ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume VI-4/W2-2020, 2020
5th International Conference on Smart Data and Smart Cities, 30 September – 2 October 2020, Nice, France

SPATIALLY-EXPLICIT TOOLSET FOR ESTABLISHING AND ASSESSING HETEROGENEOUS PARKING PRICES IN THE SMART CITY

N. Fulman [1] *, I. Benenson [1]

[1] Dept. of Geography and Human Environment, Tel Aviv University, Tel Aviv, Israel - nirfulma@post.tau.ac.il

Commission IV

KEY WORDS: Parking Search, Performance Parking Prices, Spatial Simulation, Parking Policy

ABSTRACT:

Cruising for parking stems from local mismatch between the patterns of demand and supply for parking, which reflect urban heterogeneity in a complex non-linear way. We propose ParkSage, a set of spatially-explicit algorithms for establishing spatially heterogeneous parking prices that guarantee target levels of occupation and parking search time. We apply ParkSage for establishing overnight parking prices that guarantee 85% occupation in the Israeli city of Bat Yam. We investigate the resolution of pricing units necessary for reducing cruising and demonstrate that pricing by transport analysis zones (TAZ) produces similar benefits to the commonly proposed pricing by road links, in addition to being more comprehensible to drivers.

1. FROM UNIFORM TO PERFORMANCE PARKING PRICES

Demand for parking is determined by the attractiveness of destinations and as such, it varies substantially in space and time. On the other hand, parking prices in most cities are typically uniform over large urban areas and remain unchanged for years. In city centres, where the demand exceeds supply, parking usage is near capacity, cruising time is long and traffic is congested (Arnott, Inci, 2006).

Donald Shoup championed the idea of establishing parking prices that maintain a minimal level of parking available on every block, thereby eliminating cruising for parking (Shoup, 2006). This view has made its way to practice and in recent years, a number of cities around the world have initiated pilot programs for enforcing predetermined occupation levels using Performance Prices (e.g. SFMTA, 2014; SDOT, 2019). Common to these programs is variation of prices by time of day and location, and periodical update of the prices until occupancy converges to the desired range of typically 60-80%. The spatial unit for pricing may be a block face (SFMTA, 2014), as suggested by Shoup (2006), or larger units such as a neighborhood, which is easier to conduct and more comprehensible to drivers but comes at the risk of within-unit mismatch between demand and supply. Existing programs also diverge on other factors including payment exemptions to various populations, the enforcement of illegal parking, price ceilings and the spatial and temporal scope of charging, which may influence the efficiency of the policy.

We present ParkSage, a set of spatially-explicit algorithms that allows municipal regulators to establish and evaluate parking prices in highly heterogeneous urban space that guarantee a predefined occupancy rate based on standard GIS layers of buildings, parking lots and streets. ParkSage is free for download at https://www.researchgate.net/profile/Nir_Fulman. The novelty of ParkSage is in integrating distinct methods into a workflow process sufficient for establishing and evaluating the efficiency of any urban pricing scheme.

To be applied, ParkSage demands standard high-resolution municipal GIS database, as that of the Tel Aviv municipality (2019). A GIS layer of buildings that contains its use (residential/office/commercial), foundation area and height serves as a proxy for estimating demand, while the layers of street links, preferably with parking permission information, and of parking lots with their total capacity, serve for estimating supply.

2. PARKSAGE STRUCTURE

This section describes the three algorithms that make up ParkSage.

2.1 The MDPP Algorithm for Estimating Parking Occupancy Pattern for the Given Pattern of Parking Prices

The *Maximally Dense Parking Pattern (MDPP)* algorithm generates parking occupancy pattern based on high-resolution demand (buildings) and supply (street links and parking lots) GIS layers.

Informally, MDPP can be considered as a dispatching system that manages parking in a smart city of automated (yet not shared) cars with complete information on all arriving vehicles, their destinations, occupied and vacant parking places and parking prices. When a car arrives to the city, the system reserves the vacant parking spot that is optimal to its passengers in terms of the tradeoff between price and walking time from parking place to destination.

