Article

Patronage of urban commercial clusters: A network-based extension of the Huff model for balancing location and size

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Abstract
We introduce a version of the Huff retail expenditure model, where retail demand depends on households' access to retail centers. Household-level survey data suggest that total retail visits in a system of retail centers depends on the relative location pattern of stores and customers. This dependence opens up an important question—could overall visits to retail centers be increased with a more efficient spatial configuration of centers in planned new towns? To answer this question, we implement the model as an Urban Network Analysis tool in Rhinoceros 3D, where facility patronage can be analyzed along spatial networks and apply it in the context of the Punggol New Town in Singapore. Using fixed household locations, we first test how estimated store visits are affected by the assumption of whether shoppers come from homes or visit shops *en route* to local public transit stations. We then explore how adjusting both the locations and sizes of commercial centers can maximize overall visits, using automated simulations to test a large number of scenarios. The results show that location and size adjustments to already planned retail centers in a town can yield a 10% increase in estimated store visits. The methodology and tools developed for this analysis can be extended to other context for planning and right-sizing retail developments and other public facilities so as to maximize both user access and facilities usage.

Keywords
Huff model, retail patronage, simulation, spatial network analysis, urban design

Introduction

Commercial amenities are essential to vibrant urban neighborhoods. Having shops, restaurants and personal service establishments near places of residence or employment

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not only increases people's choices but also encourages walking (Forsyth et al., 2008; Hoehner et al., 2005; Rundle et al., 2007), reduces urban energy usage (Frank and Pivo, 1994; Krizek, 2003; Newman and Kenworthy, 1999; Zegras, 2004), fosters social cohesion (Jacobs, 1961) and generates local jobs. Many city planning departments have adopted policies to encourage pedestrian-oriented commerce. But influencing retail location patterns requires complex policies. Retail clusters are interdependent and work as a system; the patronage of one cluster depends not only on its own characteristics—its size, choice of goods, location—but also on the characteristics of competing clusters around it. In order to understand how a district-wide system of retail centres could be improved, accessible tools and models are needed.

This paper introduces an extension to the Huff model (Huff, 1962), where the patronage of each retail center is proportional to its size and inversely proportional to its accessibility to potential patrons. We propose small, but important modifications that relate the overall frequency of retail visits with patrons' accessibility to retail centers. Whereas the traditional Huff model assumes that the pattern of stores does not affect the overall number of retail trips that take place, we show that households with better access to retail centers visit them more frequently.

Our main focus lies in exploring how location and the size configuration of centers can maximize collective store visits and therefore benefit both store revenues and customer welfare alike. Keeping the total retail area constant, patrons' visits to retail centers in a Huff model vary according to two key factors—the attractiveness of centers (or size as a proxy) and the spatial accessibility of the centers. This means that placing numerous small stores closer to customers does not necessarily increase customer visits, which depend jointly on access and destination size. Similarly, a single large center might not be preferable if customers are sensitive to travel costs. Both of these sensitivities—to destination size and to travel costs—must be empirically determined. But once they are known, a fundamental question remains—is there a particular spatial configuration of stores that would maximize collective visits? The question has implications for the planning of urban retail systems, national chains as well as centrally provisioned neighborhood retail centers common in some countries (e.g. China and Singapore), but it has not received much attention in previous research.

Our model is implemented as part of the Rhinoceros 3D urban Network Analysis Toolbox plugin, freely available for download. Departing from the traditional application of the Huff model, which measures trip distances and accessibilities along simplified straight-line connections, we apply the model on spatial networks, where relationships between customers and retail destinations are captured along actual circulation routes. This makes the model more precise and opens up interesting applications in dense and complex urban environments. Implementation in Rhino allows planners to evaluate retail visits in a specific development proposal within seconds, incorporating patronage analytics into a fast and iterative design process, where proposals can be altered, evaluated and redesigned in seamless cycles to rapidly improve the outcome. The tool offers a simple interface that allows users to receive immediate graphic feedback about patronage changes in each retail centre that can result from changes in any of the centres' size or position. Outcomes in retail patronage can also be tested against changes in circulation networks, e.g. changes in the walking routes that lead to centres or changes in demand locations.

The tool also includes a simulation environment that allows the user to automatically test numerous combinations of centre sizes at given locations in order to maximize collective patronage across all clusters in the system. The latter functionality can help planners to "right-size" planned retail developments.

Both one-off estimations and automated simulations can be integrated with existing retail developments, whose sizes and locations remain unaltered in simulations. The tool can therefore be used to analyze incremental changes to established shopping environments, as well as to plan retail centers in new urban developments.

The paper is structured as follows. First, the literature review introduces the Huff model and some of its variations. Second, we introduce the proposed extension of the Huff model and demonstrate its fit with empirical data from Singapore. Third, the practical value of the proposed model is demonstrated in a case study of the Punggol New Town. Finally, the discussion section highlights our shortcomings and points to future work.

Literature

Although retail interaction studies go back to the 1930s (Converse, 1949; Reilly, 1931), the most widely utilized retail patronage model was introduced by Huff (1963). Albeit formulated several decades ago, only fairly recently has its application reached a wide audience with software and data applications.[1] The model has generated considerable research on retail catchments (Dramowicz, 2005; Jones and Simmons, 1993) and produced a number of alternative specifications (De Beule et al., 2014). Fotheringham (1983), for instance, has shown that trips to individual stores are not made independently of the larger clusters they are part of and proposed an alternative "competing destinations" model. Dolega et al. (2016) have experimented with specifying retail catchments at different geographic scales, all the way up to the national level in the UK. Comparative overviews of alternative specifications of retail catchment models are given by Yrigoyen and Otero (1998) and Joseph and Kuby (2011). Hu and Pooler (2002) and Birkin et al. (2010) describe how different input specifications affect the model. Wilson (2010) and Birkin et al. (2010) have generalized the Huff and other spatial interaction models as part of entropy maximization in statistical mechanics.

Lakshmanan and Hansen (1965) have developed a version of the model that estimates the total sales at each centre based on the Huff probabilities for consumers to visit each centre. Weisbrod et al. (1984) and Di Pasquale and Wheaton (1996) have developed an alternative discrete choice model of shopping centre patronage. Their models can use a more detailed list of attributes about each shopping centre, including tenant mix, parking availability, marketing expenses, etc. An empirical coefficient is estimated for each of the attributes using regression analysis on surveyed data from actual centre visits. The model also allows the attractiveness coefficients to vary for households of different income ranges (Di Pasquale and Wheaton, 1996). The calibration of such a regression-based model requires detailed attributes of each retail centre as well as empirical data on patronage to these very centres. The model we use is a simpler adaptation of the Huff model of market areas.

The classical Huff model assumes that the probability of a consumer to visit a given commercial destination is a function of its attractiveness, accessibility and competing sites around it. The attractiveness attribute of each destination centre can describe any kind of feature that has a positive effect on consumer patronage. In practice, retail area is often used as a proxy for the choice of merchandize at each destination, which is known to have a positive effect on patronage. But destination attractiveness could also capture variations in retail prices, parking spaces, street frontage, advertising expenditure and so on, all of which are typically combined into a single index.

Since a certain proportion of each consumer's visits are allocated to each destination, an interaction ensues between all consumers and all destinations. For each consumer, a Hansen accessibility ratio is computed to each retail destination (Hansen, 1959). This accessibility is proportional to the attractiveness of a particular destination divided by the travel cost of getting there. The probability for the consumer to visit any particular centre is found as a ratio between the accessibility to that centre, divided by the sum of accessibilities to all centres, including the one under question. More attractive destinations and closer destinations obtain relatively higher probabilities. But as long as each destination has non-zero attractiveness, no centre is left with a zero probability. Even the most remote and poorly attractive stores get some customers.

