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Pricing Options as a Curbside Management Tactic for the City of Toronto

Report prepared for the Pembina Institute

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EXECUTIVE SUMMARY

Parking is a limited resource and in high demand in urban cities. The common mismatch between supply and demand of parking leads to adverse consequences such as long cruising times as drivers search for spaces near their final destinations. Pricing is a viable method of balancing the supply and demand of parking. This report analyzes three pricing policies in the City of Toronto which include hourly pricing, progressive hourly pricing, and time-of-day pricing.

The methods employed in this study include data analysis, econometric modelling, optimization, and simulation. This study first analyzes data provided from Green-P and the City of Toronto to develop and asses parking pricing strategies. The data is used in an econometric model to replicate parking behavior, mainly the parking duration of the drivers given a specific pricing structure. The econometric model is then used as input in an optimization model that derives the optimal design of the pricing structures. This optimal policy design then serves as the the basis for which scenarios are developed in the VISSIM micro-simulation software.

Results from the case study simulation developed in VISSIM show that a progressive hourly pricing policy in high-occupancy parking locations (greater than 60%) can reduce average parking occupancy. On average, implementing a progressive pricing policy in these locations reduced parking occupancy by 5.53% while implementing the same policy for low-occupancy locations only reduced parking occupancy by 1.03%. Additionally, results show that progressive hourly pricing reduces the number of vehicles that were rejected to park in their initial desired spaces due to their full occupancy. During peak conditions the percent share of vehicles declined parking decreased by 13.62% while in off-peak conditions it was reduced by 6.68%. Lastly with regards to time-of-day pricing, a reduction of 50% in the price level of the hourly policy does not negatively influence parking occupancy.

This report finds that the prospects of implementing a progressive hourly pricing policy for on-street parking locations within the downtown area are beneficial, especially for parking locations that experience a high parking occupancy. It is recommended that the econometric model is used for optimization of pricing levels for parking locations with high occupancy within the study area. By optimizing pricing for the on-street parking locations, reduction of network travel times, parking occupancy, and percent of vehicles that are unable to find parking can be achieved.

Contents

1 INTRODUCTION

Parking is a limited resource and in high demand in urban cities. The common mismatch between supply and demand of parking often causes drivers to cruise in search of convenient spaces near their final destinations. Studies conducted from 1927 to 2001 in various cities including San Francisco, Sydney, London and New York show that on average 30% of traffic is cruising for parking and the average search time is 8.1 minutes [Shoup, 2006]. Cities seek to alleviate the such adverse consequences by implementing parking policies such as pricing, time-of-day restrictions, and payment systems. The objective of this report is to evaluate the efficacy of different curbside pricing schemes in Toronto.

The case study is chosen as the city of Toronto's Curbside Management Strategy as shown in Figure 1. Three pricing policies are considered which include: 1- Hourly pricing, 2- Progressive hourly pricing, 3- Time-of-day pricing. Hourly pricing is a common pricing strategy that charges drivers a fixed rate per hour of parking. Progressive pricing charges drivers an initial hourly rate for the beginning hours of parking which increases if the parking duration surpasses a given threshold. Time-of-day pricing charges drivers at a high hourly rate during peak (high demand) hours and a lower hourly rate during off-peak (low demand) hours.

An example of the three pricing strategies is depicted in Figure 2. In the left panel, which represents hourly pricing, drivers pay $4 per hour of parking. In the middle panel, which represents progressive pricing, drivers pay $4 per hour if they park less than 4 hours, however, this rate increases to $8 per hour if they park for longer than 4 hours. In the right panel, which represents time-of-day pricing, drivers pay $8 per hour during the peak hours and $4 per hour during the off-peak hours.

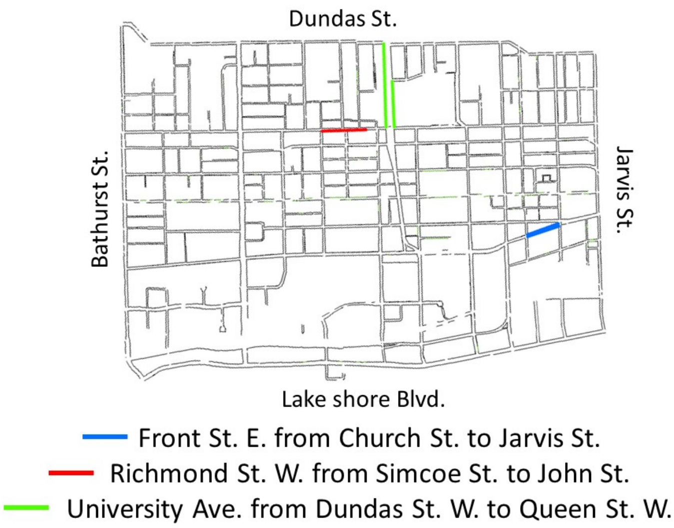

FIGURE 1: CASE STUDY BOUNDARIES. THE THREE HIGHLIGHTED STREETS AMONGST THE MANY THAT HAVE ON-STREET PARKING SPACES.

The framework of this study is presented in Figure 3 comprised of four steps: data analysis, econometric modelling, optimization, and micro simulation. This study first analyzes data provided from Green-P and the City of Toronto to develop and asses parking pricing strategies. The data is first used in an econometric model to replicate parking behavior, mainly the parking duration of the drivers given a specific pricing structure. The econometric model is use as input in an optimization model that derives the optimal design of the pricing structures. As an example, in the progressive pricing strategy the optimization model finds the shape of the step-wise pricing structure as shown in Figure 2b. The outcomes of the optimization models, i.e., optimal pricing structures, are implemented in a micro-simulation model developed in VISSIM to assess policy impacts and cross-compare them against each other.

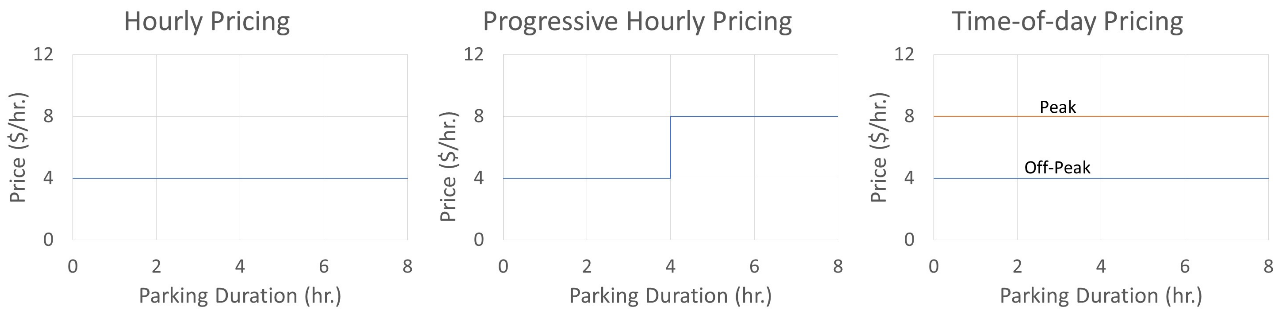

FIGURE 2: THREE PRICING STRATEGIES.

The main insights of this reports are the following:

- Progressive hourly pricing reduces total network travel time and increase the average travel speeds under peak and off-peak conditions. During peak conditions the total network travel time decreased by 1.14% while in off-peak conditions travel time was reduced by 1.35%.
- Progressive hourly pricing in high-occupancy parking locations (greater than 60%) can reduce parking occupancy. On average, implementing a progressive pricing policy in these locations reduced parking occupancy by 5.53% while implementing the same policy for low-occupancy locations only reduced parking occupancy by 1.03%.
- Progressive hourly pricing reduces the number of vehicles that were rejected to park in their initial desired spaces due to their full occupancy. During peak conditions the percent share of vehicles declined parking decreased by 13.62% while in off-peak conditions it was reduced by 6.68%.
- The number of vehicles who do not find parking when arriving at a location exponentially increases with parking occupancy (i.e, the percentage of occupied spaces). When parking occupancy is about 70% roughly 30% of vehicles are unable to find parking while for parking a occupancy of about 80% roughly 45% of vehicles do not find parking. This means that a 10% increase in parking occupancy raises the percent share of rejected vehicles by 15%.

- For time-of-day pricing a reduction of 50% in the price level of the hourly policy does not negatively influence parking occupancy. As shown in Section 7.2, both the parking occupancy and number of vehicles who do not find parking remain constant under the full hourly price and 50% of hourly price scenarios.

The remainder of this study is organized as follows. An extensive review of relevant literature on parking strategies is presented in Section 2. Analysis of available parking and vehicle volume data is discussed in Section 3. Formulation of pricing policy equations using the marginal utilities of drivers is presented in Section 4. A comparison of optimal pricing policies is conducted for two objective functions, revenue and social welfare, in Section 5. VISSIM model development for a case study with 54 parking locations in the City of Toronto is shown in Section 6 and a summary of highlights and findings is outlined in Section 7. Finally, concluding remarks are presented in Section 8.

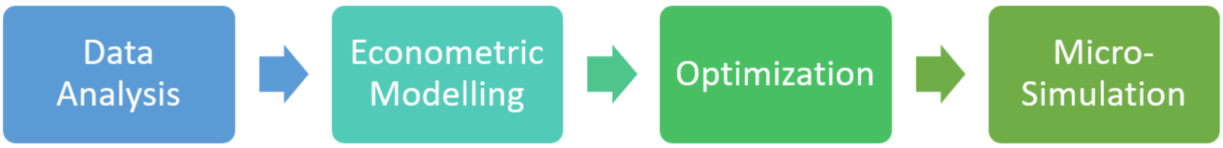

FIGURE 3: FRAMEWORK.

2 RELATED WORKS

Although the focus on this study is on the three discussed pricing mechanism, a review of other prominent parking pricing strategies is provided as well in this section. We summarize the pricing strategies as:

1. Fixed rate pricing: Charge a fixed rate per day,
2. Hourly pricing: Charge per hour,
3. Progressive pricing: Charge per hour and increase the rate if the parking time is beyond a threshold,
4. Time-of-day pricing: Charge more for peak hours and less for off-peak hours,
5. Dynamic pricing: Charge and adapt according to real-time parking availability,
6. Parking permits: Allow permit holding vehicles to park for free at the cost of the permit.

2.1 FIXED RATE PRICING

In fixed rate pricing, drivers pay a given fee for a set number of hours in the day. This pricing strategy is common for privately owned parking garages that serve daily commuters. The main benefits for the drivers is in their parking duration; those that park for longer durations benefit from economies-of-scale of paying less per hour overall. In contrast, this system is inconvenient for short parking durations (e.g., leisure trips) as drivers are forced to pay a large fee for hours extended beyond the required parking usage.

2.2 HOURLY PRICING

In hourly pricing drivers pay per hour of parking. In contrast to fixed rate pricing, hourly pricing is more convenient for leisure trips where the parking durations are short. The City of Toronto heavily implements hourly pricing in its downtown core. Drivers can pay for parking using Green-P, which is a parking lot management organization owned by the City of Toronto. Payments can be made either through parking meters, deployed on side-walks for every few parking spots, or via the online app available on smart-phones. This report uses Green-P data provided by the City of Toronto to better understand parking behavior in the downtown core. Figure 4 presents the histogram of the hourly parking prices in the case study. The prices are set at $3, $4, and $5 per hour. It is evident that majority of parking spaces have a charge of $5 per hour and a minority have charge of $3 per hour.

FIGURE 4: HISTOGRAM OF HOURLY PARKING RATES FOR 54 PARKING LOCATIONS IN THE STUDY AREA.

2.3 PROGRESSIVE PRICING

Parking is limited in supply and high in demand. As discussed earlier, pricing is a well-established method of balancing supply and demand not just in parking management but also other applications subjected to such supply and demand imbalance. An example of such applications is in consumption of water in counties were water is a limited resource. In the Metropolitan Region of Sao Paulo Brazil, water management authorities control water demand by charging less per litre for low consummations and more per litre if consumption surpasses a predefined threshold [Ruijs et al., 2008]. Similarly, the government of South Korean implemented a progressive pricing policy for the use of household electricity which aimed to achieve a more fair pricing systems which allowed lower income households with less consumption to pay a lower rate. This was achievable since electricity use increases proportionally with income [Youn and Jin, 2016].