Formally, we denote the attractiveness of a parking spot p at a distance d from the driver's c destination as $A_{c,p}(d)$, and the parking price of p as F_p. We assume that driver c is sensitive to the parking price F_p only when F_p is above a threshold "negligible" level $f_{negligible} > 0$, and $A_{c,p}(d)$ depends on F_p only when $F_p > f_{negligible}$, and decreases with the increase of the distance d:

This contribution has been peer-reviewed. The double-blind peer-review was conducted on the basis of the full paper.
https://doi.org/10.5194/isprs-annals-VI-4-W2-2020-63-2020 | © Authors 2020. CC BY 4.0 License.

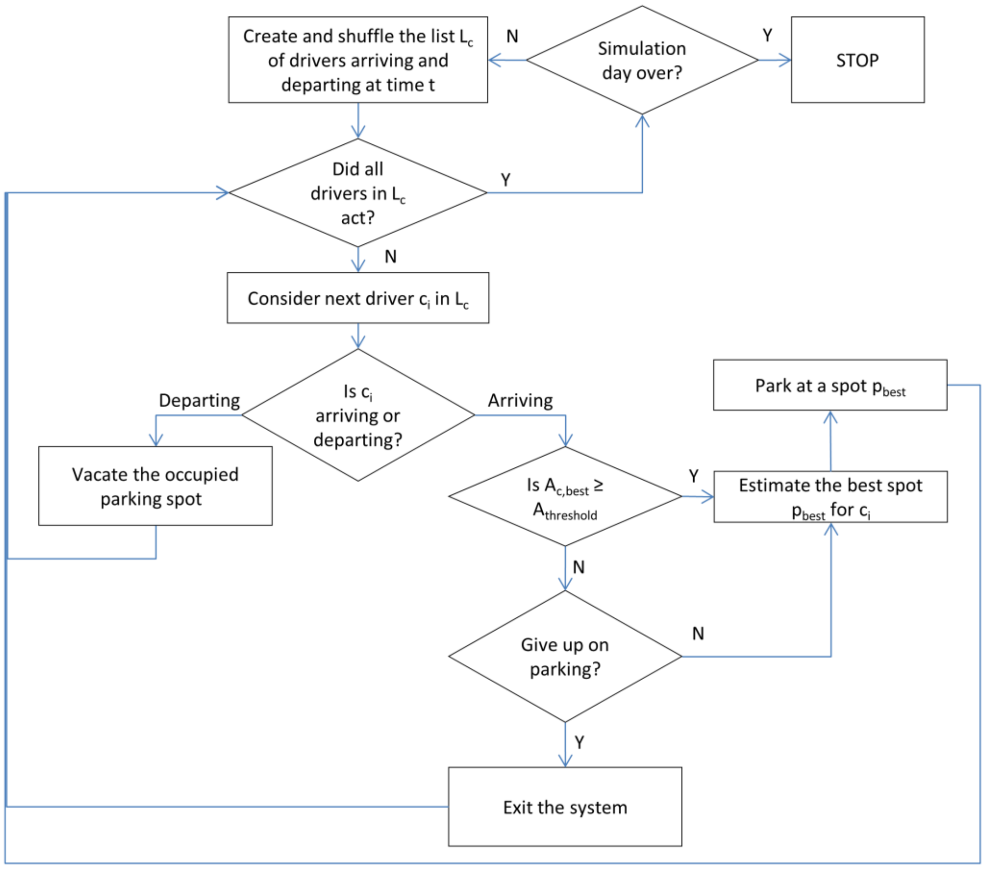


Figure 1. Flow chart of the Maximally Dense Parking Pattern (MDPP) algorithm.

$$A_{c,p}(d) = \frac{\min(1, f_{negligible}/F_p)}{d^{\alpha}} \quad (1)$$

where $0 < \alpha < 1$

We make two additional assumptions:

- Drivers are willing to walk up to 500m from parking place to destination, $d_{max} \leq 500$m.

- Drivers may give up on parking if all parking options are unattractive. Let $A_{c,best}$ be the attractiveness of the best available parking spot for the driver c. The probability $g(A_{c,best})$ to give up on parking is given by:

$$g(A_{c,best}) = \begin{cases} 0 & if\ A_{c,best} > A_{threshold} \\ 1 - \exp(\gamma(1 - A_{threshold}/A_{c,best})) & if\ A_{c,best} \leq A_{threshold} \end{cases} \quad (2)$$

where γ and $A_{c,threshold}$ are parameters.