Individual consumers are typically aggregated to groups—at the census tract, block or group level—where demographic information is available. The probability of each group is multiplied by its characteristics—number of households, residents, or dollars spent on retail goods. This works well for large market areas, such as shopping malls, but it makes it difficult to apply the model at a district or neighborhood scale, where multiple retail streets compete within a complex built environment.

The Huff model has rarely been used by urban designers and physical planners to date to predict facility patronage. It is most often used as a tool to predict the performance of a single new centre or store in a system of existing stores. The model is calibrated with an existing set of stores, and a new centre is added with an appropriate attraction index to test how many customers the new location could potentially draw. But there is also ample unexplored potential in the Huff model for more complex predictive scenarios, where multiple new stores, or even a whole system of proposed centres is simultaneously planned. There is presently a lack of tools that would readily allow planners and designers to spatially manipulate the locations of multiple centres and receive instantaneous feedback about the performance of different scenarios.

Furthermore, the effects of the spatial circulation network—sidewalks, streets, local transit networks—are currently absent from available market potential models. This simplifies the calculation, but it can misrepresent the true distances required to get to destinations over spatial networks, especially at the finer-grained neighborhood scale. In newly planned areas, street networks could potentially be planned with district centres and shopping streets in mind so as to foster better access to amenities.

Model

We have modified the specification of the Huff model in four ways. First, the model is applied on a spatial network so that all distances and trips are routed along the networks. Each demand point is assumed to access retail destinations along the shortest distance route.[2] This makes the patronage estimates more precise with respect to the actual context of each shopping destination. Network-based distances correctly account for uneven densities in urban form (e.g. small versus large blocks), discontinuities in street networks (e.g. *cul de sacs*) and barriers, such as highways or rivers (Figure 1). The application of the model in the Rhino UNA toolbox also allows networks to be three-dimensional, including underpasses, overpasses or inside multi-story buildings.

Second, the model does not rely on population zones but uses individual demand points (e.g. buildings or households). The travel distance and patronage probability for each shopping destination j is calculated from each demand point i separately, producing a more accurate, disaggregate estimation.[3,4]

Third, similar to Eppli and Shilling (1996) and Ooi and Sim (2007), we allow the store attractiveness index W to have an exponent α, which controls how patrons are expected to react to increasing destination attractiveness. If an exponent of one is used over gross floor area, for instance, then it is assumed that as net leasable area (NLA) doubles, attractiveness

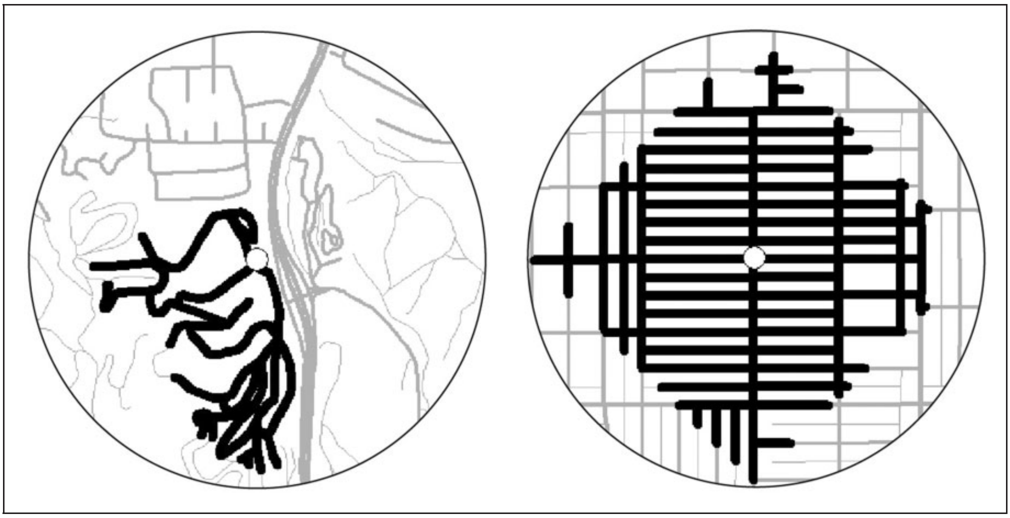

Figure 1. Comparison of straight-line and network walking distances at a neighborhood scale. The outer circle is drawn with a radius of 600 meters from the centre. The actual walkshed along the street network in the same 600 meters radius is shown inside the circle.

also doubles in a linear manner. But if an exponent of ½ is instead applied, then attractiveness only grows as a square root of NLA. This allows a diminishing rate of utility, which has been observed with many destination characteristics.

Fourth, we add an additional distance decay parameter to each demand point, which reduces the allocation of demand weights between centres, depending on how far each customer has to travel. We shall come back to this parameter below, after describing the basic model.

The model is calculated as follows. Gravity accessibility from each demand point i to visit a destination j is given as

$$G_{ij} = \frac{W_j^{\alpha}}{e^{\beta D_{ij}}} \tag{1}$$

where G_{ij} represents gravity access from i to j, W_j is the attraction weight of centre j, α is an exponent that controls the effect of attractiveness or centre size, D_{ij} is the network distance from demand point i to destination j and β is an exponent for an exponential decay in the effect of distance. This is basically the traditional gravity index as defined by Hansen (1959), but the transportation costs in the denominator are modeled in log exponential form, which has been found to approximate pedestrian trips more precisely than the original Huff model (Handy and Niemeier, 1997).

The probability P of a demand point i to visit a particular centre j is given as a ratio between accessibility to that particular centre and the sum of accessibilities to all available centres, including centre j

$$P_{ij} = \frac{\left(\frac{W_j^{\alpha}}{e^{\beta D_{ij}}}\right)}{\sum_{j=1}^{n}\left(\frac{W_j^{\alpha}}{e^{\beta D_{ij}}}\right)} \tag{2}$$

Having assigned a visiting probability from each origin point to each destination centre, the patronage of a particular centre is estimated by multiplying the visiting probability with the weight of each demand point and summing across all demand points

$$S_{jr} = \sum_{i=1}^{n} \left(W_i \cdot P_{ij} \right) \tag{3}$$

where S_{jr} represents the patronage of centre j within a demand search radius r, W_i is the weight of a demand point i, for instance, the number of people in a building, and P_{ij} is the probability of the demand point i to visit centre j from equation (2). Each demand point can have a weight W to model differences in household or building size or in their purchasing capacity. Only those demand points that are within a specified network radius r from the destination affect the destination's patronage; those that are further are assumed to be beyond the center's catchment.

In equation (3), and in the Huff model generally, it is assumed that all patronage or purchasing power in the model is fully spent among available stores. If there are 10 people on the demand side, then the sum of patronage across all stores is also 10. Under such conditions, the overall shopping frequency in the system is not affected by the spatial configuration of stores—all demand is always cleared, and the overall patronage is identical with different store patterns. This is not necessarily the case in reality. When demand is not completely inelastic, transportation costs affect store visits. The frequency of Starbucks coffee shop visits, for instance, is higher among patrons who live in a building right above the shop than patrons who come from a 10-minute distance. The former face almost zero transportation costs in getting their coffee while the latter spend \$5 on each round trip on walking time,[5] exceeding the cost of the coffee itself.

