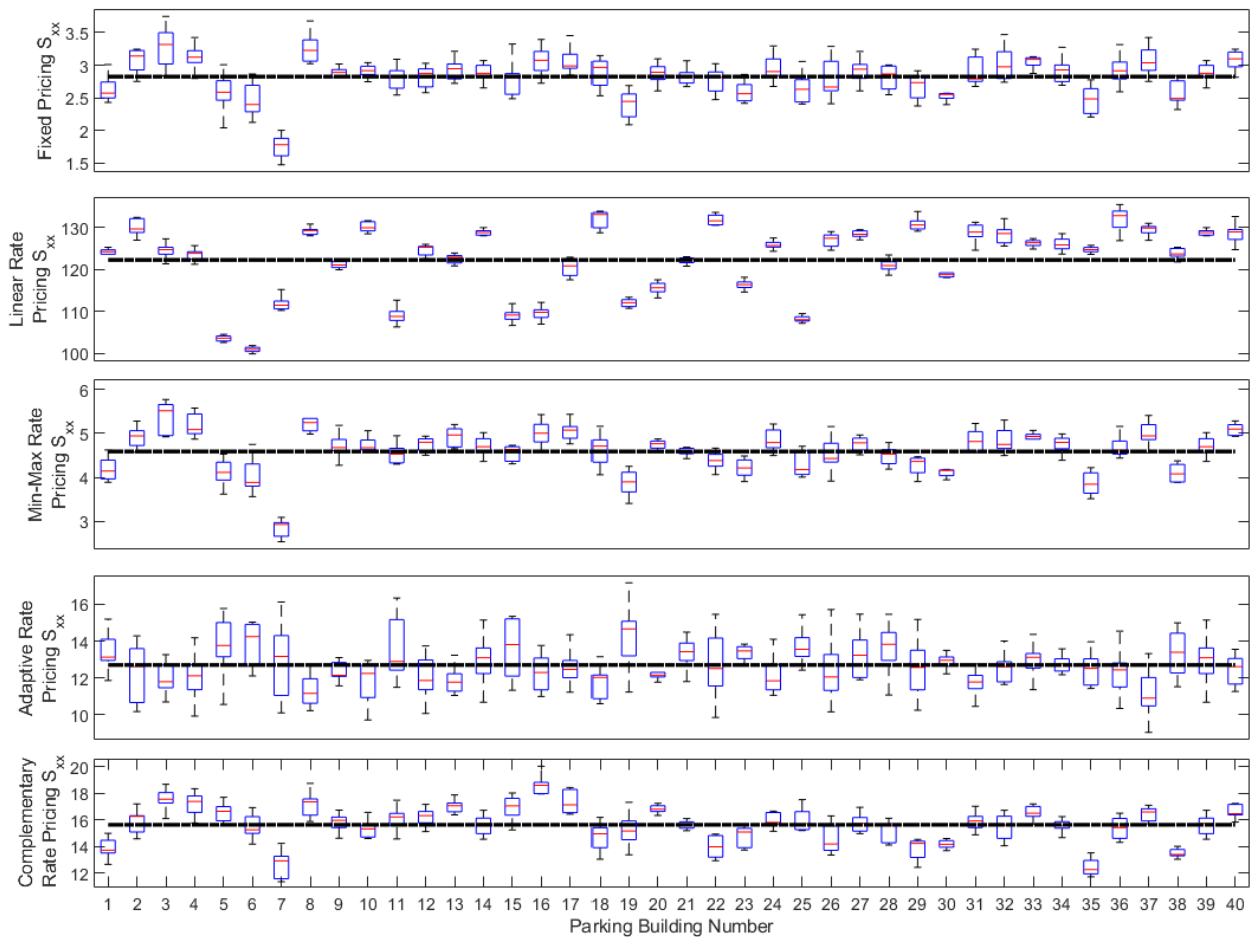


FIGURE 8. Average collected parking fees having Weibull distribution, i.e., longer parking duration.

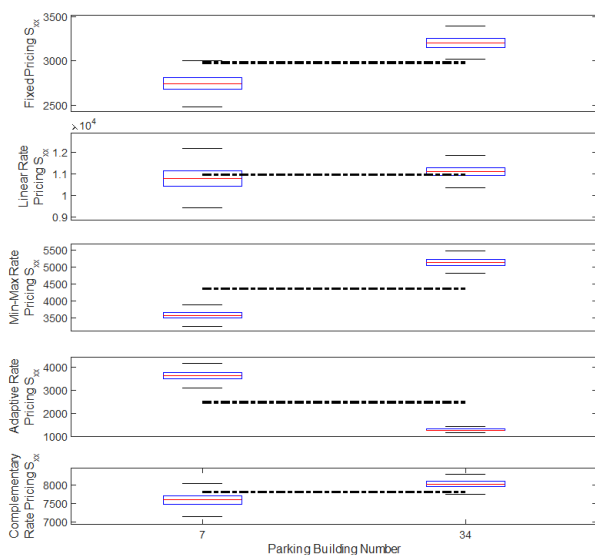


FIGURE 9. Comparing two establishments with varying vehicular parking density. Shown is the monthly rental from a regular customer utilizing the parking building.

to customers the various variables used in coming up with the parking fee.