In case all available spots at a distance d_{max} or less are too expensive, drivers are assumed to park far away and use additional means of transportation to reach their destinations. Figure 1 presents a flowchart of the MDPP algorithm (Levy, Benenson, 2015; Fulman, Benenson, 2018a).

An early version of the MDPP in which drivers choose parking based only on the distance to destination was validated in the Israeli city of Bat Yam by Levy and Benenson (2015). Regretfully, the municipal authorities gave up on cooperation and we were not able to validate drivers' sensitivity to parking prices.

2.2 The NPPA Algorithm for Establishing Parking Price Pattern

The MDPP algorithm estimates the parking occupation pattern based on the pattern of parking prices. The Nearest Pocket for Prices Algorithm (NPPA) aims at establishing a parking price pattern applying the MDPP in a recursive way. Let the target occupation level for any parking unit in the area be the same, $O_{threshold}$. The NPPA increases the price F_u of each parking unit u, for which the occupancy exceeds $O_{threshold}$, from F_u to $F_u(1 + \phi)$, and then applies the MDPP with the new price pattern. Higher parking price over the unit's spot reduces the attractiveness of this spot, and drivers who are sensitive to the new price respond by preferring a cheaper parking alternative elsewhere. The algorithm quits when the price of parking at each unit u reaches a level that guarantees unit's occupancy $O_u \leq O_{threshold}$. The NPPA's flow is presented in Figure 2 (Fulman, Benenson, 2018b).

The internal parameter of the NPPA is ϕ that defines the convergence of a price pattern to equilibrium. Below we apply

ϕ = 0.05 and the number of iterations required for convergence never exceeds 50.

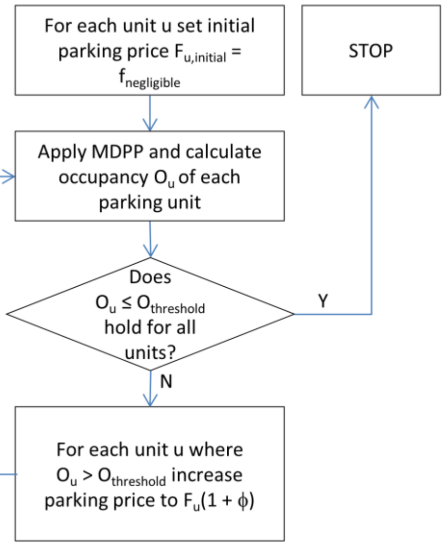


Figure 2. Flow chart of the Nearest Pocket for Prices Algorithm (NPPA) algorithm.

2.3 PST Algorithm for Approximating Parking Search Time Based on the Occupation Pattern

The Parking Search Time (PST) prediction algorithm estimates parking search time for a driver whose destination is n given the parking occupancy pattern within the neighborhood N(n), where the driver searches for parking. The PST algorithm uses the outcome of the MDPP algorithm that estimates the parking occupation rate p(u) for parking units u within the urban area and the probability w(u, n) of traversing each unit u $\in$ N(n) within N(n), depending on the distance d between u and n. Probability w(u, n) is defined based on an experimentally validated biased random walk model. As experimentally demonstrated, w(u, n) loosely, if ever depends on a driver's characteristics (Fulman, Benenson, 2019). The experimentally estimated dependence of the w(u, n) on the distance d(u, n) is as follows

$$w = 58 - 6.28 \times (d - 50)^{0.368} \tag{3}$$

Given the w(u, n) curve and the pattern of p(u) probabilities within N(n) as obtained with the MDPP, we are able to estimate probability q_{nopark} to traverse a fully occupied link per time unit (Fulman, Benenson, 2018a):

$$q_{nopark} = \frac{\sum_{l \in N(n), l\ is\ fully\ occupied} w(l,n)p(l)}{\sum_{l \in N(n)} w(l,n)p(l)} \tag{4}$$

The probability Q(τ, n) to cruise longer than τ time units, for the driver whose destination is n, is, thus:

$$Q(\tau, n) = (1 - q_{nopark})q_{nopark}^{\tau} \tag{5}$$

The PST results were validated using an agent-based model of urban parking search. The full flow chart of the algorithm for estimating cruising time is presented in Figure 3 (Fulman, Benenson, 2018a).