Survey data from a thousand households in Singapore's HDB towns, shown in Figure 2, confirm that the frequency of visits to HDB retail centers declines when residents have less access to the centers. Singapore's HDB towns house three types of centers: large town centers, smaller neighborhood centers and the smallest precinct centers. Households were asked how many times a week they visit each type of retail center in their town. Accessibility to retail centers was captured using the gravity access measure shown in equation (1) based on each respondent's home location and the location of the respective town, neighborhood and precinct centers they reported to typically visit. The numerator of the index was kept as "1," which makes the measure effectively based on proximity to the center, ignoring their sizes.[6] Pearson's r suggests that accessibility to retail centers is 42% correlated with households' total weekly visits. Households that face inferior access to retail centers tend to visit them less frequently. Households above the top 90th percentile accessibility make 10.6 visits a week, as opposed to households in the bottom 10th percentile accessibility, which make 6.8 visits per week, on average.

In order to account for this accessibility difference between customers, we add a third element to equation (3), which discounts the patronage allocated to each store by the same inverse distance decay function as used in the Gravity model.[7] Since store attractiveness is already accounted for in patronage probabilities in equation (2), this decay effect only focuses on an inverse distance, with a "1" in the numerator. Customer i's patronage of a store j is thus given as function of (a) customer's own weight, (b) its probability of going to j and (c) its distance from j

$$S_{jr} = \sum_{i=1}^{n} \left(W_i \cdot P_{ij} \cdot \frac{1}{e^{\beta D_{ij}}} \right) \tag{4}$$

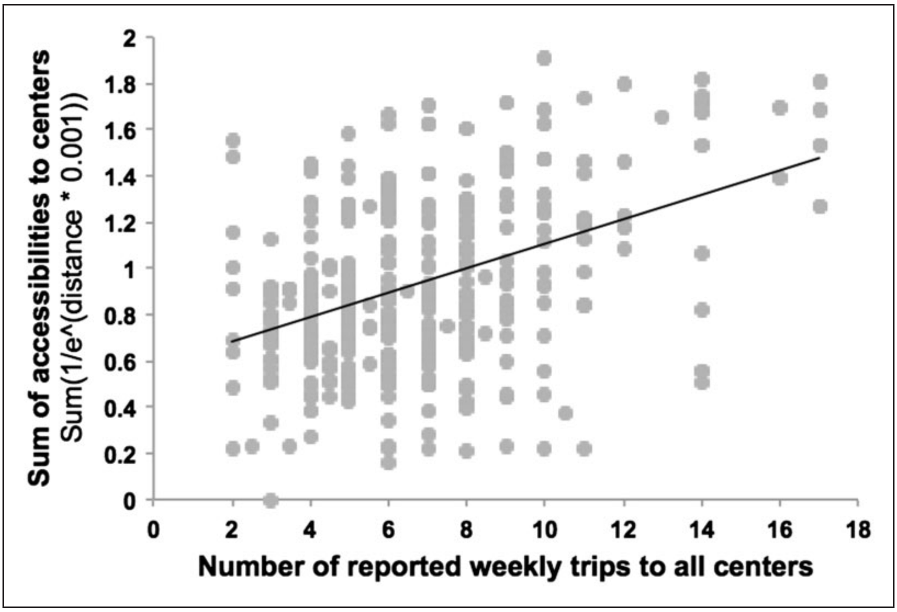

Figure 2. Relationship between households' reported weekly visits to retail centers in their town and their spatial accessibility to these centers. Pearson's correlation = 0.41.

Due to the third element in the summation, demand points that are located at a distance from stores do not allocate all of their weights between stores. Using "1" on the numerator and factoring in only proximity on the denominator ensures that the overall patronage across all stores is always less or equal to the sum of demand weights W_i. Only in a scenario where all demand points are located at the same location as stores, facing zero transportation costs, can the totality of demand weight be allocated to stores.

As a result of the additional distance decay effect, the overall patronage of stores in the system depends on the spatial configuration of stores and patrons—changing either will affect overall store visits in the system. The probability of visiting a destination increases if the destination is more attractive or closer to the demand point, but it also depends on alpha and beta parameters used to model the size and proximity effects.

Determining alpha and beta coefficients

For commercial centre visits in Singapore's HDB towns, we determined values for alpha and beta coefficients empirically, using a survey of approximately 1,000 households in nine HDB towns, administered in fall 2014.[8] Households were asked which town, neighborhood and precinct centers they typically visit in their town and how many times per week. An analysis of these data showed that mean distances for visiting town, neighborhood and precinct centers were 936 meters, 228 and 146 meters, respectively. When a couple of outlier responses were eliminated, then all remaining trips were less than 3000 meters long. We thus use 3000 meters as the limiting radius in the analysis of retail catchment areas below.

Each of the destination centers was matched with a known net leasable floor area (in square meters) in GIS and accessibility to said centers was calculated from each household's location using the gravity metric from equation (1) and walking distances along street networks.[9] This enabled us to compare the actual and estimated number of trips from each surveyed home to retail centers that respondents visited. Based on equation (4), the estimated number of trips from a home i to a center j was determined as

$$Trips_{ij} = W_i \cdot P_{ij} \cdot \frac{1}{e^{\beta D_{ij}}} \tag{5}$$

where W_i is the size of the household and P_{ij} is the estimated probability for each center from equation (2).

The Solver in Microsoft Excel was used to find the alpha and beta values that best matched the empirical response data. The best match was found using an alpha value of "0.37" and beta value of "0.001," which yielded a 38% correlation between estimated and actual number of trips. When the additional decay term $\left(\frac{1}{e^{\beta D_{ij}}}\right)$ was missing from the model—testing the traditional Huff model—the correlation between estimated and actual trips dropped to 30%, corroborating the use of the modified Huff model shown in Equation 4. Note that these trip estimates ignore most destination characteristics, such as the choice, age or quality of stores. Destination size and proximity still explain over a third of the total trips. Due to idiosyncratic variations in different household shopping frequencies,[10] we also compared the estimated and actual proportion of trips from each household to the same retail centers, instead of the raw number of trips. The correlation between the estimated percentage of trips P_{ij} from equation (5) and the actual percentage of trips was 0.67.

Figure 3 illustrates the effect of the distance decay parameter beta "0.001." For comparison, we also show a decay rate with a beta that is half this size and double this size. A larger coefficient implies a sharper decay in visitors as distance increases. This effect can vary by the extent of retail offerings in the city, climate, and culture. In moderate climates or more walkable cities, people are likely to walk longer distances. But willingness to travel to commerce also depends on what people are used to in a particular city—cities with dense retail patterns, such as London, make a longer commute unusual.

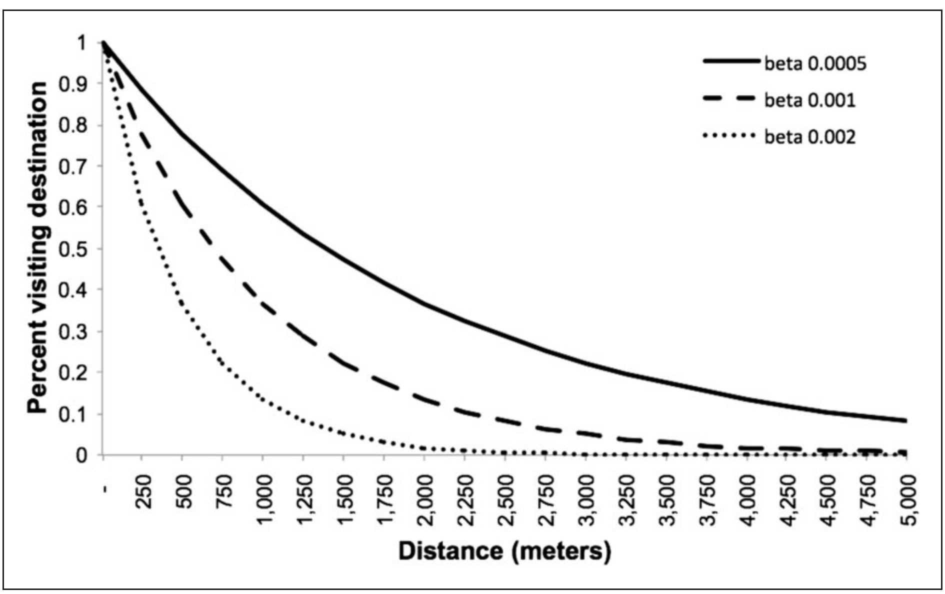

Figure 3. Distance (metres) effect on patronage, with a coefficient beta = 0.001.