From a parking perspective, a progressive pricing policy allows pricing to be more efficiently tailored towards multiple user groups. It also has the power to prohibit long parking durations when drivers are required to pay more per hour if they park for longer durations. Lowering parking durations through progressive pricing can increase parking availability and reduce the number of vehicles searching for parking spaces. Ultimately, traffic congestion can be alleviated if fewer vehicles search for parking.

2.4 TIME-OF-DAY PRICING

Increasing parking prices is often followed with public outcry. In parking pricing, a prominent strategy is to charge more only during the peak-hours when demand is high. By charging more during busy hours, the number of vehicles who want to park decreases allowing the city to decrease average parking occupancy. Time-of -day pricing is not only a pricing scheme that is already in use for on-street parking in Toronto, but also a popular pricing method in other industries such as in the household electricity industry. In Ontario, the electricity service provider Hydro One implements a time-of-day (also known as time-of-use) pricing scheme where the pricing rate takes on 3 price levels based on time of consumption. This pricing scheme better reflects the cost of producing electricity at different time of day based on demand. Since production of electricity at a given time is capped at a limit, instead of attempting to produce more electricity the pricing scheme shifts the demand from peak times to off-peak times by incentivising consumers with a lower price. In a similar manner, when the number of parking spaces that can be provided is limited due to space constraints, implementing a time-of-day policy will incentivize some of the demand to park in the off-peak periods as opposed to during peak hours.

2.5 DYNAMIC PRICING

Dynamic pricing requires adjustments in the pricing structure via real-time monitoring of the parking occupancy status. When occupancy is high (or vacancy is low), a large dynamic price is applied to reduce occupancy (increase vacancy). This allows cities to keep a certain number of spaces available at all times, reduce the possibility of cruising for parking, and improve total network travel time. Dynamic pricing is also implemented in other application such as ridesharing. Service providers such as Uber and Lyft has a surge pricing mechanism in which ridership fares are increased if demand is high or supply is low, such as in adverse weather conditions like rain and snow [Nourinejad and Ramezani, 2020].

SFpark, a pilot project in San Francisco, used parking occupancy data gathered from sensors to adjust hourly parking rates [Fabusuyi and Hampshire, 2018]. Rates were adjusted not more than one time per month by 0.25 to 0.50 dollars to achieve a desired parking occupancy of 85 percent. Such an approach not only requires parking occupancy sensors, which can be expensive to implement, but also a trial-and-error approach so as to achieve optimal price convergence. Instead of varying the price and then observing driver's parking behavior, this paper will predict driver behavior under varying parking price levels.

2.6 PARKING PERMITS

As the City of Toronto implements stricter parking enforcement in the city's downtown core, commercial vehicles (CVs) have become targets of increased ticketing and towing, often without alternate legal means of parking and loading. CV parking permits are a solution to provide lawful and affordable parking options that maintain a source of revenue for the municipality.

Parking permits around the world are reviewed on the basis of their cost and scope. Studies of historical parking citations in Toronto indicates clear patterns of parking behavior for which a permit would be beneficial. The trade-off between permit revenue and parking ticket revenue shows that optimal permit pricing, in the order of Can $300 annually, can provide an improvement in municipal revenue and achieve widespread adoption [Rosenfield et al., 2016]. An improvement in social welfare is also achieved with permit adoption through the reduction of the cost of congestion, as permit holders are encouraged to park in legal zones away from congested arterials [Rosenfield et al., 2016].

3 DATA

Data used for this case study was provided by Toronto Parking Authority and City of Toronto. The first set of data which was provided by the Toronto Parking Authority consisted of on-street parking lot information. This data set is described in Section 3.1. Secondly, City of Toronto provided traffic counts data at signalized intersections and turning movements for 23 intersections. This data is further described in Section 3.2.

3.1 ON-STREET PARKING

Data for 54 parking lot locations within the study area was provided by Toronto Parking Authority, commonly known as Green-P. The data includes aggregate information about daily

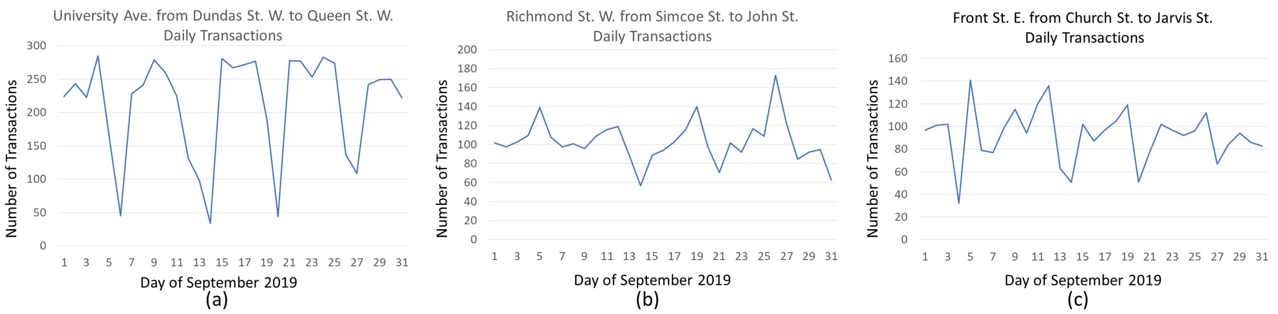

FIGURE 5: DAILY TRANSACTIONS FOR 3 PAYMENT MACHINES IN DOWNTOWN TORONTO. THESE LOCATIONS ARE HIGHLIGHTED IN FIGURE 1.

transactions at each payment machine including the generated revenue, total number of transactions, number of transactions with a parking dwell time longer than three hours, etc. The payment locations (each operated by one payment machine) display distinct parking behavior. Currently, there are only 3 pricing rates for the study area which are 3, 4, and 5 dollars per hour. There are 10 location that charge 3 dollars per hour, 20 locations that charge 4 dollars per hour and 24 locations that charge 5 dollars per hour.

A given number of parking spots are associated with each parking location (i.e, payment machine). The total number of parking spots per location ranged from 3 to 82 parking spots with an average of 18 parking spots per location. Additionally, the data included the average parking occupancy for the year of 2019. Parking occupancy was specified using three ranges labelled as low, medium and high. The parking occupancy percentage range for each label were 0% to 50%, 51% to 79%, and 80% to 100% respectively.

The daily aggregate transaction data for the month of September 2019 was analyzed. Figure 5 shows the number of daily transactions for 3 parking locations in the study area. From these three locations two locations, shown in Figure 5 (b) and (c), experience a relatively stable number of transactions throughout the month. Contrary to this, the parking location spanning from University Ave. from Dundas St. W. to Queen St. W. seen in Figure 5 (c) experiences a significant drop in number of transaction during weekends.

The mean dwell time (parking duration) for each parking location was inferred from the daily transaction data. The expected dwell time for each day was derived by dividing daily revenue by the number of daily transactions and parking price. From the analysis reported in Figure 6, it is seen that the average dwell time for each parking location is relatively constant throughout the month of September. That is to say that the average parking duration for each day for the month of September 2019 is approximately constant and is not influenced by the day of the month. As a result the the average parking duration for a specified parking location can be calculated by averaging the observations for the whole month of September. The dwell time analysis displayed a dwell time distribution resembling a normal distribution as shown in Figure 7. From the graphs, it can be noted that the mean dwell time of drivers remains relatively constant throughout the month of September. The mean and standard deviations from

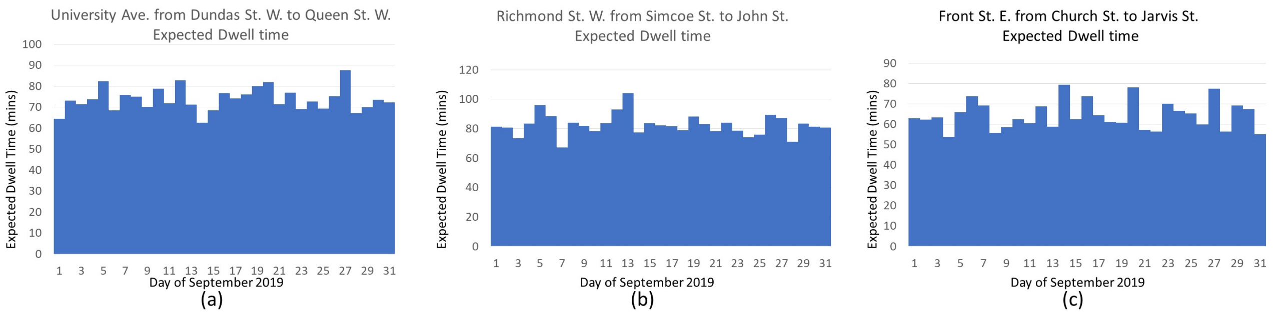

FIGURE 6: EXPECTED DWELL TIME OF 3 PAYMENT MACHINES IN DOWNTOWN TORONTO.

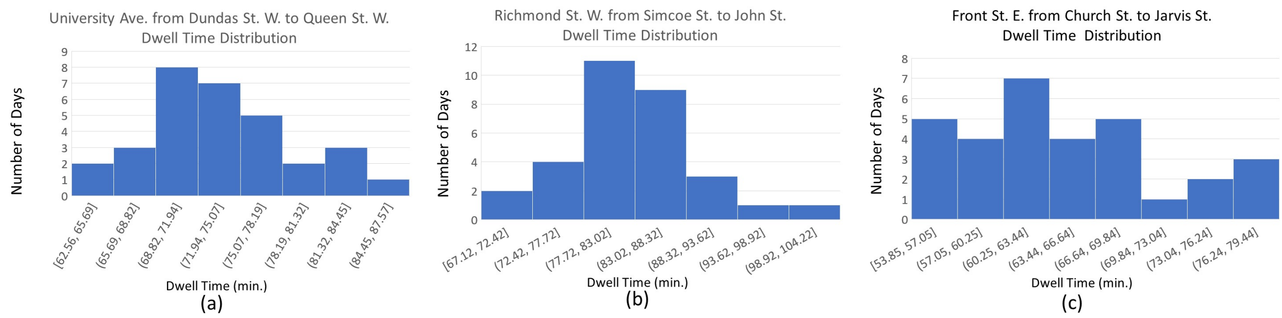

FIGURE 7: DWELL TIME DISTRIBUTION OF 3 PAYMENT MACHINES IN DOWNTOWN TORONTO.

the dwell time distributions are later used in calibration of the econometric models explained in the next section. The mean and standard deviation were calculated for each of the 54 parking locations of the study area.

3.2 VEHICLE VOLUMES

Vehicle turning movement counts were provided and used in the Vissim micro-simulation model explain in Section 6. The 23 intersections provided by City of Toronto are shown in Figure 8. The nature of the data consisted of averaged volume counts for the month of September 2019 at an hourly level. The data set contained attributes defined by day type (weekend,weekday), vehicle type, hour of day, intersection leg, movement type (left, right, through), and hourly average volume. The data set was analyzed and findings indicate that peak hour conditions occurs from 8 A.M. to 9 A.M. for the morning and from 5 P.M. to 6 P.M. in the afternoon. The morning time frame is used as the designated peak hour times for the study. For this study, two vehicle classes are taken into consideration as described in Section 4. The truck vehicle volume counts for each of the peak hour time frames under question were calculated in a similar manner. The percent share of truck type vehicles in the network was estimated by summing up all turning movements for the peak hour scenario (car and truck type vehicles) and calculating the percent share of truck vehicles from this total. The resulting truck percent share in the network that resulted from this analysis and is used for all subsequent calculations was 3.32%.

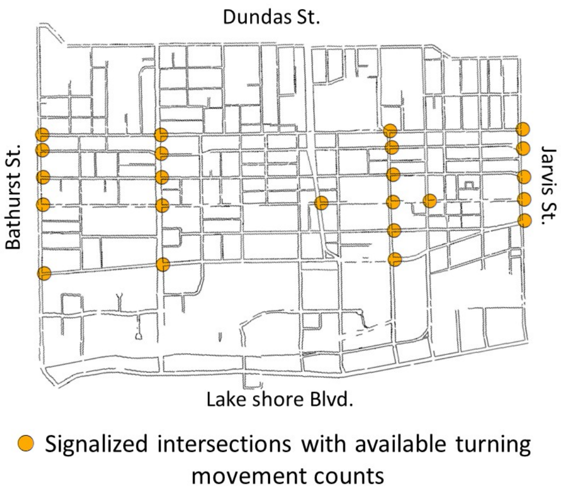

FIGURE 8: INTERSECTIONS WITH AVAILABLE TURNING MOVEMENT COUNT DATA WITHIN THE STUDY AREA.