The major computational blocks of Parksage are presented in Figure 4. It should be noted that the PST algorithm depends solely on parking occupation patterns, which can also be estimated experimentally, using remote sensing and field work. In case the parking price pattern is due to change in response to the regulator's intervention, one can apply MDPP and PST in order to estimate the expected occupation rate and search time. If performance-based pricing is planned, the NPPA algorithm can be applied to predict the future price pattern. Overall, we consider ParkSage algorithms as sufficient for establishing and evaluating the efficiency of any pricing scheme in the city. In what follows we apply it for establishing overnight on-street parking prices in the Israeli city of Bat Yam. In addition to illustrating the algorithms' employment, we investigate dependence of the parking prices on the partition of the city into priced units. The latter is critically important for parking policy, since prices defined on the level of street links are complicated and hard to adapt to by the human drivers, while very large pricing units are bound to failure as ignoring the heterogeneity of the demand and supply.

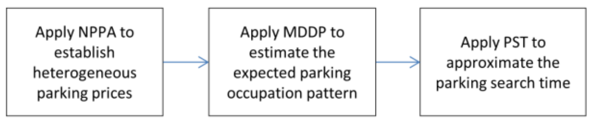


Figure 4. Major computational blocks of ParkSage.

3. ESTABLISHING PARKING PRICES IN THE CITY OF BAT YAM

We apply ParkSage for establishing overnight on-street parking prices in Bat Yam, using data from 2010. Below, we consider "parking price" as fees paid by a driver for parking for the entire night.

3.1 Bat Yam Demand and Supply

Parking supply in Bat Yam data is given in two layers from the Bat-Yam municipal GIS - a layer of streets with traffic direction and a layer of parking lots. Based on the layer of streets, 27,000 spots for curb parking were constructed automatically, 5 meters apart on both sides of two-way street links, and on the right side of one-way links, with an offset from the junction. In addition, 1,500 spots are available for the city's residents in its parking lots, where parking if free in the evening for Bat Yam residents.

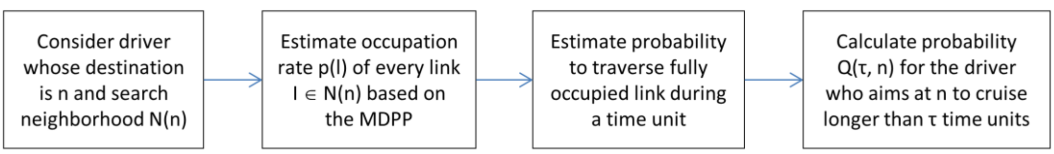


Figure 3. Flow chart of the algorithm for estimating cruising time distribution.

Parking demand is established based on the municipal layer of buildings. Bat Yam population in 2010 was ca. 130,000, car ownership 35,000, and the number of residential buildings 3,300 with 51,000 apartments. Residential buildings in Bat Yam provide their tenants a total of 17,500 dedicated parking places that we exclude from the demand and supply data.

The average overnight demand/supply ratio is thus very low (35,000 – 17,500) / (27,000 + 1,500) ≈ 0.61 car/parking spot. However, the distributions of demand and supply in the city are both highly heterogeneous, and the overnight demand in the center of Bat Yam substantially exceeds supply (Figure 5).

3.2 Arrivals and Departures

In the experiments below, we consider evening (16:00 to 23:00) on-street parking by residents and their guests. We assume that all parking spots are vacant at 16:00 and residents arrive to the area between 16:00 and 18:00 and park until the end of the evening. Guests arrive and depart throughout the whole evening, and their parking time is uniformly distributed on the $[\tau_{min}, \tau_{max}]$ interval, where τ_{min} = 1 hour and τ_{max} = 2 hours.

Drivers that aim at a destination n_i are generated by a Poisson process with a per-hour average λ_i based on the n_i's hourly demand d_i by residents and guests. We assume that for each n_i, residents comprise a constant fraction e < 1 of the total demand d_i. During that time period, we set the hourly number of arrivals to each destination n_i as $\varepsilon_i = e*d_i/2$. We adjust the hourly arrival rate of guests, to guarantee that the average number of guests arriving to n_i be equal to $(1 – e)*d_i$. Accounting for the guests' average parking time $(\tau_{min} + \tau_{max})/2$, their per hour arrival rate to a destination n_i is $\lambda_i = 2*(1 - e)*d_i/(\tau_{min} + \tau_{max})$, and we assume that it remains constant throughout the evening.