Figure 9 also illustrates the monthly expenditure of a vehicle owner when he/she parks on a facility given the dynamic parking pricing. Realistically, the Linear rate price is too much for a middle class customer and will still settle with the Fixed rate pricing.

VII. CONCLUSION

In this research work, we evaluated five different spatiotemporal dynamic parking pricing schemes according to its social optimum measure based on value for money. Parking fees based on the temporal value are highly dependent on the parking duration of a parker, while spatial value considers the number of available parking spaces upon entry of a vehicle and its land valuation. The assessment of these pricing schemes provides the impacts of such parking fee rate to the income generation of business owners and effects to the daily parking expenditures of frequent parkers. Our evaluation results reveal that the most commonly used Fixed and Linear parking pricing schemes are benefiting users and business entities for varying parking customer distribution, respectively. This means that commercial establishments earn from a group of parkers by employing Fixed rate, however, on the other hand, they acquire income from small groups

of parkers when using Linear Rate. Also, Fixed rate pricing entices long-duration parkers while Linear rate encourages short duration parking only. On the other hand, the proposed Min-Max pricing is an excellent alternative to these two well-used parking rates to separately charge short- and long-staying vehicles, thereby, encouraging all types of parkers. Finally, our proposed spatiotemporal dynamic parking rates provide a more complete valuation of an available slot. This considers the premium of a parking lot depending on the location, availability time, and services rendered. However, a rigorous set of feasibility studies is needed to arrive at the appropriate spatiotemporal values that will neither discourage customers nor allow owners and parking managers to lose their business.

In summary, a given commercial establishment or parking business can utilize the findings of this work by implementing the best dynamic parking scheme that is viable for business growth and beneficial to parking tenants without any compromise. For parkers, they can quickly compute their monthly parking expenditures. On the other hand, parking managers can straightforwardly calculate their minimum earnings and track the number of parkers that can be used to tune their prevalent parking fee. Lastly, the proposed pricing methods are adaptive to cater special cases and needs, e.g., online reservations and valet services, that will further promote the business' uniqueness and user-friendliness.