A beta coefficient of "0.001" suggests that patrons who are within a 100 meters from a retail center are more than 90% likely to visit it, but for those that are 700 meters away, the probability drops to about 50%. Probabilities also depend on centre size and the placement of competing centres.

Plugging the best fitting alpha coefficient "0.37" value into equation (1) and keeping the distance in the denominator constant, we see that as a destination's size doubles, accessibility increases by about 29%. In terms of patronage probability, a household that has two centers around it, both at the same distance but one center double the size of the other, will assign 44% of its trips to the smaller destinations and 56% to the larger destination. If the smaller center is 25% closer than the larger center, then the visiting probabilities would be roughly equal between both centers.

In contrast to Eppli and Shilling, who found that shopping center visits in the US are more strongly determined by center size than travel distance, we find that access to retail centers is more critical for Punggol residents' retail patronage than destination size (Eppli and Shilling, 1996). Unlike the US, where the majority of shopping trips take place in cars at relatively low travel costs, 65% of all trips in Singapore take place in public transit and most residents in HDB towns walk to retail destinations. In the presence of higher transportation costs, the location pattern of retail centers has a significant effect on patronage.

Punggol New Town

We use Punggol as a case study to demonstrate the practical value of the model to planners and urban designers. Punggol is one of the newest HDB towns in Singapore, consisting of about 300,000 residents, when complete. Figure 4 shows the town layout, including the street network, building locations as demand points, and the locations of existing, built-out commercial clusters, with their size indicated in square meters. The commercial centers are planned and built by HDB. Although building centroids in the figure are shown as uniform gray dots, each of them carries a different weight W, indicating the number of dwelling units. There are total of 96,112 dwelling units in the area.

Figure 5 shows the predicted patronage of each of the centres according to the traditional Huff model (using equation (3)), calculated with a network radius of 3000 meters, a distance decay beta value of 0.001 and an attraction parameter alpha of 0.37. A *FindPatronage* tool for this procedure is available in the UNA Rhino toolbox.

The individual destination results in Figure 5 suggest that patronage varies from 3412 households at the smallest centre to 15,935 at the largest. The overall patronage across all retail centres is 96,112—the same number as the number of households—as the Huff model requires.

In Figure 6, we estimate store patronage on the same configuration as in Figure 5, but applying the additional distance decay function from equation (4). The relative number of visits to each centre remains similar, but the additional decay effect drops overall patronage by 65%, reducing total patronage from 96,112 (the number of total households in the area) to 33,211.

Note that in both estimations shown in Figures 5 and 6, we assume that shoppers start their trips from residential buildings. But shopping from home does not necessarily reflect the dominant pattern of store visits. In Singapore's HDB towns, over 65% of residents use Mass Rapid Transit (MRT) for daily home–work–home trips.[11] Having shops that are located conveniently *en route* to MRT stops could enable residents to patronize retailers without incurring extra transportation costs that are involved in designated trips from homes.

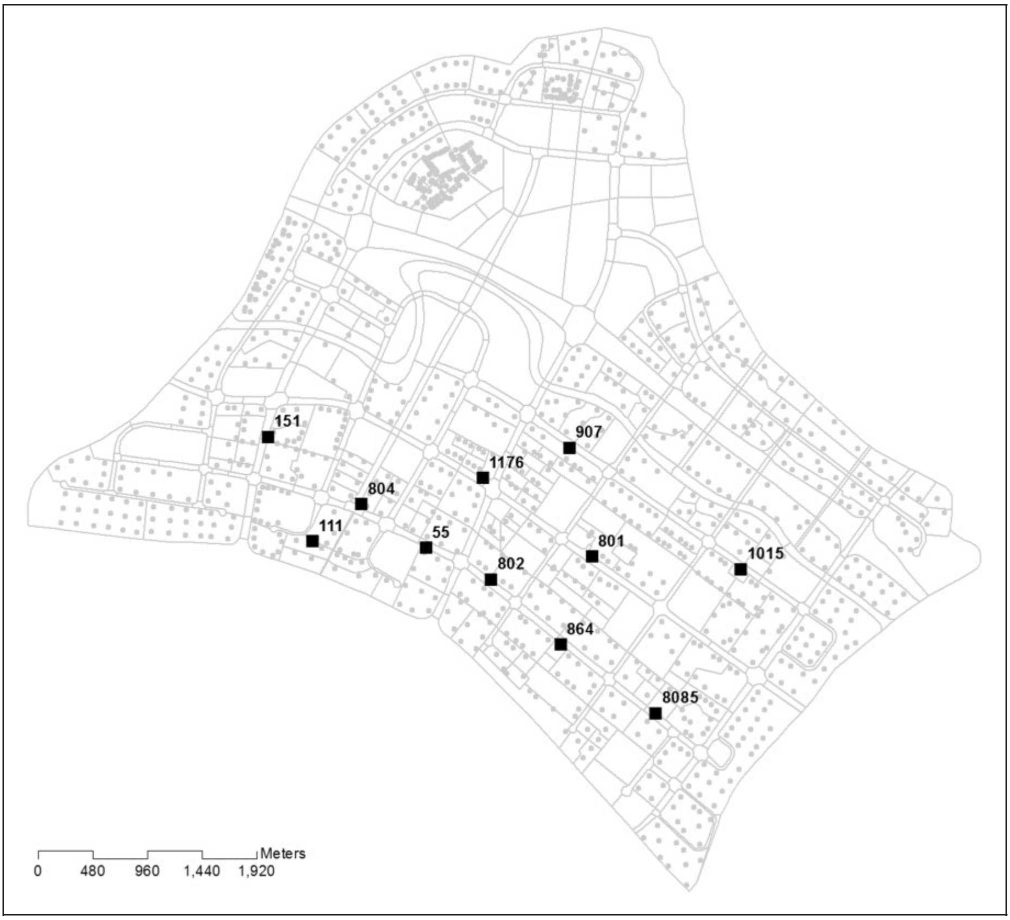

Figure 4. Punggol town layout with its street network, building locations and existing commercial centres. Numbers indicate the Net Leasable Area of each existing commercial cluster.