At each 30 seconds model tick, the list of arriving and departing drivers is created, randomly re-ordered, and each driver acts in its turn, facing the parking pattern created by the actions of its predecessors. Average occupation rate in the city converges to equilibrium towards 20:00 and then fluctuates, very slightly, over time.

3.3 Cruising for Parking in Bat Yam with the Existing Free of Charge Parking

Let us estimate evening cruising time in Bat Yam, assuming that the ratio between residents and guests seeking parking is 85:15, and that parking on-street and in public lots is free to residents of Bat Yam whereas outsiders are required to pay a yearly fee of 300 ILS for a parking permit. We consider the permit price as the negligible threshold of locals (Eq. (2)) and establish $f_{negligible}$ per night as $f_{negligible}$ = 1 ILS, roughly equivalent to \$0.3. In what follows, we refer to this price as the base price.

The patterns of supply and residential demand for overnight parking at a resolution of buildings, street links and lots, and the demand to supply ratio aggregated over Transport Analysis Zones (TAZ), are presented in Figure 5.

Drivers aim to park as close as possible to their destinations. Where night parking is free, Bat Yam drivers clog up links within the residential blocks where demand exceeds supply and spill over to adjacent areas, worsening parking conditions there. As a result, in Bat Yam's center, parking in the evening becomes unavailable over large continuous areas. The resulting cruising time is long: The estimated average cruising time for most destinations in and around the city center is, on average, 2.5 minutes; and cruising for longer than 5 minutes becomes very common (Figure 6).

3.4 Establishing Parking Prices That Guarantee Close-to-Zero Cruising Time

We establish parking prices for the traditional threshold occupation $O_{threshold}$ = 85% (1 of 7 spots is vacant) in each street segment. We set the distance-payment tradeoff coefficient in formula (1) α = 0.5, the coefficient γ in formula (2) γ = 0.1 and the minimal attractiveness threshold $A_{threshold}$ = 0.1.
As a result of the high demand for parking in the center of the city, maintaining an average occupancy rate of 85% requires prices in the busiest blocks to be 25-30 ILS, whereas at the periphery of the city the prices can remain at the base level (Figure 7). Twofold difference between parking prices for two adjacent street links are common, reflecting the heterogeneity of demand and supply.

The established parking prices ensure that almost none of the street links is fully occupied for longer than an hour and clusters of two or more connected links that are fully occupied for longer than half an hour almost never emerge. With parking available on every link almost always, cruising time is reduced nearly to zero. The average parking search time over all destinations is shorter than 60 seconds and less than 1% of drivers' cruise for longer than 150 seconds.

3.5 Pricing Parking by Large Spatial Units

We establish parking prices for coarse partitions that are convenient for drivers, starting with Bat Yam's 6 largest administrative units, referred to as quarters (Figure 8). Each quarter contains 2700-5800 parking places, and their area varies between 0.7-1.4 square km. Applying ParkSage with $O_{threshold}$ = 85% results in upper-than-base prices only in the core quarter of Bat Yam, which is 1 km^2 with 3000 parking places. The parking price in this quarter is 8.5 ILS.

Priced parking in the central quarter reduces cruising for almost all destinations there by close to 3 minutes on average, compared to the case of no pricing, and 75% of the drivers whose destinations are in this quarter cruise for less than 90 seconds. However, the new price pushes some drivers to adjacent quarters, while the occupation rate of some links within the core remains above 85% (Figure 9).

Similarly, in other quarters, clusters of fully occupied links emerge in the locations where demand exceeds supply and in areas bordering the central quarter (Figure 10). The problem is thus not resolved but partially displaced.

We investigate the consequences of pricing by the partition of Bat Yam into 42 Transport Analysis Zones (TAZ). The average TAZ is 0.16 square km with an average parking capacity of 600 spots, making it larger than a street link and smaller than a quarter. Figure 11 presents TAZ-based parking prices that guarantee 85% occupation rate.

The prices are above the base level in 24 TAZ, all located in and around the center of the city, and prices range up to 17.5 ILS.