4 ECONOMETRIC MODEL

Consider an urban area with a total parking demand of T vehicles per hour. A ratio α of the demand represents high-value driver, and the remaining $1-\alpha$ represents low-value drivers. Let $T_h = T\alpha$ and $T_l = T(1-\alpha)$ be the demand of high- and low-value drivers, respectively, where "h" and "l" are memonics for the two groups. Drivers benefit from each (fraction of) hour of parking as this time is used to engage in activities occurring the urban area. Let $u_i(d)$ be a group i driver's benefit from the d^{th} hour of parking. $u_i(d)$ is regarded as the *marginal utility* of parking, which satisfies $\partial u_i(d)/\partial d < 0$ representing the Law of diminishing returns, indicating for example that the first hour of parking for shopping purposes provides a higher level of satisfaction than the second hour. We further assume the marginal utility function is convex and satisfies $\partial^2 u_i(d)/\partial d^2 > 0$ for both groups. The Green-P data from the previous section is used to calibrate two marginal utility functions of high and low value drivers.

We define two pricing policies: *hourly pricing* and *progressive pricing*. In the former the price is fixed and imposed in dollars per hour, and in the latter the price of parking increases for those whose parking duration is larger than a threshold. We do not explicitly develop an off-peak pricing model because it is a special case of hourly pricing with the difference of having a lower demand during the off-peak. Thus, the same model developed for hourly pricing can have two variants: one for peak and the other for off-peak hours.

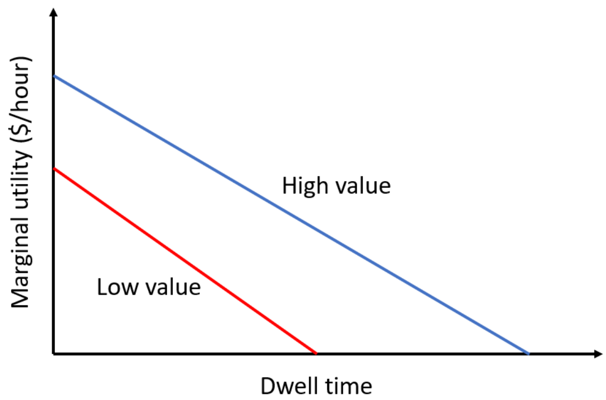

FIGURE 9: MARGINAL UTILITY.

4.1 HOURLY PRICING:

In hourly pricing, the drivers pay p per hour. Let $U_i(d)$ be the *utility* of group i drivers with parking duration d. The utility is the benefit from engaging in activities (the integral of marginal utility from zero to d) minus the price of parking, given as

$$U_i(d) = \int_0^d u_i(w)\mathrm{w}d - pd. \tag{1}$$

We note that the parking cruising cost (i.e., the monetary value of the time spent searching for parking) is not included in the total utility because (1) accounts for the utility gained from the moment a driver finds parking. We later consider the cost of the cruising when maximizing social welfare to develop policies that alleviate excessive cruising and its adverse impacts on traffic, emissions, and welfare.

Drivers maximize their utility by choosing an optimal parking duration denoted by d_i^* for group i. From the first order condition, setting the derivative of (1) to zero gives

$$d_i^* = u_i^{-1}(p), \tag{2}$$

where $u_i^{-1}(.)$ is the inverse of the marginal utility function. Given the convexity of $u_i(d)$ w.r.t. d, there exists a single and unique d_i^* for each group's drivers.

4.2 PROGRESSIVE PRICING:

In progressive pricing, the drivers pay p_1 per hour if their parking duration is less than q. For those whose parking duration is larger than q, the price is p_1 for the first q hours and p_2 for the remainder (from q to d). By definition of progressive pricing policies, we have $p_2 \geq p_1$ as this policy is designed to truncate parking dwell times. The utility of group i drivers in progressive pricing is

$$U_i(d) = \int_0^d u_i(w)\mathrm{d}w - C(d), \tag{3}$$

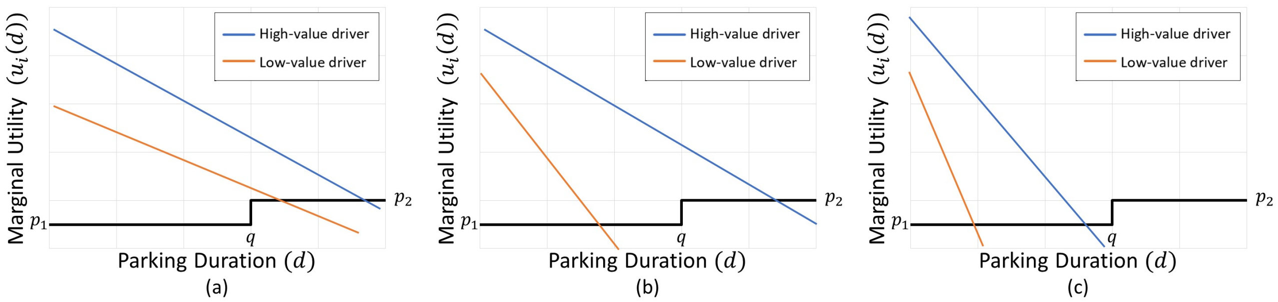

FIGURE 10: THREE POSSIBLE RELATIONSHIPS BETWEEN DWELL TIME AND THE PROGRESSIVE PRICING POLICY.

where

$$C(d) = \begin{cases} p_1 d & d \leq q \\ p_1 q + p_2(d-q) & d > q \end{cases}$$

is the cost of parking for drivers.

Similar to hourly pricing, the drivers maximize their utility by choosing an optimal parking duration denoted by d_i^* for group i. From the first order condition, setting the derivative of (3) to zero gives

$$d_i^* = \begin{cases} u_i^{-1}(p_1) & u_i(q) \leq p_1 \\ q & p_1 < u_i(q) \leq p_2 \\ u_i^{-1}(p_2) & p_2 < u_i(q). \end{cases} \tag{4}$$

We note that the hourly pricing policy is a spacial case of progressive pricing if we set $q = 0$ and $p_1 = p_2 = p$. Thus, it is straightforward that the latter outperforms the former regardless of the policy's objective. Hereafter, we focus on the progressive pricing policy and consider the special case of hourly pricing wherever needed.

5 OPTIMIZATION

5.1 REVENUE MAXIMIZATION

Parking policies are designed to achieve a certain objective for the decision makers. Private parking operators (e.g., garage owner) seek to maximize their revenue, whereas public agencies (e.g., on-street parking managers) maximize the social welfare of the community which accounts for the benefits gained by drivers and the revenue generated from parking. We consider both objectives in the optimal design of parking policies.

We seek to design the progressive pricing policy to maximize the revenue by choosing the optimal prices, p_1 and p_2, and the threshold q. The total revenue, denoted by π, is the sum of payments from each group, denoted by π_i, such that $\pi = \pi_l + \pi_h$. The revenue from each group is

$$\pi_i = \begin{cases} T_i p_1 d_i^* & u_i(q) \leq p_2 \\ T_i(p_1 q + p_2(d_i^* - q)) & p_2 < u_i(q). \end{cases} \tag{5}$$

According to (5), one of three cases may occur as shown in Figure 1. In case 1 (Figure 10a), both marginal utility functions only cross the horizontal p_2 line. We refer to this as the case where both groups "fall" on the second step of the price profile. Using the same terminology, in case 2 (Figure 10b), one group falls on the first step and the other group falls on the second step. In case 3 (Figure 10c), both groups fall on the first step, thus making the progressive pricing policy ineffective as both user groups only pay p_1 and no driver's dwell time is longer than the threshold q. As such we do not consider case 3.

5.2 SOCIAL WELFARE MAXIMIZATION

We now seek to design the progressive pricing policy to maximize social welfare. We first define the cruising cost of parking as the following. Let s denote the supply of parking in the study area, i.e., number of parking spaces. Parking occupancy under steady state conditions and according to Little's Law is $o = T_h d_h^* + T_l d_l^*$. Cruising time is conventionally defined w.r.t. the ratio of parking occupancy to supply. Similar to Nourinejad and Roorda [2017], we define the cruising time as o/s. Let γ be the marginal cost of cruising such that $\gamma o/s$ is the cost of cruising per driver.

Social welfare is the sum of the revenue generated from the parking payments, and the utility of drivers (i.e., consumer surplus of the drivers), minus the negative externality of cruising. We present social welfare, denoted by W, as

$$W = T_l U_l(d_l^*) + T_h U_h(d_h^*) + \pi - \gamma T(T_h d_h^* + T_l d_l^*)/s, \tag{6}$$

where the first two terms are the total utility of the low and high value drivers, the third term is the revenue, and the last term is the negative externality of cruising for parking.

5.3 COMPARISON OF PRICING POLICIES

The marginal utility function can be of any form, however, some common functions includes the negative exponential, power, and linear function [Samuelson, 1937]. For exposition purposes we consider a the linear marginal utility function because is has properties that enable closed-form derivations of the optimal policies, which is suitable for cross comparison of the policies.

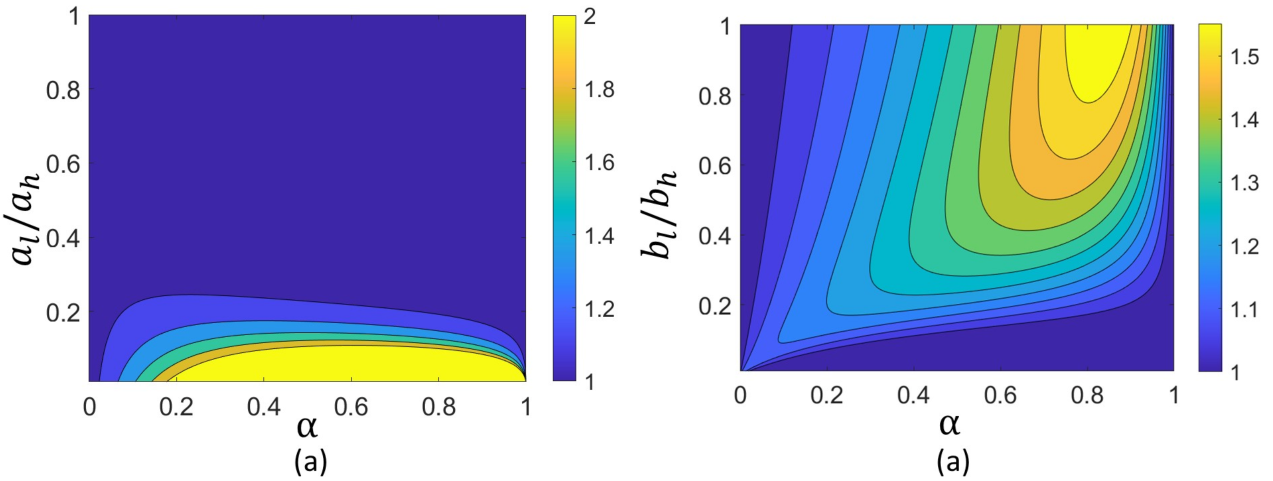

FIGURE 11: REVENUE POLICY PLOTS FOR VARYING VALUES OF α, a_h AND b_h WHILE ALL OTHER PARAMETERS ARE CONSTANT($a_l = 0.2, b_l = 0.2, a_h = 1,$ AND $b_h = 1$).

Assume the utility functions of the groups are linear and defined as

$$u_i(d) = a_i - b_i d, \tag{7}$$

where $a_i, b_i > 0$. Without loss of generality we let $u_l(d) \leq u_h(d)$ for all d. Note that the *maximum dwell time* according to (7) is a_i/b_i for group i drivers, which is the dwell time at which the marginal utility function is zero. We use the equilibrium conditions of the previous section to derive the dwell time of group i drivers as

$$d_i^* = \begin{cases} (a_i - p_1)/b_i & a_i - b_i q \leq p_1 \\ q & p_1 < a_i - b_i q \leq p_2 \\ (a_i - p_2)/b_i & p_2 < a_i - b_i q. \end{cases} \tag{8}$$

For a given policy defined by p_1, p_2, and q, one of three cases may occur as explained previously and depicted in Figure 10. Given the linear marginal utility function, in case 1 both groups “fall” on the second step as long as $q \leq (a_l - p_2)/b_l$. In case 2, the lower value group falls on the first step, and the higher value group falls on the second step as long as $(a_l - p_1)/b_l \leq q \leq (a_h - p_2)/b_h$. In case 3 both groups fall on the first step. We do not consider case 3 as explained above.