In order to model retail demand on routine walks between homes and MRT stations, the demand weights found at home locations can be distributed along walkways leading to MRT stations at given distance intervals (e.g. 10 meters). If a building's original demand weight was "100 dwelling units," for instance, it was located 1000 meters from the nearest MRT station, and the distributed demand points are placed at 10 meters intervals along the walk, then we obtain 100 distributed demand points, each getting "1" as their demand weight. When multiple routes overlap on particular network segments, then the same distributed points are used and their values are summed. As a result, points on highly trafficked segments, such as those near MRT and bus stations, accumulate higher demand weights. A *DistributeWeights* tool for automating this procedure is available in the UNA toolbox. Instead of only relying on shortest paths, the tool also allows the allocation to occur along all routes that are up to a given percentage longer than shortest paths, using an allowable *DetourRatio* variable. Based on a survey of pedestrian activity in HDB towns, we used a 15% *DetourRatio* to allocate household weights evenly between all routes that were up to 15% longer than the shortest path from home to MRT.[12] As a result of distributing the original demand weights from buildings to MRT walking routes, the sum total of the weights

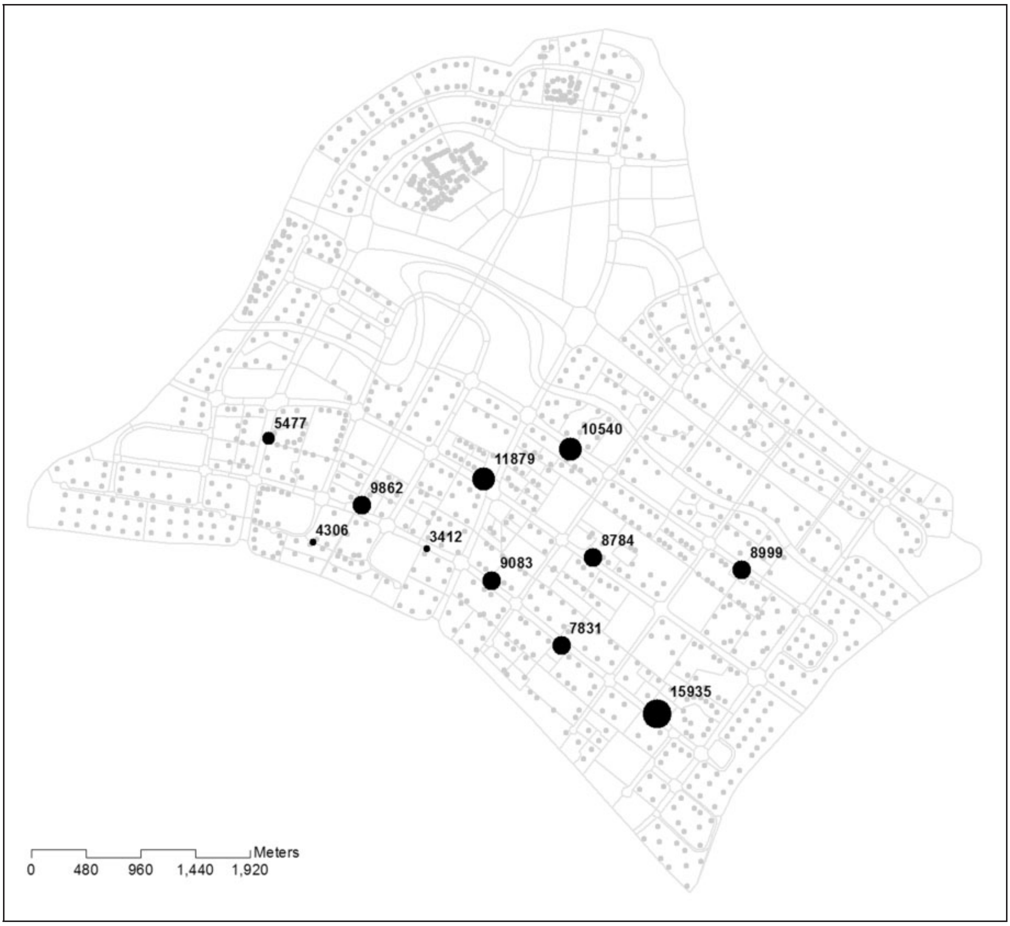

Figure 5. Estimated store patronage with existing stores in Punggol. Beta = 0.001; Search radius = 3000 meters; Alpha = 0.37. Total patronage in town = 96,112 households.

does not change—it stays at 96,112 corresponding to the number of original households in the area.

Figure 7 describes the distributed demand weights on estimated walking routes from each dwelling unit location to the nearest MRT, light rail and bus station.[13] On top of these, the figure also shows the new patronage estimates for the same set of existing stores as we saw in Figure 6. A change in the behavioral assumptions about shoppers can trigger a change in estimated shop patronage. Overall, patronage across all stores slightly increases from the previous 33,211 to 35,055 as a result of modeling demand from walks to MRT stops rather than homes (5.5% increase). This suggests that a typical Punggol resident would find stores more accessible on walks to or from MRT than from their home locations.

Simulating new stores

At the time of the study, Punggol was roughly half built, with less than half of the commercial spaces constructed. A town centre—the largest commercial cluster in the plan, located at the Punggol MRT junction—had not yet broken ground. A number of

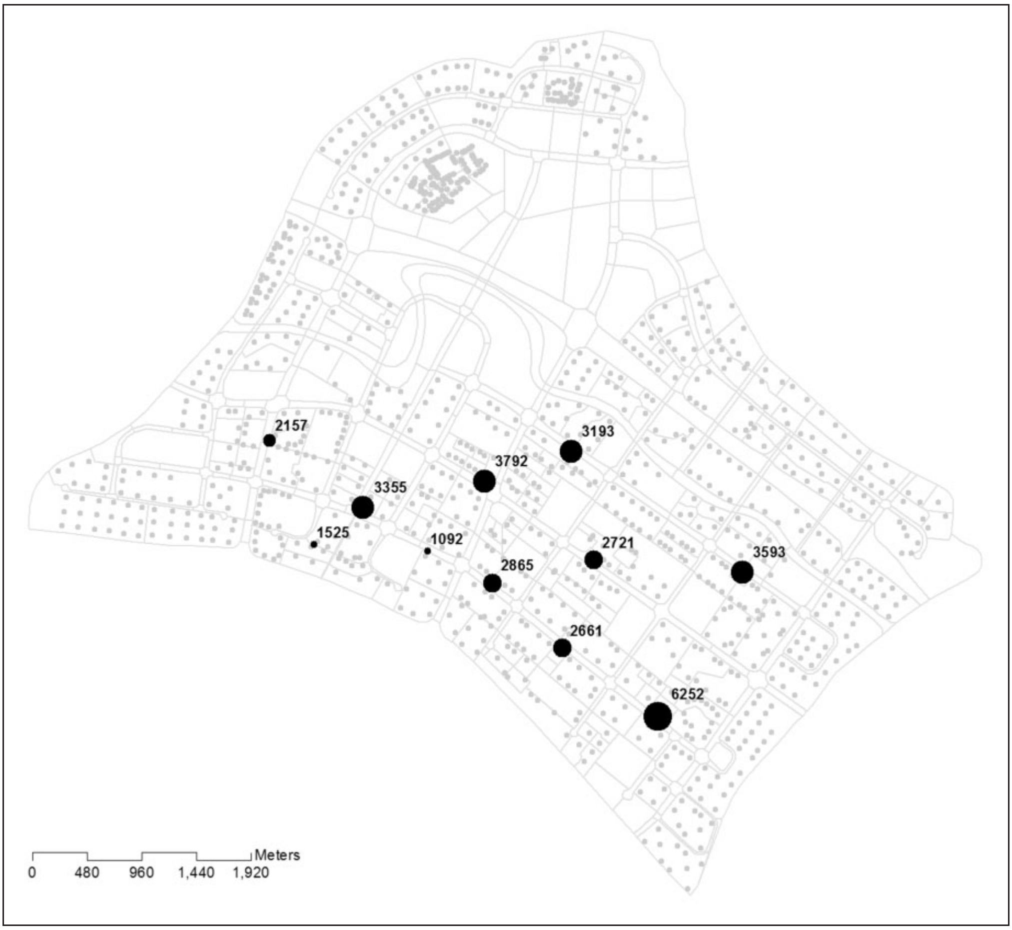

Figure 6. Estimated store patronage with existing stores in Punggol using a distance decay effect introduced in equation (4). Total patronage in town = 33,211 households. Beta = 0.001; Search radius = 3000 meters; alpha = 0.37.

neighborhood centres were also in planning phase. A few precinct centres were complete. The partially built nature of the project offered an opportunity to explore how the remaining commercial space could be best positioned and sized so as to maximize overall retail access in the town.