Despite being smaller than quarters, pricing by TAZ does not guarantee 85% occupation for every single link, and in many of them parking is still unavailable for most of the evening. However, with TAZ-based pricing, overly-occupied links rarely form large clusters and parking is always available on nearby links. As a result, the average search time does not exceed 2.5 minutes for any destination and the average cruising time for the 500 destinations around which visitors cruise the longest, is only 75 seconds (Figure 12).

4. A TOOL FOR ESTABLISHING AND ASSESSING URBAN PARKING POLICY

ParkSage, a toolset for establishing and assessing parking prices, allows the municipal regulator to establish educated and reliable policies in their city, and to compare different pricing scenarios. We demonstrate ParkSage by establishing performance-based parking prices in the Israeli city of Bat Yam. To account for the drivers' convenience, we consider three different partitions of the city into priced units. Based on the Bat Yam study we can conclude that:

- Performance-based pricing can reduce parking search substantially.

- Pricing by units too large, such as city quarters, is insufficient for reducing cruising.

- Limited spatial scope of pricing results in spillovers of drivers outside the priced area and unnecessary cruising.

- There is no need for price variation at the level of individual street links. Pricing by medium sized units, such as Transport Analysis Zones, is sufficient to preserve a level of parking occupation that prevents cruising.

ParkSage can be used for studying the impact of additional pricing components and constraints, including parking permissions and prices that vary by population group, illegal parking, price ceilings or even time-varying pricing. Possible variation in the sensitivity of different population groups to the parking price can be discovered in experimental studies and expressed by the parameters of the parking attractiveness (Eq. (1)) (Fulman, Benenson, 2019).

Building on the state-of-the-art studies of parking search, ParkSage was designed to be simultaneously simple and reliable. Extensions to its algorithms may be considered, but at the cost of model tractability. The MDPP formula of parking attractiveness can be extended with additional factors that influence parking choice, such as the available information regarding parking price and occupancy. The PST probability to traverse a parking unit is based on experiments that assume spatial homogeneity of occupancy, which may have encouraged the observed homogeneity of search behavior. Experiments with realistic heterogeneous occupancy may uncover more sophisticated tactics, such as searching far away from destination to reduce parking search time at the expense of longer walking time to destination. Moreover, The PST prediction method does not take into account traffic congestion and the interaction between cruising cars and through-traffic. Additional investigation is needed to study their influence on the cruising time curve. The role of local topology and traffic rules may also be studied and incorporated in order to tailor fit ParkSage to local conditions.

ACKNOWLEDGEMENTS

This research was supported by the ISRAEL SCIENCE FOUNDATION (grant No. 1160/18) "Tessellation of urban parking prices".

REFERENCES

Arnott, R., Inci, E., 2006: An integrated model of downtown parking and traffic congestion. *J. Urban Econ.* 60(3), 418-442.

Fulman, N., Benenson, I., 2018a: Agent-based Modeling for Transportation Planning: A Method for Estimating Parking Search Time Based on Demand and Supply. In *ATT@ IJCAI* (pp. 31-39).

Fulman, N., Benenson, I., 2018b: Establishing Heterogeneous Parking Prices for Uniform Parking Availability for Autonomous and Human-Driven Vehicles. *IEEE INTEL TRANSP SY.* 11(1), 15-28.

Fulman, N., Ben-Elia, E., Benenson, I. 2019: Revealing Drivers' Parking Behavior with a Serious Game. In *2019 European Colloquium in Theoretical and Quantitative Geography (ECTQG 2019)* (pp. 180-181).

Levy, N., Benenson, I., 2015: GIS-based method for assessing city parking patterns. *J. Transp. Geogr.* 46, 220-231.

San Francisco Municipal Transportation Agency (SFMTA). (2014). *SFpark Pilot Project Evaluation*. Available at: http://sfpark.org/about-the-project/.