The progressive pricing policy always outperforms the hourly pricing policy when maximizing either social welfare or revenue as discussed earlier. We define the *revenue (or social welfare) ratio* as the ratio of progressive pricing revenue (social welfare) to the hourly pricing revenue (social welfare). The revenue ratio is presented in Figure 11a for various marginal utility parameters. According to Figure 11 when a_l is between the values of 0.3 and 0.5, the two policies are close in revenue, while when the value of a_l is closer to 0 or 1 the progressive policy outperforms the hourly policy. This can be explained by the relationship between the two price levels and the progressive pricing structure. As the value of a_l increases, the optimal price level p_1^*

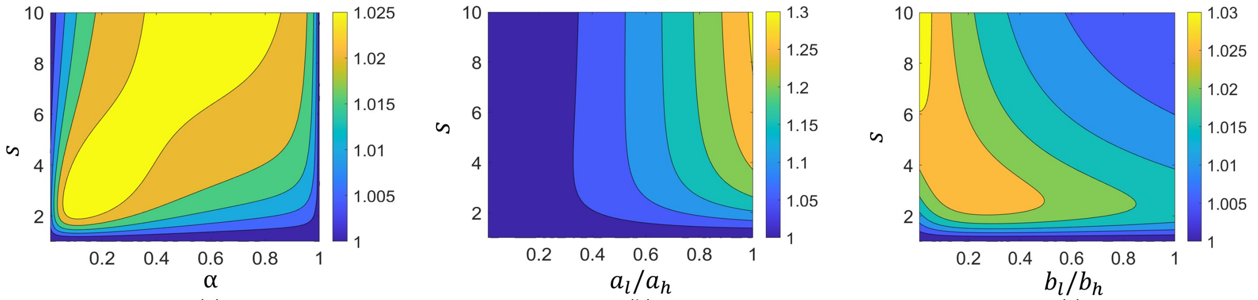

FIGURE 12: SOCIAL WELFARE POLICY PLOTS VARIOUS s, α, a_h AND b_h. OTHER PARAMETERS ARE CONSTANT($T_h = 0.2, a_l = 0.2, b_l = 0.2, a_h = 1,$ AND $b_h = 1$).

increases while the optimal price level p_2^* decreases. In view of this there will exist a point a_l^* at which the two price levels,p_1^* and p_2^*, are equal to each other. For values of a_l greater than a_l^* the price level p_2^* is lower than p_1^* and for values of a_l less than a_l^* the price level p_2^* is higher than p_1^*. As expected, at boundary conditions $T_h = 0$ and $T_h = 1$ the revenue ratio between both policies is equal to one since demand consists of only one group.

With regards to social welfare, the progressive pricing policy can outperform the hourly pricing policy by up to 3%. As noted from Figure 12a, an increase in the supply of parking will require an increase in the proportion of high-value drivers in order to maintain the same level of performance. An increase in the ratio of a_l and a_h will increase the performance of the progressive pricing policy with regards to social welfare. It is important to note that as the supply of parking increases, the ratio between the social welfare generated by the progressive pricing policy and the hourly pricing policy will increase. From this observation we can suggest that for areas with a high level of parking supply, the progressive parking policy is more fitting than the hourly pricing policy. In Figure 12b we observe that as the value of a_l increases from 0 to 1 the social welfare ratio between the two policies also increases. Such result is expected because as the low-value drivers shift their marginal utility line upwards(a_l becomes closer to 1), the social welfare from parking will also increase. As seen in Figure 12c, the social welfare ratio increases when the value of b_l is small. Since the value of b_l represents the slope of the marginal utility line, then a lower value for this slope will shift the market equilibrium point subsequently increasing the parking duration of drivers. All other parameters remaining the same, a higher parking duration will yield a higher social welfare.

6 VISSIM MICRO-SIMULATION

The potential impacts of the before-mentioned curbside pricing policies are quantified with the use of a micro-simulation. The software package PTV VISSIM is used to develop a multi-modal traffic flow simulation which will quantify network wide impacts of the policies. Performance measurements extracted from the VISSIM simulation include total network travel time, average speed, parking occupancy, and percent of vehicles who are not able to park and cruise for parking. A description of network components, simulation calibration, and the two developed scenarios are given in Sections 6.1, 6.2, and 6.3.

6.1 NETWORK DESCRIPTION

The road network was built in VISSIM using data gathered from google maps. Attributes including the number of lanes, speed limit, and permitted turning movements were collected for each road of the study area. Additionally, the number of parking lots available at each intersection and their approximate location were noted. Moreover, the TTC streetcar network was modelled in VISSIM to get a closer representation of the current network conditions of the study area as TTC streetcars can have a significant traffic flow in the area of consideration. Figure 13 shows the developed network.

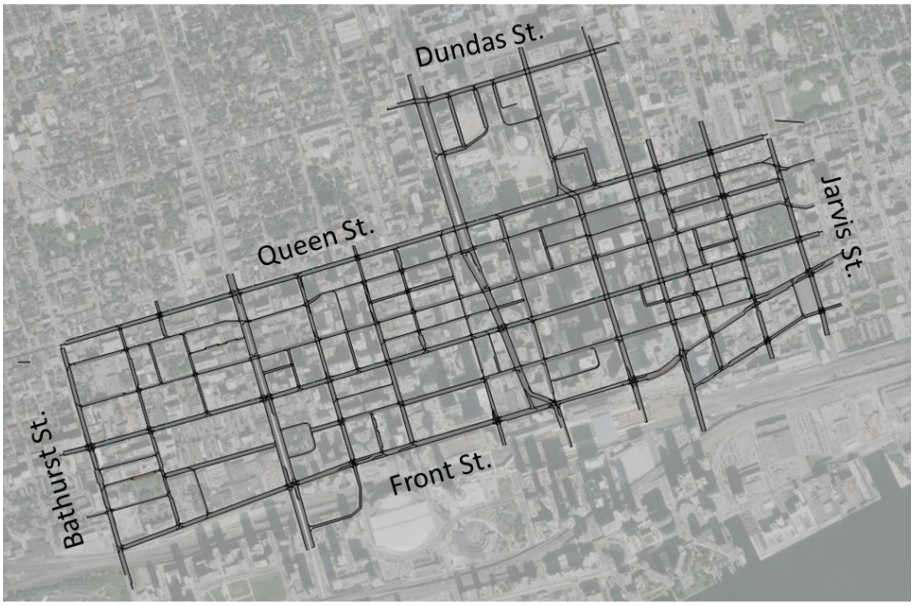

FIGURE 13: AERIAL VIEW OF ROAD NETWORK BUILT IN VISSIM.

Vehicles in the network were assigned travel routes based on the percent share of vehicles which performed a movement. From data obtained regarding vehicular movements at intersections described in Section 3.2, the percent share of vehicles which performed a left turn, right turn and through movement was calculated and used as input in the simulation. Similarly, vehicular traffic inputs with a share of 96.68% passenger vehicles and 3.32% truck vehicles was inputted as per calculation completed in Section 3.2.

Furthermore, signal timings were implemented into the network by creating a signal controller for each intersection. A ring barrier controller was used as the signal type and detectors were used for each movement. Since signal timing data was not available and out of scope for this project, a standard timing with cycle length of 78 seconds was used. Figure 14 shows the components included at each intersection of the network. A total of 75 signalized intersections were implemented in the study area.

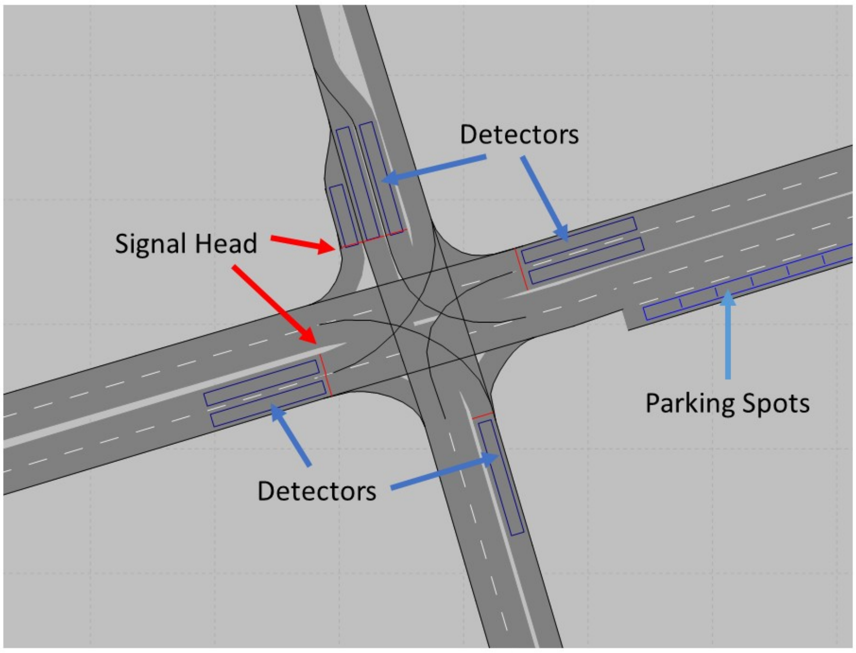

FIGURE 14: ONE OF 75 SIGNALIZED INTERSECTIONS BUILT IN VISSIM.

6.2 SIMULATION CALIBRATION

To ensure that the developed network represents current network conditions, the VISSIM simulation was calibrated. Calibration was completed with the use of available parking occupancy data. As mentioned in Section 3.1, parking occupancy was given as a percentage. The three ranges were 0% to 50%, 51% to 79%, and 80% to 100% for labels "low", "medium" and "high" respectively. Parking rates were calibrated to ensure that parking occupancy from the simulation matched the occupancy provided in the data set. After calibration, 43 out of 54 parking locations were calibrated to match their known parking occupancy, while the remaining 11 parking locations showed a parking occupancy within 20% of the known parking occupancy.

6.3 SCENARIO DESCRIPTION

The first time-frame of importance to the study was the A.M. peak scenario. As described in Section 3.2, the morning peak vehicular volume occurred from 8 A.M. to 9 A.M. For this time frame, two scenarios were created within the simulation. The first scenario labeled as hourly pricing implements an hourly pricing rate at each of the parking locations. Secondly, a progressive hourly pricing scenario was also developed for the morning peak conditions. All parameters in the simulation remained the same for both scenarios except.

The off-peak time-frame is also of importance to the study. For this scenario, vehicular volumes were reduced by 50% to compensate for the the reduced traffic flow during this time frame. All other parameters remaining the same, three scenarios were created. Similarly to the A.M.peak time frame, the first two scenarios consisted of hourly and progressive hourly pricing policies. The third scenario for this time frame was that of an hourly pricing policy but with a 50% reduction in price. That is to say for parking locations that were charged $5 per hour in the hourly policy, will now have a rate of $ 2.5 per hour in the second hourly pricing scenario. This scenario is labelled as "time-of-day pricing" for all subsequent sections of the report. The assumption of reducing the price by 50% has been made in accordance to various time-of-day pricing schemes implemented around the world. For example, in Sydney Australia the hourly rate decreases from $7.2 to $3.9 during off-peak times. For each scenario, 30 simulation runs were performed and averaged.

7 RESULTS

With he use of data described in Section 3, two time intervals were taken into consideration for the VISSIM simulation. The first time interval spanned from 8 A.M. to 9 A.M. and represents the peak morning traffic volume conditions. Results of this scenario are further described in section 7.1. The second time frame of interest was the off-peak scenario. The off-peak scenario consisted of a 50% traffic volume reduction from the peak morning conditions and results of this scenario are described in Section 7.2.

7.1 A.M. SCENARIO

As described in Section 3.2, the 1 hour time interval during the morning period which showcased the highest traffic volumes was from 8 A.M. to 9 A.M. The resulting data from the VISSIM simulation can be seen below. In Figure 15 the total network travel times for each of the 30 simulation runs is displayed. Total network travel time is defined as the summation of travel time experienced by all vehicles in the network. As noted from the figure, the general trend showcases a decrease in total travel when implementing a progressive hourly pricing policy. This information is also presented as a box plot in Figure 16 were we can identified a mean travel time of 2249.76 hours for the hourly pricing policy and 2224.09 hours when implementing a progressive pricing policy.