In the following, we compare two planning scenarios, using the same distributed points on MRT walking routes shown in Figure 7 as demand locations. The first scenario reflects the current HDB plan for the distribution of future commercial centres in Punggol, including both those that are already built out as well as those that remain yet to be built. The second scenario illustrates a *tabula rasa* approach, where the same number of centres as HDB has planned is positioned at optimized locations to maximize access from MRT and bus stop walking routes. We assess how the positioning and sizing of stores impacts overall retail patronage in both scenarios.

In order to make the two scenarios comparable, we made sure that both contained one town centre (30,000 m^2), seven neighborhood centres (9000 m^2 each) and 29 precinct centres (1500 m^2 each). The use of such hierarchical centre types (TC, NC, PC) reflects a typical

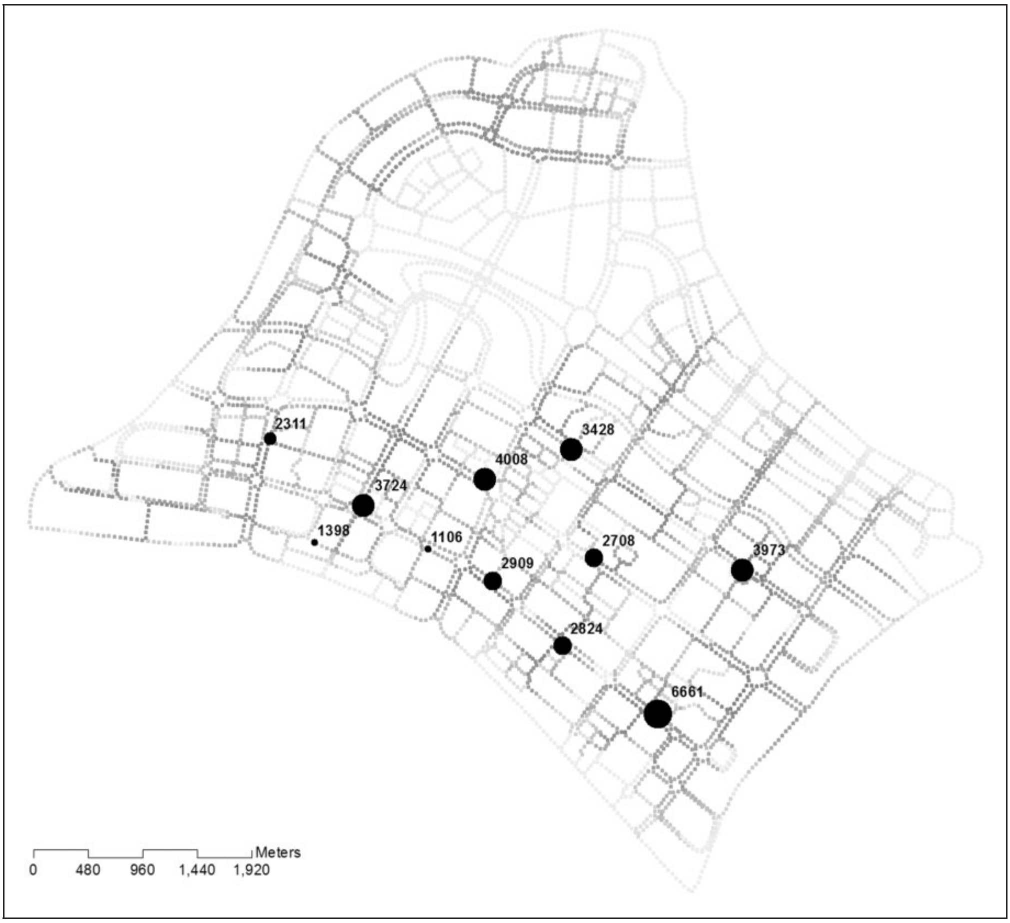

Figure 7. Estimated patronage of existing clusters with demand originating from MRT walk routes. Total patronage in town = 35,055 households. Beta = 0.001; search radius = 3000 meters; alpha = 0.37.

division of commercial centre typologies used by the HDB. At present, Singapore's HDB towns have allocated 9% of retail space to town centres, 44% to neighborhood centres and 47% to precinct centres (MIT Economic Review Committee Sub-committee on Domestic Enterprises, 2002). The overall quantum of retail space was kept constant, corresponding to the amount foreseen for Punggol.

Figure 8 illustrates the results for scenario one, where existing and future commercial clusters are located according to HDB's current plans. Total patronage across all commercial centres is estimated at 38,243 households. This result increases to 38,899 in scenario two (Figure 9), when the same number and size combination is shifted closer to the most trafficked MRT walkways.[14] Although the improvement resulting from slightly closer store locations is relatively small (1.7% increase), it could be more substantial with less stores and bigger market areas.

Another way to affect patronage at a given set of center locations is to reallocate destination sizes. In Figure 9, we optimized retail destinations to be closer to MRT walking routes, but used a typical size allocation of HDB centres—30,000 m^2 NLA for a town centre, 9000 m^2 for neighborhood centres and 1500 m^2 for precinct centres.

Figure 8. Existing built-out patronage estimate for scenario one, where existing and future commercial clusters are located according to HDB's current plans. Total quantum of commercial space is 136,500 m^2. Centre allocation: 1 town centre (30,000 m^2), 7 neighborhood centres (9000 m^2 each), 29 precinct centres (1500 m^2 each). Total patronage in town: 38,243 households. Beta = 0.001; search radius = 3000 meters; alpha = 0.37.

Keeping total retail space constant, could overall patronage be increased with a different center size pattern?

The UNA Rhino toolbox includes a simulation tool called *unaPatronageSim* to test what size combination between centres achieves most estimated visits. Similar to above, inputs include demand point locations and destination locations. Additionally, a total retail area limit to be allocated between centres is required. This area is then tested between all centre types at a chosen percent interval—1% at town centre and the rest between other types of centres, 2% at town centre and so on, until 100% has been tested at each centre type.[15] Just like above, the attraction of each retail cluster depends on its size and network distance from potential customers, and the highest result is obtained when accessibility to stores is maximized with respect to a given demand pattern. This accessibility, in turn, depends both on the proximity and size of destinations, and the alpha and beta coefficients used.