REFERENCES

- [1] E. R. Magsino and I. W. H. Ho, "An intelligent highway toll-gate queue selector for improving server utilization and vehicle waiting time," in *Proc. IEEE Region 10 Symp. (TENSymp)*, May 2016, pp. 271–276.
- [2] I. Malygin, V. Komashinskiy, and O. Korolev, "Cognitive technologies for providing road traffic safety in intelligent transport systems," *Transp. Res. Proc.*, vol. 36, pp. 487–492, Jan. 2018.
- [3] T. Perković, P. Šolić, H. Zargariasl, D. Čoko, and J. J. P. C. Rodrigues, "Smart parking sensors: State of the art and performance evaluation," *J. Cleaner Prod.*, vol. 262, Jul. 2020, Art. no. 121181.
- [4] M. Khalid, K. Wang, N. Aslam, Y. Cao, N. Ahmad, and M. K. Khan, "From smart parking towards autonomous valet parking: A survey, challenges and future works," *J. Netw. Comput. Appl.*, vol. 175, Feb. 2021, Art. no. 102935.
- [5] A. M. Said, A. E. Kamal, and H. Afifi, "An intelligent parking sharing system for green and smart cities based IoT," *Comput. Commun.*, vol. 172, pp. 10–18, Apr. 2021.
- [6] N. Zheng and N. Geroliminis, "Modeling and optimization of multimodal urban networks with limited parking and dynamic pricing," *Transp. Res. B, Methodol.*, vol. 83, pp. 36–58, Jan. 2016.
- [7] M. V. Sudhakar et al., "Development of smart parking management system," *Mater. Today, Proc.*, Jul. 2021, doi: [10.1016/j.matpr.2021.07.040](https://doi.org/10.1016/j.matpr.2021.07.040).
- [8] W. Yang and P. T. I. Lam, "Evaluation of drivers' benefits accruing from an intelligent parking information system," *J. Cleaner Prod.*, vol. 231, pp. 783–793, Sep. 2019.
- [9] A. Rodríguez, R. Cordera, B. Alonso, L. dell'Olivo, and J. Benavente, "Microsimulation parking choice and search model to assess dynamic pricing scenarios," *Transp. Res. A, Policy Pract.*, vol. 156, pp. 253–269, Feb. 2022.
- [10] E. R. Magsino, G. P. Arada, and C. M. L. Ramos, "Assessing temporal-based parking pricing schemes," in *Proc. Int. Conf. Decis. Aid Sci. Appl. (DASA)*, Mar. 2022, pp. 858–862.
- [11] H. Qin, F. Zheng, B. Yu, and Z. Wang, "Analysis of the effect of demand-driven dynamic parking pricing on on-street parking demand," *IEEE Access*, vol. 10, pp. 70092–70103, 2022.
- [12] D. Reebadiya, R. Gupta, A. Kumari, and S. Tanwar, "Blockchain and AI-integrated vehicle-based dynamic parking pricing scheme," in *Proc. IEEE Int. Conf. Commun. Workshops (ICC Workshops)*, Jun. 2021, pp. 1–6.
- [13] Q. Tian, L. Yang, C. Wang, and H.-J. Huang, "Dynamic pricing for reservation-based parking system: A revenue management method," *Transp. Policy*, vol. 71, pp. 36–44, Nov. 2018.
- [14] Z. Mei, C. Feng, L. Kong, L. Zhang, and J. Chen, "Assessment of different parking pricing strategies: A simulation-based analysis," *Sustainability*, vol. 12, no. 5, p. 2056, Mar. 2020.
- [15] Z. Gu, A. Najmi, M. Saberi, W. Liu, and T. H. Rashidi, "Macroscopic parking dynamics modeling and optimal real-time pricing considering cruising-for-parking," *Transp. Res. C, Emerg. Technol.*, vol. 118, Sep. 2020, Art. no. 102714.
- [16] V. K. Sarker, T. N. Gia, I. B. Dhaou, and T. Westerlund, "Smart parking system with dynamic pricing, edge-cloud computing and LoRA," *Sensors*, vol. 20, no. 17, p. 4669, Aug. 2020.
- [17] R. Kakkar, J. Alzubi, A. Dua, S. Agrawal, S. Tanwar, R. Agrawal, G. Sharma, P. N. Bokoro, and R. Sharma, "PADaaV: Blockchain-based parking price prediction scheme for sustainable traffic management," *IEEE Access*, vol. 10, pp. 50125–50136, 2022.
- [18] H. Fotouhi and E. Miller-Hooks, "Optimal time-differentiated pricing for a competitive mixed traditional and crowdsourced event parking market," *Transp. Res. C, Emerg. Technol.*, vol. 132, Nov. 2021, Art. no. 103409.
- [19] V. Hassija, V. Saxena, V. Chamola, and F. R. Yu, "A parking slot allocation framework based on virtual voting and adaptive pricing algorithm," *IEEE Trans. Veh. Technol.*, vol. 69, no. 6, pp. 5945–5957, Jun. 2020.
- [20] A. Mirheli and L. Hajibabai, "Utilization management and pricing of parking facilities under uncertain demand and user decisions," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 5, pp. 2167–2179, May 2020.
- [21] T. Nakazato, Y. Fujimaki, and T. Namerikawa, "Parking lot allocation using rematching and dynamic parking fee design," *IEEE Trans. Control Netw. Syst.*, early access, Apr. 5, 2022, doi: [10.1109/TCNS.2022.3165015](https://doi.org/10.1109/TCNS.2022.3165015).
- [22] M. Nourinejad and M. Amirgholy, "Parking design and pricing for regular and autonomous vehicles: A morning commute problem," *Transportmetrica B, Transp. Dyn.*, vol. 10, no. 1, pp. 159–183, Dec. 2022.
- [23] A. Najmi, M. Bostanara, Z. Gu, and T. H. Rashidi, "On-street parking management and pricing policies: An evaluation from a system enhancement perspective," *Transp. Res. A, Policy Pract.*, vol. 146, pp. 128–151, Apr. 2021.
- [24] B. Mo, H. Kong, H. Wang, X. C. Wang, and R. Li, "Impact of pricing policy change on on-street parking demand and user satisfaction: A case study in Nanning, China," *Transp. Res. A, Policy Pract.*, vol. 148, pp. 445–469, Jun. 2021.
- [25] T. Fiez and L. J. Ratliff, "Gaussian mixture models for parking demand data," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 8, pp. 3571–3580, Aug. 2020.
- [26] S. Wang and T. Hu, "A game-theory based parking pricing policy," in *Proc. IEEE Int. Conf. Eng. Eng. Manage. (IEEM)*, Dec. 2020, pp. 230–234.
- [27] S. Saharan, N. Kumar, and S. Bawa, "An efficient smart parking pricing system for smart city environment: A machine-learning based approach," *Future Gener. Comput. Syst.*, vol. 106, pp. 622–640, May 2020.
- [28] S. Saharan, S. Baway, and N. Kumar, "OP3 S: On-street occupancy based parking prices prediction system for ITS," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, Dec. 2020, pp. 1–6.
- [29] E. R. Magsino and I. W.-H. Ho, "An enhanced information sharing roadside unit allocation scheme for vehicular networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 9, pp. 15462–15475, Sep. 2022.
- [30] E. R. Magsino, "Investigating the operational dynamics of different transportation modes in vehicular networks," in *Proc. Int. Conf. Inf. Technol. (ICIT)*, Jul. 2021, pp. 246–250.
- [31] M. Nourinejad and M. J. Roorda, "Impact of hourly parking pricing on travel demand," *Transp. Res. A, Policy Pract.*, vol. 98, pp. 28–45, Apr. 2017.
- [32] S. C.-K. Chau, S. Shen, and Y. Zhou, "Decentralized ride-sharing and vehicle-pooling based on fair cost-sharing mechanisms," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 3, pp. 1936–1946, Mar. 2022.
- [33] A. O. Kotb, Y.-C. Shen, X. Zhu, and Y. Huang, "iParker—A new smart car-parking system based on dynamic resource allocation and pricing," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 9, pp. 2637–2647, Sep. 2016.
- [34] I. W.-H. Ho, S. C.-K. Chau, E. R. Magsino, and K. Jia, "Efficient 3D road map data exchange for intelligent vehicles in vehicular fog networks," *IEEE Trans. Veh. Technol.*, vol. 69, no. 3, pp. 3151–3165, Mar. 2020.