The next measure which was taken into consideration was average parking occupancy. Average parking occupancy is defined as the percentage of spots that are occupied during a specified time interval. Parking occupancy for the 54 parking locations can be seen in Figure 17. It can be noted that the general trend showed a decrease in parking occupancy when implementing a progressive hourly pricing policy. Additionally, all parking locations that experienced a parking occupancy greater than 65% with an hourly pricing policy showed a decrease in oc-

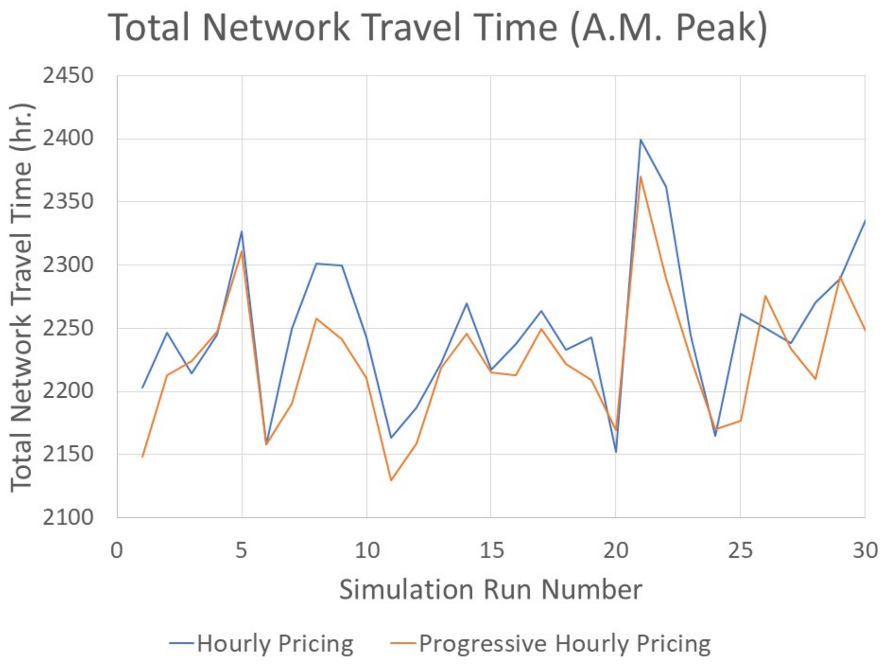

FIGURE 15: TOTAL NETWORK TRAVEL TIMES FOR 30 SIMULATION RUNS FOR THE HOURLY AND PROGRESSIVE PRICING POLICIES.

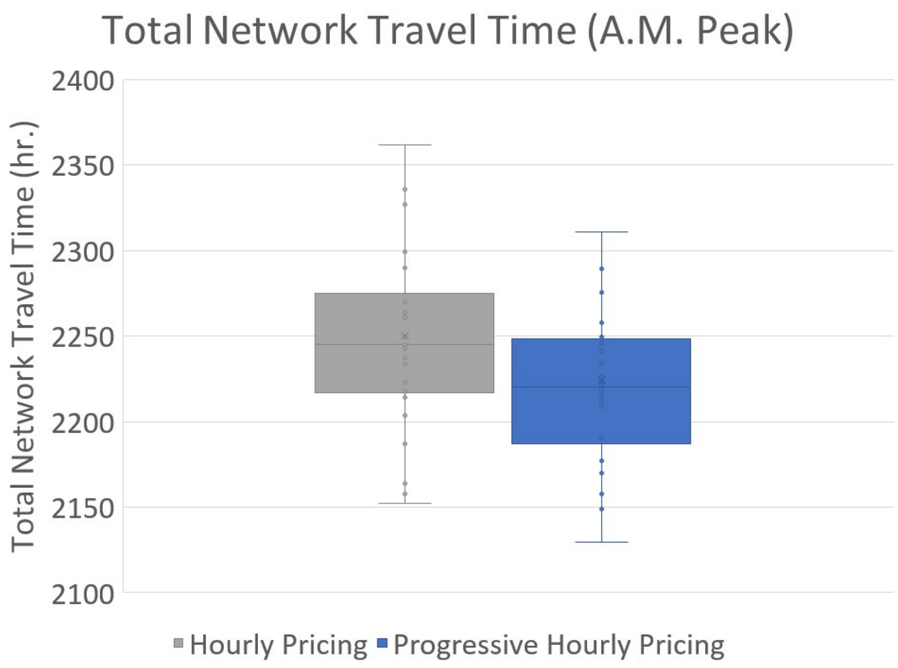

FIGURE 16: BOX PLOTS FOR THE HOURLY AND PROGRESSIVE PRICING POLICIES.

cupancy when the progressive hourly pricing policy is implemented. Therefore, the resulting data from the 30 simulations led to the proposition that progressive hourly pricing reduces the average occupancy for parking locations that experience a high occupancy (greater than 60%) under an hourly pricing policy. For parking locations with parking occupancy of less than 60% under the hourly pricing policy the implementation of a progressive hourly pricing did not negatively impact average occupancy. In Figure 18 the parking locations with the highest and lowest occupancy are mapped. Additionally, the figure also contains parking locations that experienced a large decrease in parking occupancy with the implementation of the progressive pricing policy. From this it can be noted that the implementation of a progressive pricing policy tends to decrease parking occupancy not only for the parking locations with high occupancy but also parking locations in the surrounding area.

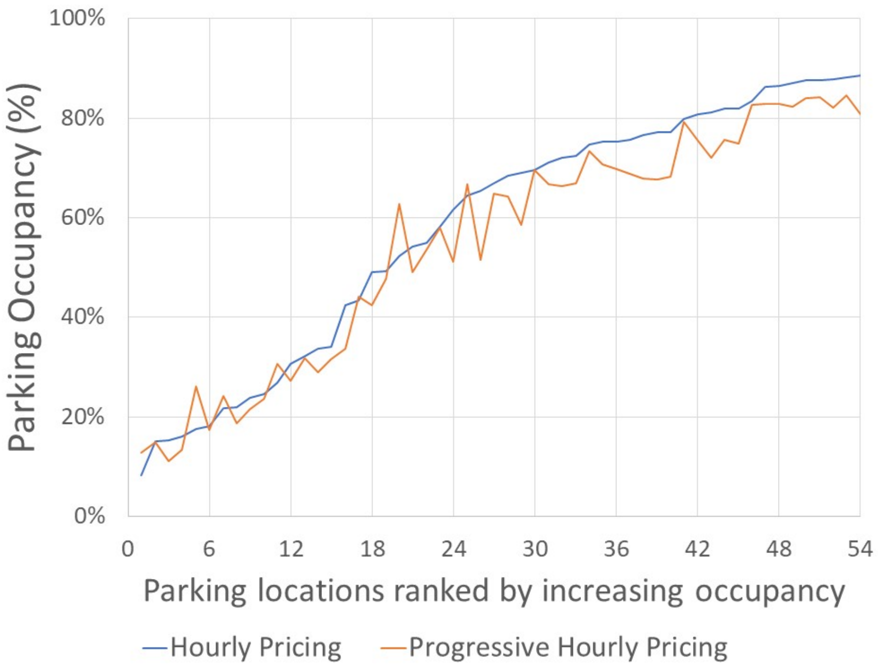

FIGURE 17: PARKING OCCUPANCY FOR 54 PARKING LOCATIONS IN THE STUDY AREA.

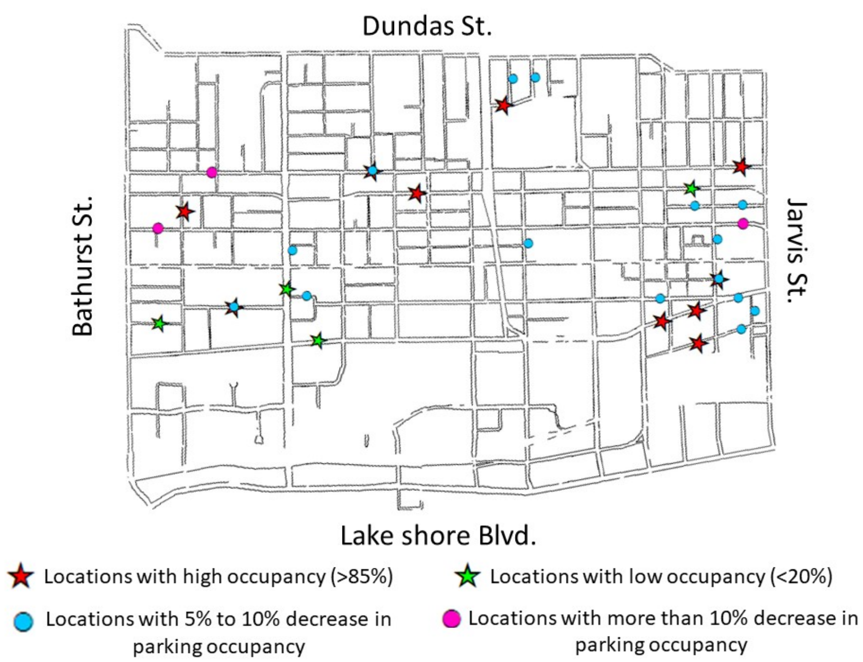

FIGURE 18: LOCATIONS WITH HIGHEST DECREASE IN OCCUPANCY WITH IMPLEMENTATION OF PROGRESSIVE PRICING POLICY.

It is of importance to take into consideration the number of vehicles that are unable to find parking since these vehicles will remain in the network, cruise for parking, and increase congestion the area. The measure which was used in order to get an understanding of the number of vehicles that are rejected from parking due to no parking spaces available is parking requests declined. As seen in Figure 19, the parking requests declined is shown as a percentage of all requests received. When comparing the hourly pricing policy with progressive hourly pricing it can be noted that the number of parking requests declined decreases for the later one. Since the progressive hourly pricing policy decreases the average dwell time of the driver which in turn decreases occupancy, the number of vehicles that are able to park in the same period of time increases leading to a fewer number of vehicles that are unable to park. The implementation of the progressive pricing was on average able to decrease the percent parking requests declined by 11%.

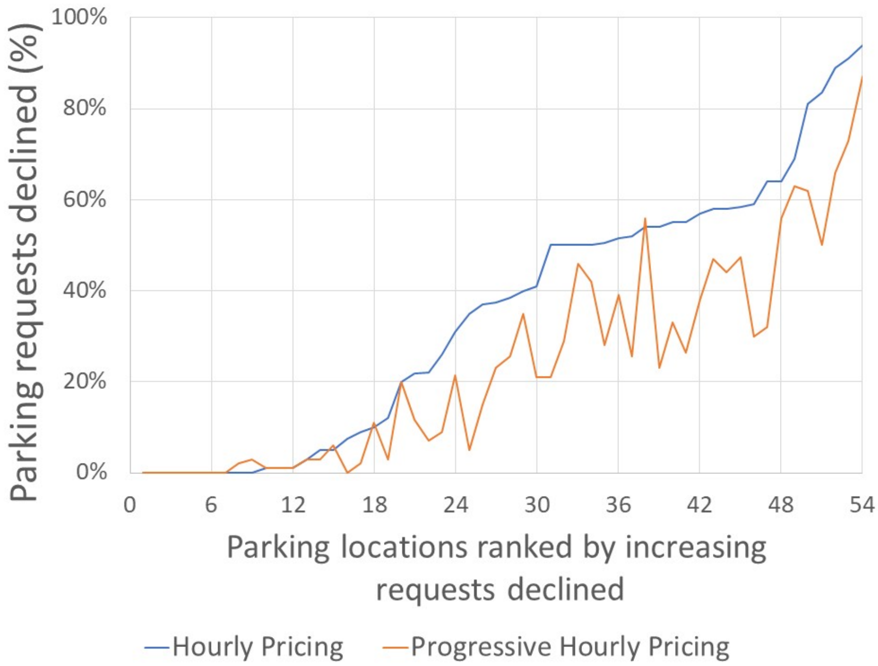

FIGURE 19: PERCENT OF PARKING REQUESTS WHICH WERE DECLINED FOR THE 54 PARKING LOCATIONS.