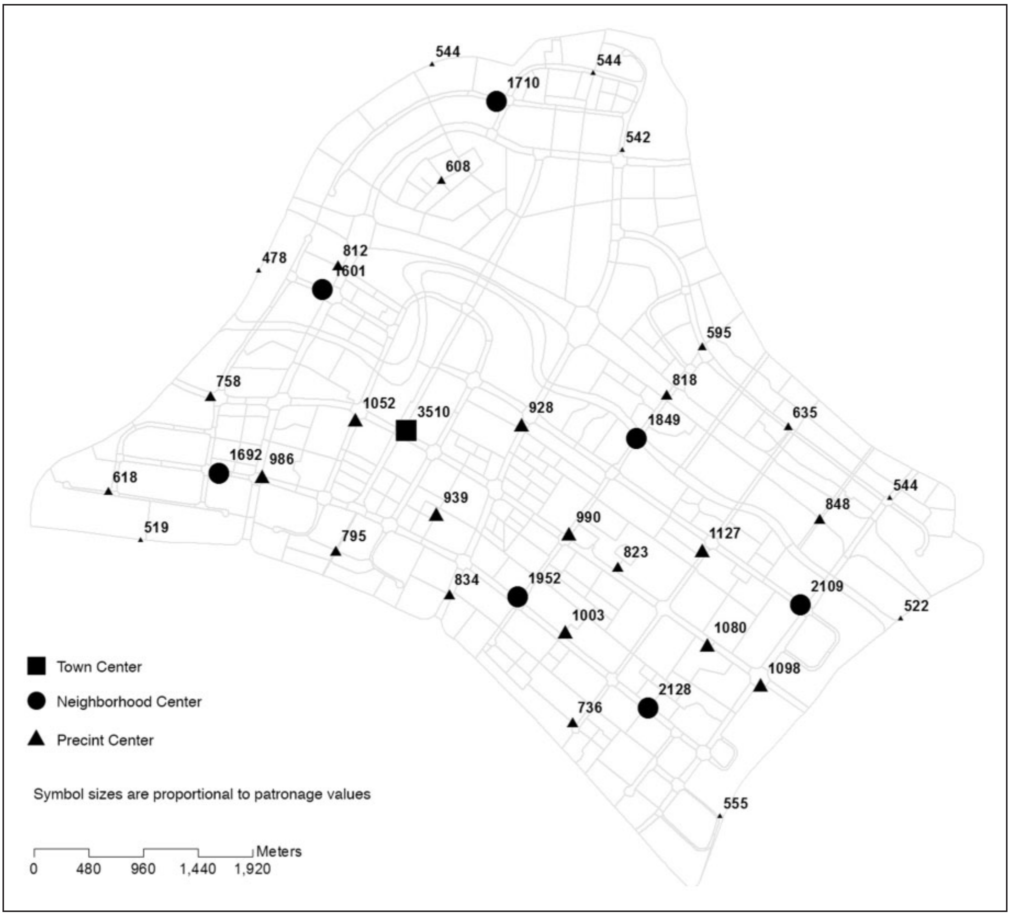

Figure 9. Patronage estimate for scenario two, where the same number and size of commercial centres are located deliberately closer to MRT walk routes. Total quantum of commercial space is 136,500 m^2. Estimated patronage across all clusters is 38,899 households. Beta = 0.001; Search radius = 3000 meters; alpha = 0.37.

Figure 10 illustrates simulation results, where the total quantum of 136,500 m^2 of NLA was iteratively allocated at 5% intervals to different centre types.[16] The graph depicts the resulting patronage estimates on the vertical axis and the percent of total space given to the town centre on the horizontal axis. The sum total of retail NLA is kept constant in each iteration, while different areas were allocated between centre types. Within each zigzag hump, allocations move from 100% at the precinct centres on the left, to the reverse, 100% at neighborhood centres on the right. The overall pattern suggests that with every town centre proportion, patronage is highest when all of the remaining retail space is only allocated to the medium-sized neighborhood centres and none at the smallest precinct centres. The maximum result of 41,254 is achieved when the town centre and seven neighborhood centers are all the same size—17,065 m^2.

Note that the simulation results do not have a single sharp peak—there are multiple peaks with town centre sizes ranging from 5 to 55%, where overall total patronage remains within 1% of the maximum. Even with a 75,500 m^2 NLA town centre (55% of total) and seven 8775 m^2 NLA neighborhood centres, patronage reaches 40,896 households. No one centre

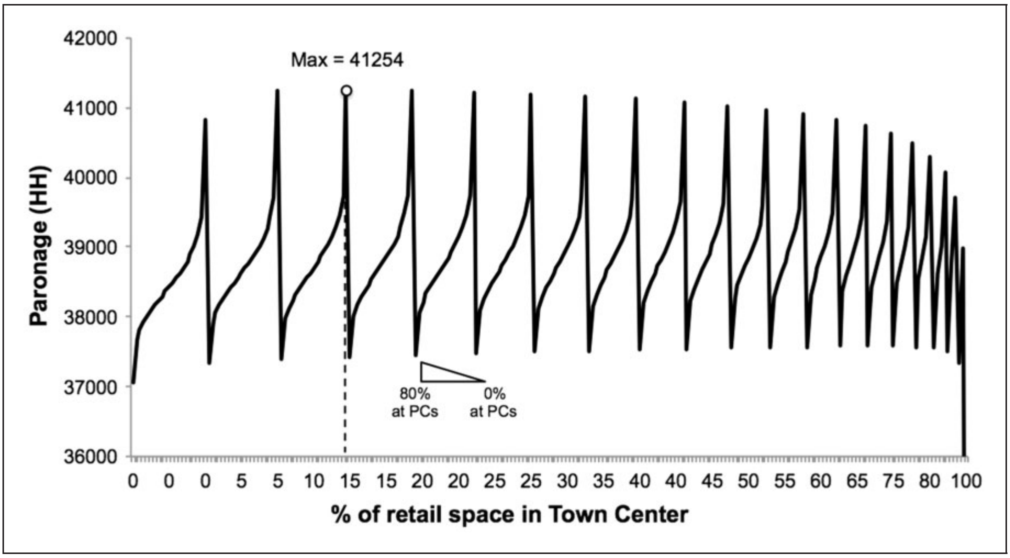

Figure 10. Patronage simulation results, where the total quantum of 136,500 m^2 was iteratively allocated to town, neighborhood and precinct types using allocation 5% steps. Maximum patronage is 41,254 households. Beta = 0.001; search radius = 3000 meters; alpha = 0.37.

size configuration is clearly above others, but overall patronage is maximized when retail floor area is distributed among seven or eight (if counting the TC) neighborhood centres, each accommodating around 9000–18,000 m^2 NLA. This result suggests that a network of bigger neighborhood centers could benefit both residents and businesses more than the current hierarchical size order with a single large town center, a few medium-sized neighborhood centers and lots of small precinct centers.

These results apply to Punggol. A different size combination may work in other towns, depending on their layouts and customer densities. However, since the most important determinants of optimal size configuration—the alpha and beta values—were based on survey data that was combined from nine HDB towns throughout Singapore, a stronger emphasis on medium-sized neighborhood centers should also be explored in other HDB towns.

Overall, optimizing the sizes of retail clusters within the same locations, as in scenario two (Figure 9), increased estimated retail patronage from 38,899 to 41,254 (6%). Destination size optimization thus had a bigger positive effect on patronage than our location adjustments above. But if we take the location optimization that placed centers closer to MRT walking routes and the size optimization together, the combined gain compared to the baseline HDB scenario is a 10.2% increase in estimated retail patronage.

Discussion

The model we have described enables planners and urban designers to better understand how spatial planning decisions could influence the viability of retail developments. Successful planning of urban commerce requires that stores receive sufficient customers and revenue to break even. The siting of buildings, their densities and the layout of circulation networks play an important role in shaping the demand that sustains urban retailers. Not every street can be a main street and not every corner is fit for a store.

The presented model can be used to assess the viability of individual stores, clusters or a system of clusters as a whole.