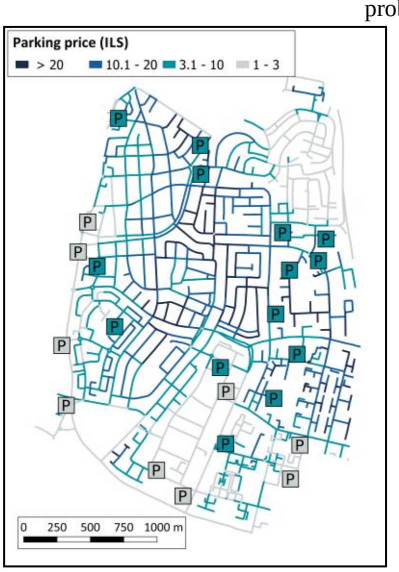
Seattle Department of Transportation (SDOT). (2019). *Performance-Based Parking Pricing Program*. Available at: https://www.sfmta.com/sites/default/files/reports-and-documents/2018/08/sfpark_pilot_project_evaluation.pdf.

Shoup, D.C., 2006: Cruising for parking. *Transp. Policy* 13(6), 479-486.

Tel Aviv Yafo Municipality. (2019). *Municipal GIS*. Available at: https://gisn.tel-aviv.gov.il/.

Figure 5. Bat Yam: (left) Parking demand by buildings; (middle) parking supply by street links and lots; (right) Demand-to-Supply.

Figure 6. The percentage of time that street segments are fully occupied (left); the average parking search times (middle); and the probability to cruise for over 5 minutes (right) in Bat Yam.



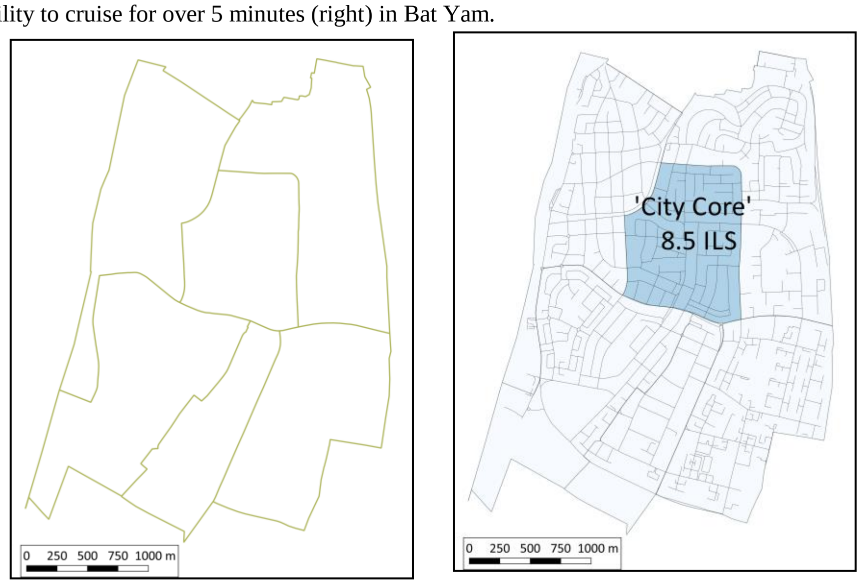


Figure 7. Equilibrium parking prices, for 85% occupation threshold established by street links and parking lots as pricing units

Figure 8. Six quarters of Bat Yam (left); and equilibrium parking prices, in ILS, for 85% occupation threshold estimated by city quarters as pricing units (right).

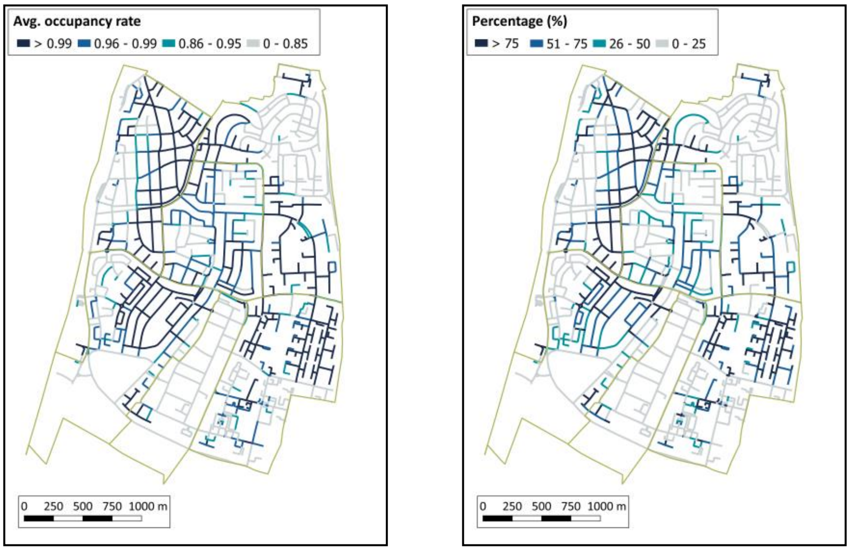


Figure 9. Bat Yam parking pricing by quarters: Average occupancy rate by street segments (left); percentage of time that street segments are fully occupied (right).