Furthermore, there exists a relationship between the two above-mentioned measures, occupancy and parking requests declined. The relationship between both measures is displayed in Figure 20. The general trend from the scatter plot shows that as the average occupancy increases, the percent of parking requests declined will also increase. However, the rate at which parking requests declined increases is lower for the progressive hourly pricing policy when compared to its counterpart. This leads us to propose that for a parking location that experiences a given occupancy (let us say 80%), the number of vehicles that are not able to find parking is larger under an hourly pricing policy as opposed to a progressive hourly policy.

Moreover, the average speed of vehicles in the network increased with the implementation

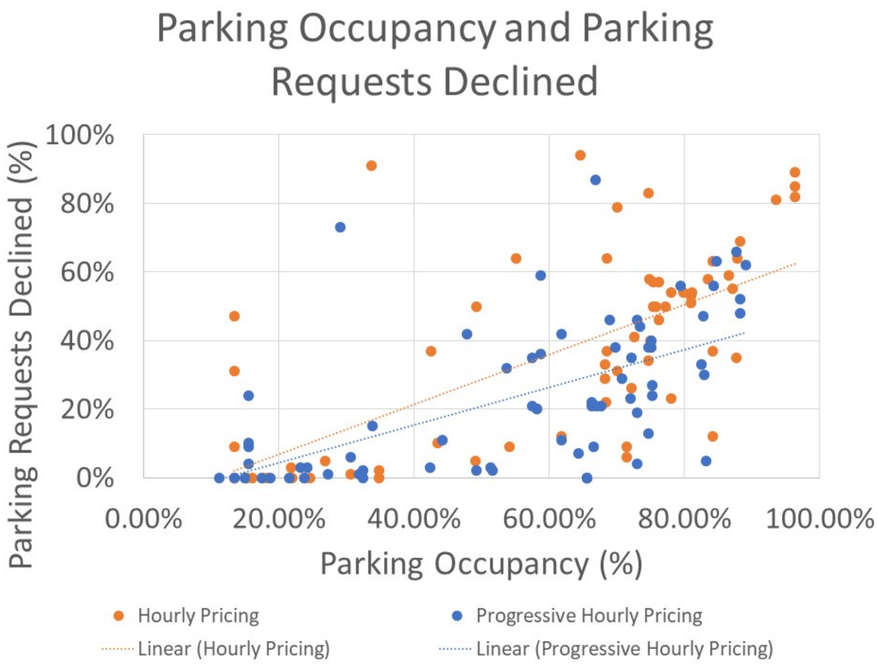

FIGURE 20: PERCENT SHARE OF PARKING REQUESTS DECLINED FOR VARYING PARKING OCCUPANCY.

of the progressive hourly pricing policy as seen in Figure 21. An increase in average speed is the resultant from the lower number of vehicles in the road at a given time. A decrease in the number of vehicles that do not find parking and must cruise for parking leads to a decrease in congestion in the surrounding area. This decrease in congestion permits the network to operate under conditions which are closer to the free flow speed of the network.

Lastly, the summary of resulting measures from the simulation can be seen in Table 1. In addition to the previously discussed measures, GHG emissions and parking revenue values are included in the table. With regards to parking revenue, it can be noted that the progressive pricing policy significantly increases revenue as the implemented optimal price levels are higher than the current pricing rate. GHG emissions were calculated from the simulation with he addition of one assumption. Vehicles in the network were assumed to have a fuel economy of 8.9 L/100km. With this assumption, the CO_2e (carbon dioxide equivalent) values for hourly pricing and progressive pricing policies were found to be 6,569 kg CO_2 and 6,494 kg CO_2.

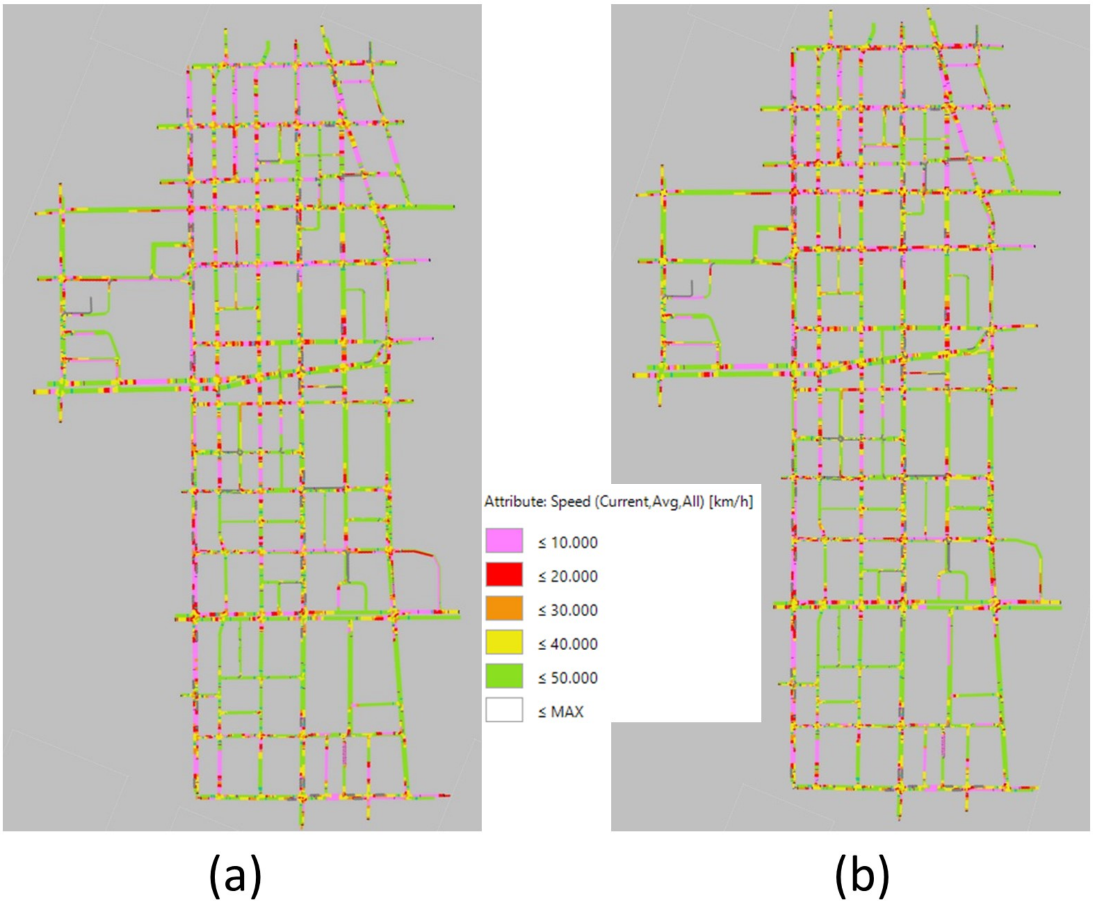

FIGURE 21: AVERAGE SPEED HEAT MAPS FOR THE CASE STUDY. HOURLY PRICING ON THE LEFT AND PROGRESSIVE HOURLY PRICING ON THE RIGHT.

TABLE 1: SUMMARY OF RESULTS FOR EACH PRICING POLICY FOR THE A.M. PEAK SCENARIO.

Measure	Scale	Units	Hourly Pricing	Progressive Pricing
Parking Occupancy (High Demand Locations, occupancy >50%)	Street Block	Percentage (Weighted based on number of parking spots)	76.64%	71.00%
Parking Occupancy (Low Demand Locations, occupancy <50%)	Street Block	Percentage (Weighted based on number of parking spots)	24.48%	23.99%
Parking Revenue	Street Block	$/hour	$2,522.58	$5,790.19
Cruising for parking	Street Block	Percent of vehicles declined. (Weighted based on number of parking spots)	32.29%	19.81%
Total Network Travel Time	Study Area-Wide	Hours	2249.76	2224.09
GHG Emissions	Study Area-Wide	CO_2e Kg/hour	6,569	6,494

7.2 OFF-PEAK SCENARIO

The simulation of off-peak conditions in the study consisted of 3 scenarios. The first scenario was the current hourly pricing policy for the study area labelled as ”Hourly Pricing” in Figures 22 to 26. Secondly, scenario labelled as ”time-of-day pricing” consists of a reduction of 50% to the current hourly rates. Lastly, scenario belled ”Progressive Hourly Pricing” consists of the optimal progressive pricing levels calculated from the econometric model. The progressive hourly pricing policy performed marginally better when compared to the two hourly pricing policies for the 30 simulation runs as seen in Figure 22. The average total network travel times for hourly pricing, time-of-day pricing, and progressive hourly pricing are 1074.55hrs., 1088.89hrs., and 1060.04hrs. respectively as seen in Figure 23.

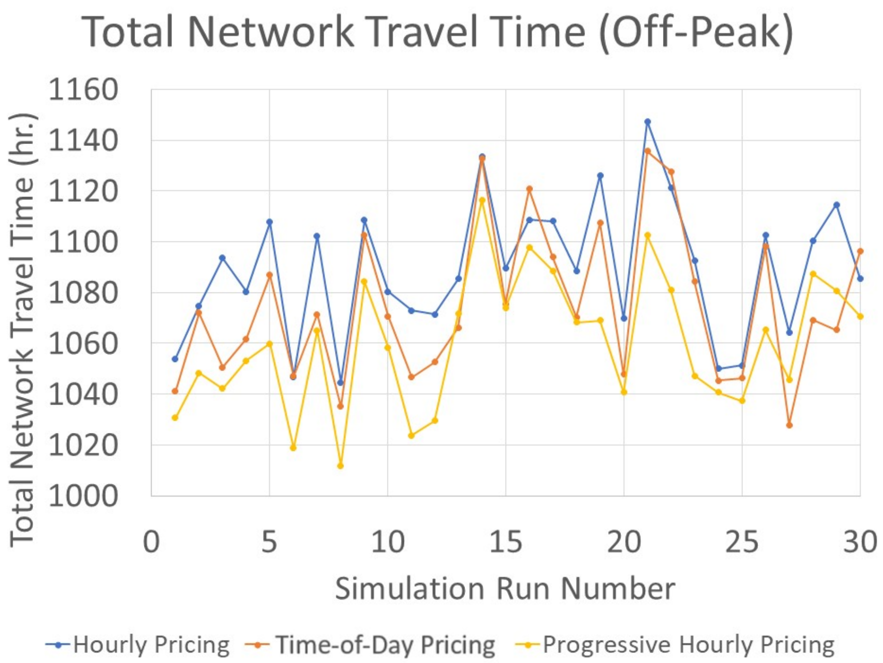

FIGURE 22: TOTAL NETWORK TRAVEL TIMES FOR 30 SIMULATION RUNS FOR THE HOURLY AND PROGRESSIVE PRICING POLICIES.

With regards to parking occupancy, as expected the off-peak conditions resulted in a decrease of parking occupancy when compared to the A.M. conditions due to the decrease in vehicular volumes in the network. The three policies under question hourly pricing, time-of-day pricing, and progressive hourly pricing resulted in similar parking occupancy for most of the parking locations. For two parking locations, parking lot number 2 and 7 in Figure 24, the parking occupancy significantly increased with the implementation of time-of-day pricing and progressive hourly pricing. This results are anomaly in the data as the general trend for all other 54 parking locations does not show the same trend. The results from this two locations can be labelled as outliers, possible reasons for this inconsistency could be in proper calibration of parking rate for these specific locations. Additionally, the two parking locations only contain 11 and 3 parking spots each while the average number of parking spots is 17 for all parking

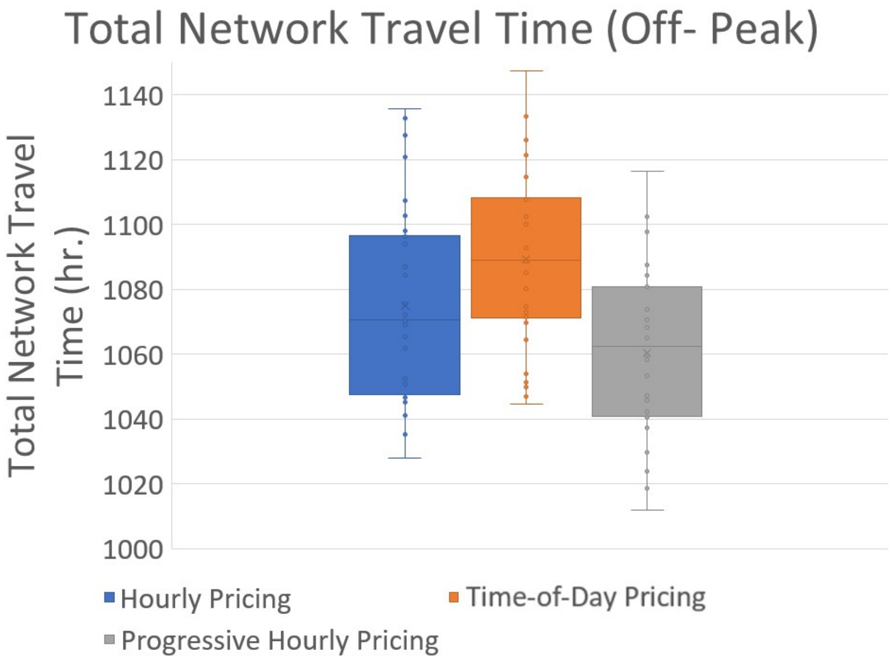

FIGURE 23: BOX PLOTS FOR THE HOURLY AND PROGRESSIVE PRICING POLICIES.

locations in the study area. The small number of parking spots could drastically influence the parking occupancy since for a parking location with 3 spots, the arrival off one additional vehicle represents a 33% in parking occupancy. Nonetheless the general trend observed from the three policies is that of the three pricing policies performing similarly when parking occupancy is low while the progressive pricing policy achieved a slight reduction of parking occupancy when occupancy was high.