At present, Singapore's HDB towns have around 500 precinct centres, 123 neighborhood centres and 17 town centres. Roughly 47% of HDB shops are located in small precinct clusters. Our simulation results suggest that a stronger emphasis on the medium scale neighborhood centre development may be warranted in future HDB developments. The current distribution of precinct centres aims to make convenience goods accessible near people's place of residence. But precinct centres are typically small, ranging from 500 m^2 to 3000 m^2, accommodating 5–10 shops each. Precinct shops receive rent subsidies from the government and are meant to please residents with convenience. Our model suggests that a proliferation of precinct centers in Punggol does not benefit overall retail patronage as well as larger neighborhood centres would. Since the patronage of stores depends on both the proximity and size, a smaller set of larger centers appears to be more beneficial for residents and shopkeepers alike. Similarly, too big of an emphasis on a large town centre could produce an adverse effect on patronage, since town centres are few and far from patrons. Across simulations, the largest estimated patronage was achieved when the bulk of a town's retail space was placed in medium-sized (9000–18,000 m^2) neighborhood centres.

This result cannot be generalized to other towns at this point. Further research is needed to establish whether model coefficients and people's travel behavior to commercial destinations might vary by town. Additional research is also needed to clarify the extent to which the results depend on the distribution of demand points, retail destinations and the circulation networks that connect them. And further experimentation is needed to understand the robustness of the alpha and beta coefficients as well as the sensitivity of the model outcomes with different coefficient values. In future studies, an attractiveness index could combine a series of known factors, such as store selection, brand availability, parking and age in a combined index. Similarly, accessibility estimates in the model could be improved if different travel modes were explicitly combined—access on foot, by bike, by car or transit.

We have focused our attention on optimizing retail locations and sizes. But similar gains could probably be achieved by manipulating demand locations and access routes—housing layouts, residential and employment densities, pedestrian paths as well as transit locations. In planning new residential towns in Singapore, it would make sense to coordinate residential, commercial and transit planning, such that residents have easy access to stores while walking to and from MRT stations.

If applied in an existing retail system in other cities, the model could be used to assess how an expansion of a given cluster of stores could impact patronage at the named, as well as competing clusters around it. This could inform policy makers on how and where zoning alterations and policy incentives are best placed.

An analogous model can be specified for different types of urban facilities, using appropriate coefficients and parameters for each. The planning of urban parks or playgrounds, for instance, could benefit from a patronage model that too aims to maximize overall usage. The placement of electric car chargers and shared bicycle stations face similar issues.

There are other software tools available for computing Huff models. The model presented here is aimed at physical planning and urban design applications, where patronage estimates can be computed over networks in multiple design scenarios and the effects of different configurations compared with little effort in the Rhino design software. The introduction of the additional decay element in the Huff equation makes the model unique for assessing the impacts of spatial layouts and site plans on overall facility patronage. The simulation engine allows destination sizes to be optimized through automated trials, which would be too labor intensive to undertake manually. Jointly, these features are meant to make computerized facility patronage estimation freely accessible to a wider audience of spatial planners and urban designers.

Supplementary material

The *unaFindPatronage*, *unaPatronageSim* and the *unaDistributeWeights* tools can be freely downloaded as part of the Urban Network Analysis plugin for Rhinoceros 3D at the following link: http://cityform.gsd.harvard.edu/projects/una-rhino-toolbox

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Notes

1. ESRI's ArcGIS Business Analyst package (http://www.esri.com/software/businessanalyst, accessed 10 September 2016) first started offering a Huff market area tool in 2003. This was upgraded to an advanced Huff model in 2008. The model uses straight-line distances and population zones to estimate retail patronage or sales. Another free ArcGIS toolbox for calculating Huff probabilities for stores was published as a plugin by Flater in 2012 (https://www.arcgis.com/home/item.html?id=f4769668fc3f486a992955ce55caca18, accessed 25 August 2016), which applies the traditional Huff model with straight-line distances between origin and destination locations.
2. No time-based estimates were available, since this would require timing each wait at a traffic light, crossing, etc. But since we are dealing with pedestrians, where unlike cars, there are no variable speed limits on segments, we are confident that network distances offer a fairly accurate representation of travel costs. Furthermore, a sizable portion of walks in HDB towns are internal to blocks that are pedestrian only, with no crossings slowing pedestrians down.
3. This requires user information about residential densities or household numbers at each building or parcel, which can be interpolated from census blocks or obtained from local assessor's databases.
4. The tool also allows an aggregated estimation of demand from zones (e.g. census tracts instead of individual houses) when desired.
5. Assuming an average wage of $15/h in some US states.
6. The centers that were used as part of the destination set were based on reported responses, where respondents indicated which town, neighborhood and precinct centers they typically patronize.
7. This additional element is optional in the Rhino toolbox and can be turned on or off by the user.
8. The Survey of Residents' Shopping Experience in HDB Towns (n = 1088) was commissioned by the HDB and carried out by Singapore based Nexus Link Pte Ltd as part of Savills' and City Form Lab's Research on Commercial Facilities.
9. A network distance from each HH to their indicated retail destinations was calculated using GIS network analyst. Since origins and destinations can be at a distance from the street network, a distance from the surveyed longitude/latitude points of both homes and retail centers to the nearest network segment was added to the actual route distance along the network to achieve a more accurate total route length.

10. The number of reported trips varied widely—while the average household makes 6.7 trips to various retail centers in their town per week, some households make as few as two and others as many as 17. This variation is not only explained by varying accessibility to retail destinations as discussed above, but also family-specific economic, cultural and habitual factors, which are not included in the Huff model.
11. Source: Singapore Land Transport Authority's HITS travel survey, 2012.
12. The survey was carried out as part of a class experiment with students at the Singapore University of Technology and Design, where respondents at HDB retail centers, and MRT stations were asked how they walked there. Comparing the actual walks with shortest paths showed that the average deviation was 15% longer than the shortest available path (in terms of distance).
13. The *DistributeWeights* tool does not only place weights on the shortest paths to the destinations, but can use multiple "plausible" paths, each of which must be shorter than a given detour ratio (e.g. 15%) above the shortest path. The details can be found in the UNA toolbox help documentation. In this example, all routes that were up to 15% longer than the shortest available route from a building to an MRT station were given equal likelihood. Depending on station availability around their house, it was assumed that people were most likely to walk to MRT, then Light Rail (LRT) and finally bus stations. If an MRT station was available within an 800 meters distance, then 70% of the demand points' weights were allocated to that MRT, 20% to LRT and 10% to bus stops. The allocation changed when only LRT and bus or just bus stops were present around a building.
14. The location optimization in Figure 8 was performed in ArcGIS, using the *Location Allocation* tool in the Network Analyst extension. First, the Town Centre was located alone. Then the resulting town centre location was taken as a "required" facility and seven additional Neighborhood centre locations were optimized. In the final step, both the 1 TC and 7 NCs were taken as "required" and 29 more precinct locations were identified. Since HDB plans PCs as small convenience clusters near homes, for the latter, demand was modeled from building locations, not MRT walkways. PCs were solved with a constraint that allowed no home to be more than 400 meters from a PC. This resulted in 29 PCs.
15. With a step size of "1" percent, this required 5151 simulated iterations. A step reflects the percent increment in integers, whereas step size needs to be a factor of 100 (e.g. 1, 2, 4, 5, 10, 20, 25, 50). The following formula can be used to find the required number of iterations with different step sizes:
    step = a factor of 100 chosen by the user
    steps = 100/step
    iterations = (steps × steps + 3 × steps + 2) / 2
16. A 1% allocation produces a similar result, but the visual graph includes a 100 instead of 20 humps, which is visually harder to read.

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