- [35] *House Approves Bill 7725 Regulating Parking Fees*. Accessed: Aug. 15, 2022. [Online]. Available: <https://unbox.ph/editorials/house-approves-bill-7725-regulating-parking-fees/>
- [36] G. Dalla Chiara and L. Cheah, "Data stories from urban loading bays," *Eur. Transp. Res. Rev.*, vol. 9, no. 4, pp. 1–16, Dec. 2017.
- [37] *Uptown Mall Parking Rate: A List of Popular Parking Lots With Corresponding Rates*. Accessed: Aug. 17, 2022. [Online]. Available: <https://philtoyota.com/stories/uptown-mall-parking-rate-a-list-of-popular-parking-lots-with-corresponding-rates-str104>



ELMER R. MAGSINO (Member, IEEE) received the B.Sc. degree in electronics and communications engineering and the M.Sc. degree in electrical engineering from the University of the Philippines–Diliman, in 2002 and 2006, respectively, and the Ph.D. degree in electronic and information engineering from The Hong Kong Polytechnic University, Kowloon, Hong Kong, in 2021, focusing on data dissemination in vehicular networks.

Before undertaking the academic career, he served as a Design Engineer at a Power Electronics Company. He is currently a Full Professor with the Department of Electronics and Computer Engineering, Gokongwei College of Engineering, De La Salle University, Philippines. He has served as the Program Coordinator for the Computer Engineering Program of the same department from 2013 to 2015. Since 2012, he has published his research studies in various local and international conferences and journals, e.g., IEEE, ACM, IAENG, and IOP.

Dr. Magsino is a member of the Institute of Electronics Engineers of the Philippines (IECEP), International Association of Engineers (IAENG), and the National Research Council of the Philippines (NRCP). Along with his students, they were awarded as the Best Paper in the 2012 ICCSCE 2021 ACIDS Conferences. He has served as a reviewer and a committee member for various journals and international conferences, respectively.



GERALD P. ARADA (Member, IEEE) received the B.S. degree from the Polytechnic University of the Philippines, (Metro Manila, Philippines), in 1997, and the M.Eng. degree from De La Salle University, (Metro Manila, Philippines), both in electronics and computer engineering, and the Ph.D. degree from The Hong Kong Polytechnic University, in 2018. He was an Instructor at the Polytechnic University of the Philippines, from 1997 to 2006, then an Engineer with Analog Devices Inc., (Cavite, Philippines), from 2006 to 2009. Since 2009, he has been a faculty of De La Salle University, where he is currently an Associate Professor. His research interests include antennas, array signal processing, and wireless communications.



CATHERINE MANUELA L. RAMOS received the bachelor's degree in electrical engineering from the University of the Philippines, Diliman, and the Master of Science degree in electrical engineering from Purdue University, USA. She is currently an Assistant Professor at the Manufacturing Engineering and Management (MEM) Department, De La Salle University, Manila. She has done a research on electrophysiology of cardiac muscles remodeled using porcine stomach submucosa. She was a Biomedical Engineering Consultant for Increasing the Rates of Newborn Hearing Screening with Novel Technologies and Telehealth, "HeLe: Hearing for Life" which was funded by the Commission on Higher Education–Philippine California Advanced Research Institute (CHED-PCARI). She was awarded the Hong Kong Ph.D. Fellowship Scheme (HKPFS) and the NUS Research Scholarship to work on detection of gastric ulcer and gastric cancer using Raman Spectroscopy.

...