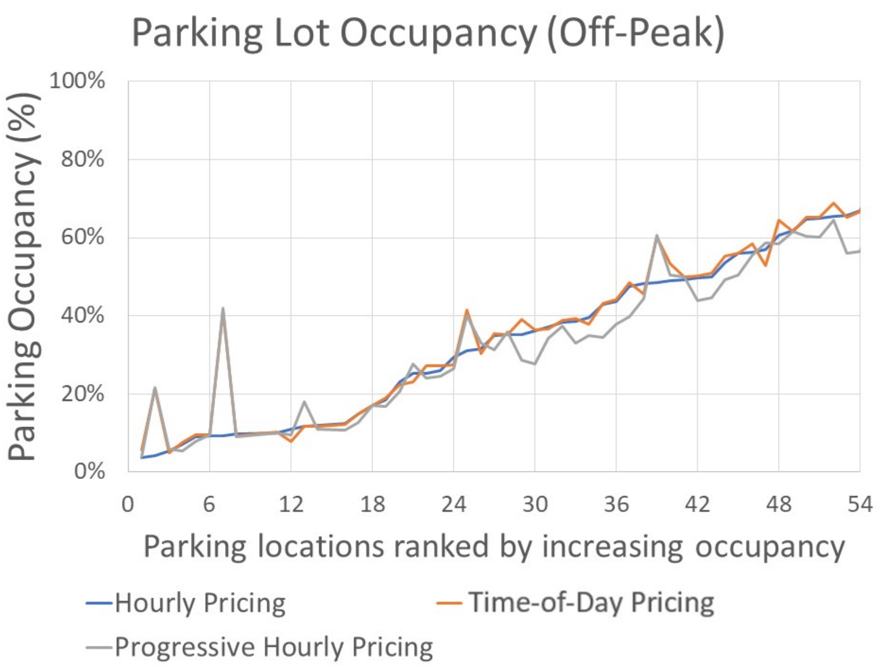

FIGURE 24: PARKING OCCUPANCY FOR 54 PARKING LOCATIONS IN THE STUDY AREA.

The percent of vehicles who are declined parking due to unavailability of spaces for each of the three policies can be seen in Figure 25. The two hourly policies yielded similar results in terms of the number of vehicles that are declined parking while the progressive pricing consistently decreased the number of declines for each parking spot. From all the before-mentioned figures it can be seen that during off-peak conditions a parking price reduction (in this case 50%) does not have a significantly affect the parking occupancy, requests declined, and total network travel time. With respect to the progressive hourly pricing, implementation of this policy will only outperform the two hourly policies if the occupancy of the parking location is high. As seen in Figure 26, as the average parking occupancy increases, the percentage of parking requests will also exponentially increase. This exponential relationship outlines the importance of maintaining a parking occupancy lower than 100%. Additionally, it can be noted from Figure 26 that the exponential rate at which the percentage of parking requests increases is lower for the progressive hourly pricing when compared to the two hourly pricing policies.

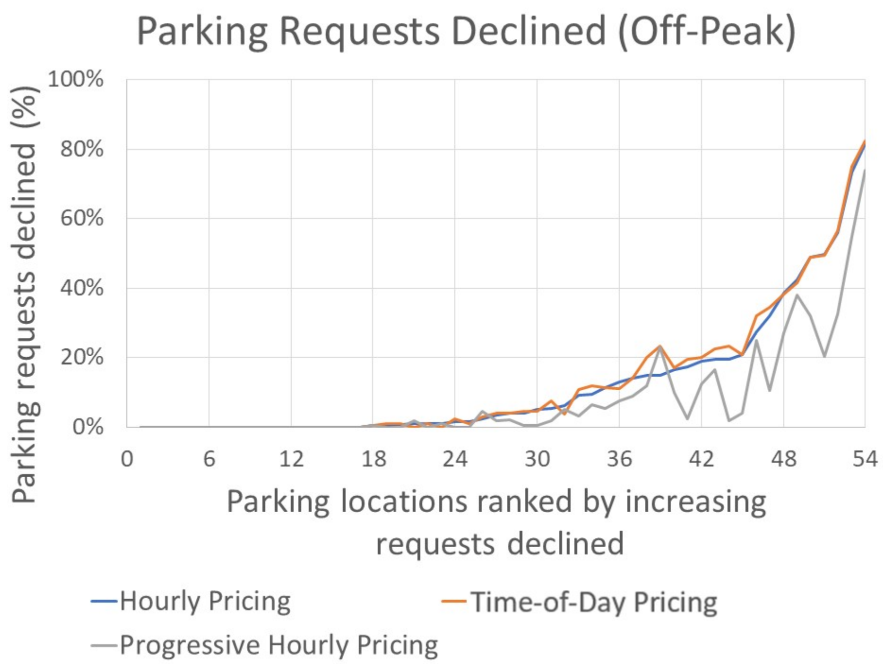

FIGURE 25: PERCENT OF PARKING REQUESTS WHICH WERE DECLINED FOR THE 54 PARKING LOCATIONS.

Furthermore, Table 2 contains the summary of all measures taken into consideration.With regards to parking revenue, the progressive pricing policy once again generates more revenue as expected. In addition, the time-of-day pricing policy which lowers the hourly rate by 50% generates the lowest revenue of all policies. GHG emissions, which were calculated from the simulation with he addition of the previously discussed assumption (fuel economy of vehicles is 8.9 L/100km) shows a similar patter as travel time. That is to say the progressive pricing policy achieves the lowest GHG emissions followed by the hourly policy and lastly the time-of-day policy. That being said, the difference between these policies is not of significant magnitude.

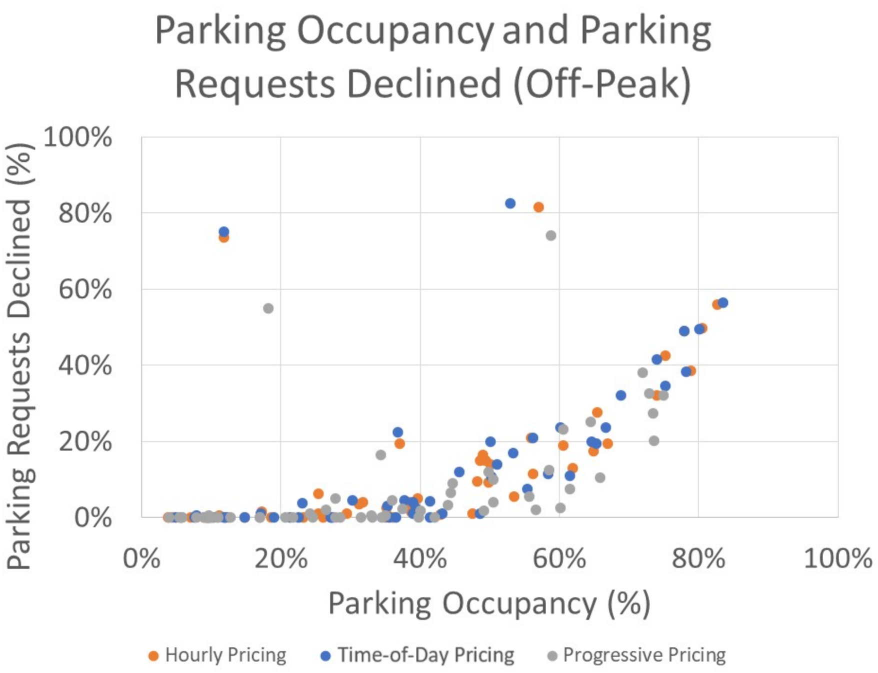

FIGURE 26: PERCENT SHARE OF PARKING REQUESTS DECLINED FOR VARYING PARKING OCCUPANCY.

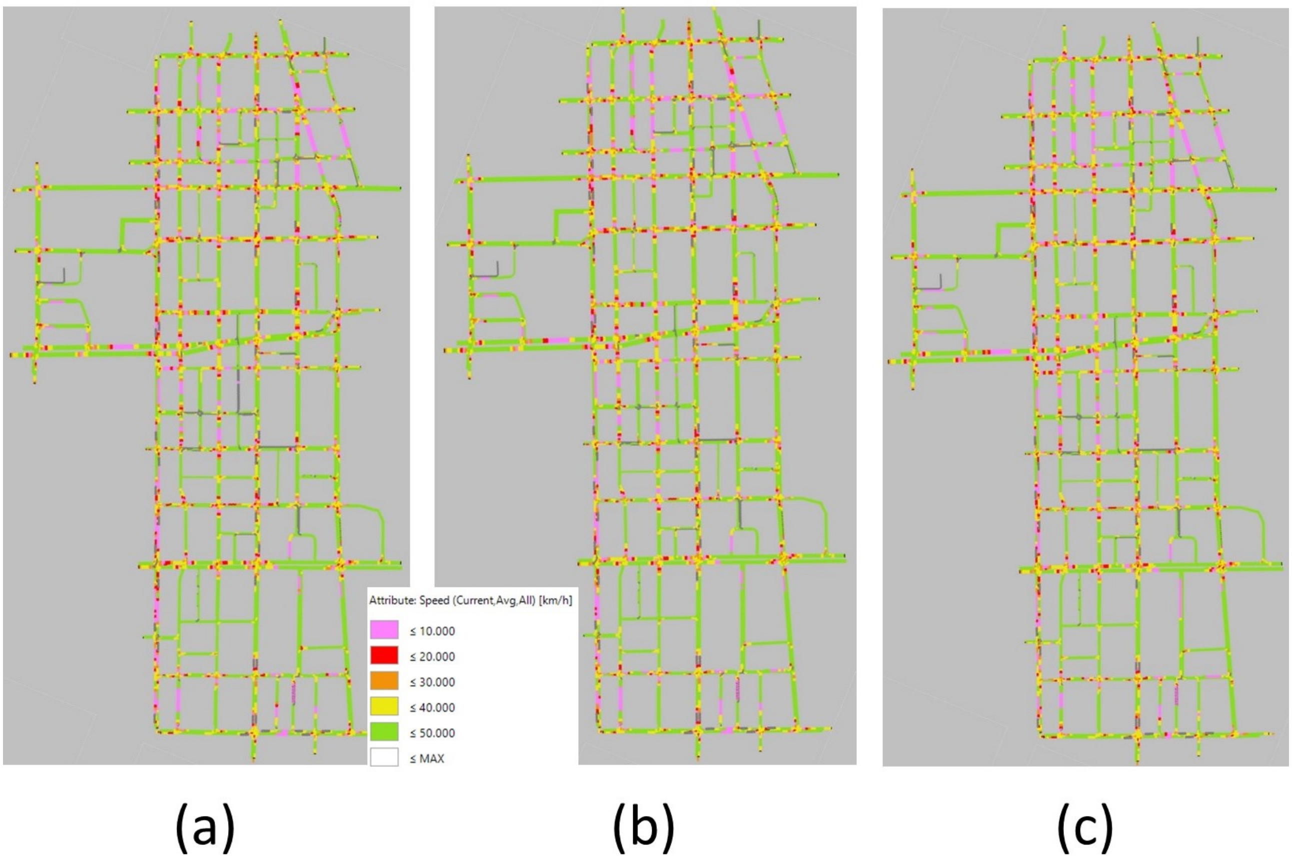

FIGURE 27: AVERAGE SPEED HEAT MAPS FOR THE CASE STUDY. HOURLY PRICING ON THE LEFT, TIME-OF-DAY PRICING ON THE MIDDLE, AND PROGRESSIVE HOURLY PRICING ON THE RIGHT.