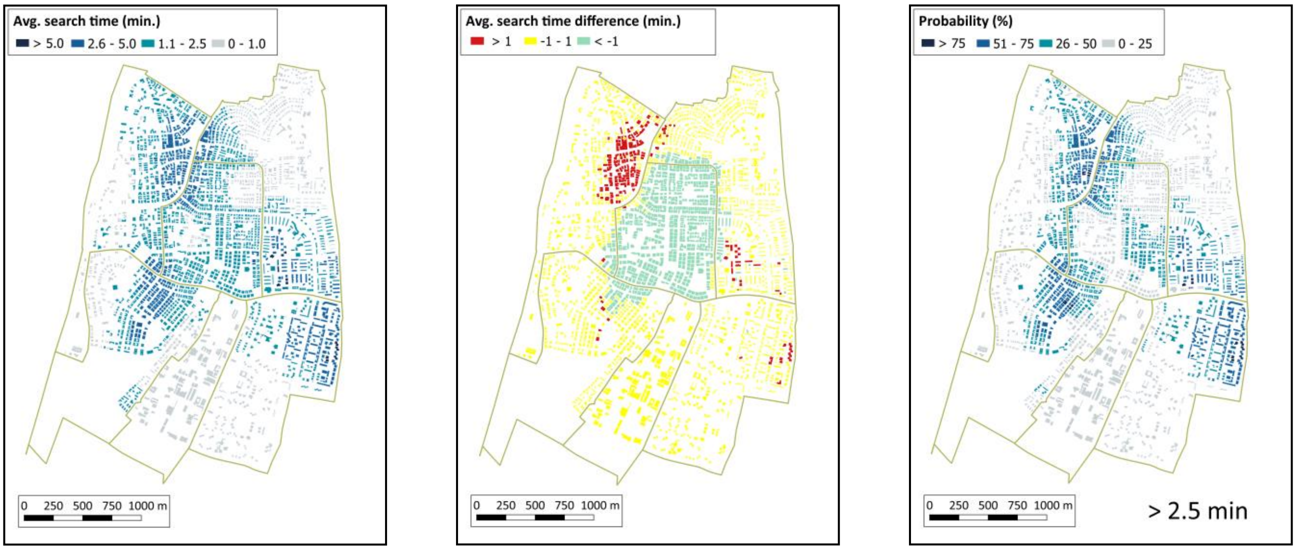


Figure 10. Parking search times in Bat Yam with city quarter pricing: Average parking search times (left); average difference in search times compared to non-priced parking (middle); and probability to cruise longer than 2.5 minutes (right).

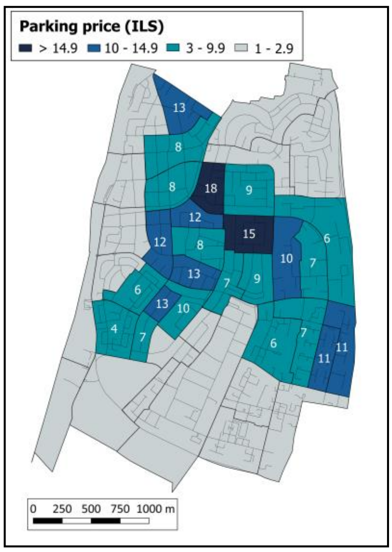


Figure 11. Equilibrium parking prices, in ILS, for 85% occupation threshold based on Bat Yam's 42 transportation analysis zones (TAZ) as pricing units.

Figure 12. Characteristics of Bat Yam TAZ-based pricing: Average occupancy rate by links (upper-left); average parking search time (upper-right); average difference in search times compared to non-priced parking (lower-left); probability to cruise longer than 2.5 minutes (lower-right).