TABLE 2: SUMMARY OF RESULTS FOR EACH PRICING POLICY FOR THE OFF-PEAK SCENARIO.

Measure	Scale	Units	Hourly Pricing	Time-of-day Pricing	Progressive Pricing
Parking Occupancy (High Demand Locations, occupancy >50%)	Street Block	Percentage (Weighted based on number of parking spots)	67.07%	67.31%	61.59%
Parking Occupancy (Low Demand Locations, occupancy <50%)	Street Block	Percentage (Weighted based on number of parking spots)	28.47%	30.53%	27.70%
Parking Revenue	Street Block	$/hour	$1,880.55	$873.47	$4,617.18
Cruising for parking	Street Block	Percent of vehicles declined. (Weighted based on number of parking spots)	11.11%	11.49%	6.13%
Total Network Travel Time	Study Area-Wide	Hours	1074.55	1088.89	1060.04
GHG Emissions	Study Area-Wide	$CO_{2}e$ Kg/hour	3,572	3,620	3,524

8 CONCLUSIONS

To conclude, as shown in the results for both the A.M. peak conditions and off-peak conditions the progressive hourly pricing policy can reduce the number of parking requests which are declined. During peak conditions the percent share of vehicles declined parking decreased by 13.62% while in off-peak conditions it was reduced by 6.68%. Additionally, the progressive hourly pricing is able to achieve a reduction of total network travel time of 1.14% during the peak time frame and 1.35% during the off-peak. From the analysis completed on the data extracted from the simulation, the main findings indicate that implementing a progressive pricing policy can positively impact the parking occupancy for locations with high occupancy not only for peak conditions but also off-peak. For parking locations that experience a parking occupancy greater than 60% with an hourly pricing policy, the implementation of a progressive hourly policy is able to reduce the parking occupancy by 5.53%. Reduction in parking occupancy for high-occupancy locations is also shown to be highly correlated with the number of vehicles declined parking due to space unavailability. For time-of-day pricing, a reduction of 50% in the price level of the hourly policy during off-peak hours does not negatively influence parking occupancy. Supporting the claims that during low-demand hours, the implementation of a lower price level for low-occupancy locations does not negatively affect the transportation network. It is of recommendation that to reduce total network travel times and increase mean speeds of the network links, a progressive pricing policy with the optimal price levels is to be implemented for high occupancy parking locations.

9 APPENDIX

9.1 PROFIT UNDER LINEAR MARGINAL UTILITIES

We separately consider the above two cases when maximizing parking revenue. The optimal policy under case 1 is obtained from the following mathematical model denoted by [M1]:

$$[M1]: \quad \max_{q,p_1,p_2} \quad \pi = T_l(qp_1 + (d_l^* - q)p_2) + T_h(qp_1 + (d_h^* - q)p_2)$$
$$\text{s.t.} \quad 0 \le q \le (a_l - p_2)/b_l,$$

where d_i^* is obtained from (8). In the objective function of [M1] the two terms are the revenue of the low and high value groups, respectively. The constraint ensures case 1 happens. We show in the appendix that the optimal solution of $[P1]$ is $q^* = 0$ and $p_2^* = (a_h b_l(T_h - 1) - T_h a_l b_h)/(2b_l(T_h - 1) - 2T_h b_h)$. Because $q^* = 0$, we have a single step hourly pricing structure, where p_2 is the price per hour and p_1 can have any value. In other words, the first step of the price profile does not exist, and we have an hourly pricing policy instead.

The optimal design under case 2 is obtained by the following mathematical model denoted by [M2]:

$$[M2]: \quad \max_{q,p_1,p_2} \quad \pi = T_l p_1 d_l^* + T_h(qp_1 + (d_h^* - q)p_2)$$
$$\text{s.t.} \quad (a_l - p_1)/b_l \le q \le (a_h - p_2)/b_h,$$

where the two terms are the revenue of the low and high value groups, respectively. The constraint ensures case 2 happens. The optimal solution of $[M2]$ is $p_1^* = a_l/(1 + T_h)$, $p_2^* = 1/2(a_h - (T_h a_l b_h)/(b_l(1 + T_h))$, and $q^* = (T_h a_l)/(b_l(1 + T_h)$. We compare the revenue of the two cases in the following proposition.

Proposition 1. The optimal revenue of the progressive pricing policy is achieved when the low value group "falls" on the first step and the high value group "falls" on the second step.

According to Proposition 1, case 2 always outperforms case 1 in revenue maximization.

9.2 SOCIAL WELFARE UNDER LINEAR MARGINAL UTILITIES

We separately consider the two cases when maximizing social welfare. The optimal design under case 1 is obtained by the following mathematical model:

$$[W1]: \quad \max_{q,p_1,p_2} \quad W = T_l U_l(d_l^*) + T_h U_h(d_h^*) + \pi - \gamma T(T_h d_h^* + T_l d_l^*)/s$$
$$\text{s.t.} \quad 0 \le q \le (a_l - p_2)/b_l,$$

where the first two terms of the objective function indicate the consumer surplus of the groups, the third term is the profit, and the last term is the negative externality of cruising. The constraint ensures case 1 happens.

The optimal solution of $[W1]$ is

$$p_2^* = (2((T_h-1)b_l - T_hb_hs)(a_h(T_h-1)b_l - T_ha_lb_hs))/(2T_h^2b_h^2s^2 \\ +T_hb_lb_hs(4-4T_h+b_hs)+b_l^2(T_h-1)(-2+2T_h-b_hs^2)).$$

Since social welfare under case 1 is only a function of p_2, the optimal solution is unaffected by parameters p_1 and q.

The social welfare maximizing policy under case 2 is obtained by the following mathematical model:

$$\begin{aligned}[W2]: \quad & \max_{q,p_1,p_2} \quad W = T_lU_l(d_l^*) + T_hU_h(d_h^*) + \pi - \gamma T(T_hd_h^* + T_ld_l^*)/s \\ & \text{s.t.} \quad (a_l-p_1)/b_l \le q \le (a_h-p_2)/b_h.\end{aligned}$$

We show in that the optimal solution of $[W2]$ is $p_1^* = (2s(a_h(b_l - T_hb_l) + a_lT_hb_hs))/(-2b_l(-1+T_h) + b_hs^2(2T_h+b_l))$ and $p_2^* = (2a_hb_l(-1+T_h) - 2a_lT_hb_hs/(2b_l(-1+T_h) - b_hs^2(2T_h+b_l))$. Since social welfare under case 2 is only a function of p_2 and p_1 , the optimal solution is unaffected by parameter q. We compare the social welfare of the two cases in the following proposition.

Proposition 2. The optimal social welfare of the progressive pricing policy is achieved when the high value group "falls" on the first step and the low value group "falls" on the second step.

According to Proposition 2, case 2 always outperforms case 1 in social welfare maximization.

9.3 OPTIMAL PRICE LEVELS

TABLE 3: OPTIMAL PRICE LEVELS FOR THE 54 PARKING LOCATIONS IN THE STUDY AREA.

Location ID	Street	Side of Street	From	To	Price #1	Price #2
3008	Elizabeth St.	East and West	Dundas St. W.	Hagerman St.	$5.00	$6.82
3009	Chestnut St.	East and West	Dundas St. W.	Armoury St.	$5.00	$9.05
3010	Centre Ave.	East and West	Dundas St. W.	Armoury St.	$5.00	$13.55
3012	Armoury St.	North	Centre St.	University Ave.	$5.00	$6.02
3102	Simcoe St.	West	Queen St. W.	Richmond St. W.	$5.00	$10.39
3104	Richmond St. W.	South	Simcoe St.	John St.	$5.00	$16.57
3106	Adelaide St. W.	North	Simcoe St.	Spadina Ave.	$5.00	$17.29
3108	Spadina Ave.	East	Adelaide St. W.	King St. W.	$4.00	$7.63
3111	Simcoe St.	West	Adelaide St. W.	King St. W.	$4.00	$5.23
3112	Pearl St.	South	Duncan St.	Simcoe St.	$5.00	$8.00
3116	Front St. W.	South	Spadina Ave.	Blue Jays Way	$5.00	$14.41
3117	Front St. W.	North and South	Simcoe St.	University Ave./York St.	$5.00	$4.96
3118	York St.	West	King St. W.	Richmond St. W.	$5.00	$12.35
3120	Clarence Sq.	North	Spadina Avenue	Wellington St. W.	$5.00	$8.53
3215	Queen St. W.	North	Soho St.	Spadina Ave.	$4.00	$13.87
4101	Queen St. E.	South	Church St.	Jarvis St.	$4.00	$9.18
4102	Richmond St. E.	South	Victoria St.	Church St.	$5.00	$9.17
4103	Richmond St. E.	South	Church St.	Jarvis St.	$4.00	$7.90
4105	Victoria St.	East	Richmond St. E.	Adelaide St. E.	$4.00	$4.80
4106	Lombard St.	North and South	Victoria St.	Church St.	$5.00	$16.27
4107	Lombard St.	North and South	Church St.	Jarvis St.	$4.00	$17.06
4108	Adelaide St. E.	North	Victoria St.	Church St.	$5.00	$13.05
4109	Adelaide St. E.	North	Church St.	Jarvis St.	$4.00	$8.54
4111	Toronto St.	East and West	Adelaide St. E.	King St. W.	$5.00	$14.27
4112	Church St.	East and West	Adelaide St. E.	King St. W.	$5.00	$14.30
4115	Colborne St.	North	Yonge St.	Victoria St.	$5.00	$5.70
4118	Church St.	West	Colborne St.	Wellington St. E.	$4.00	$8.87
4119	Church St.	East	King St. W.	Wellington St. E.	$4.00	$11.57
4120	Wellington St. E.	South	Yonge St.	Scott St.	$5.00	$9.90
4121	Wellington St. E.	South	Scott St.	Church St.	$4.00	$8.65
4122	Front St. E.	North	Church St.	Jarvis St.	$4.00	$11.48
4123	Front St. E.	South	Church St.	Market St.	$4.00	$9.53
4124	Front St. W.	North and South	Bay St.	Yonge St.	$5.00	$10.76
4125	Front St. E.	North	Yonge St.	Scott St.	$5.00	$12.68
4126	Front St. E.	North	Scott St.	Church St.	$4.00	$9.53
4128	Scott St.	East and West	Front St. E.	The Esplanade	$4.00	$13.18
4129	Church St.	East and West	Front St. E.	The Esplanade	$4.00	$10.25
4130	Market St.	East and West	Front St. E.	The Esplanade	$4.00	$7.92
4131	The Esplanade	North and South	Scott St./ Church St.	Church St./ Market St.	$4.00	$6.82
4134	Jarvis St.	East	The Esplanade	South Limit Parking	$4.00	$6.89
4143	Victoria St.	West	Adelaide St. E.	Old Post Office Ln.	$5.00	$7.99
4144	Victoria St.	West	King St. E.	Colborne St.	$5.00	$7.66
4302	Queen St. W.	North and South	Bathurst St.	Spadina Ave.	$4.00	$11.00
4307	Richmond St. W.	South	Bathurst St.	Portland St.	$4.00	$6.29
4315	Bathurst St.	East and West	King St. W./Stewart St.	Wellington St. W.	$3.00	$8.18
4316	Stewart St.	North	Bathurst St.	Portland St.	$3.00	$9.62
4317	Portland St.	East	King St. W.	Wellington St. W.	$3.00	$7.27
4318	Wellington St. W.	North and South	Bathurst St. / Portland St.	Spadina Ave.	$3.00	$6.82
4319	Niagara St.	South	Bathurst St.	Portland St.	$3.00	$7.27
4320	Portland St.	East	Wellington St. W.	Front St. W.	$3.00	$9.79
4321	Front St. W.	North	Bathurst St.	Spadina Ave.	$3.00	$7.69
4322	Spadina Ave.	West	King St. W.	Front St. W.	$3.00	$3.39
4358	Augusta Ave.	West	Richmond St. W.	Queen St. W.	$3.00	$6.82
4359	Portland St.	East	Adelaide St. W.	Richmond St. W.	$3.00	$5.97

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