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

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Abstract

We propose a modification to the widely popular Huff retail expenditure model and apply it in a new plugin for the Rhinoceros 3D software environment, which analyzes facility patronage along spatial networks in dense urban environments. The tool has two purposes. First, it allows one to study how size and location changes in existing commercial clusters could affect patronage at all centres within a system. The graphic user interface of the model allows a planner to flexibly test different size and placement scenarios with instantaneous feedback on the estimated patronage to different centres. Second, 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 determine the size combination of retail clusters that maximizes overall shopper utility, leading to greatest patronage of commercial clusters in the system as a whole. Both functions of the tool can be integrated with existing, unchangeable retail developments. Outcomes in shopping behavior can also be tested against changes in network geometry – e.g walking routes leading to centres – or changes in demand locations.

A survey of residents' shopping behavior, implemented in 2014 in Singapore's HDB towns, is used to calibrate the model coefficients for patronage of commercial clusters. The model is then applied in the Punggol new town – presently only about half built – to compare the estimated patronage of commercial centres when all currently planned facilities will be completed against an alternative scenario, where centre locations and sizes have been refined with the simulation model.

We present two important findings. First, we demonstrate how commercial patronage in the town can be improved by optimizing retail locations around public transit stations, where people can access stores with lower transportation costs than on designated trips from homes. Second, departing from traditional space allocation quotas between town, neighborhood and precinct centers in HDB towns, we find that retail access and patronage could be improved, if the medium-scale neighborhood centers were more numerous and prominent in HDB towns. We suggest that an analogous model can be used for right-sizing retail developments in future planned towns in Singapore and beyond.

The model could also be applied in existing retail systems to assess how the expansion of a given cluster could impact patronage at the named, as well as competing clusters around it. This could inform policy makers on deciding where zoning alterations and policy incentives are best placed.

Introduction

Commercial amenities form an essential part of vibrant urban neighborhoods. Having shops, restaurants and personal service establishments near places of residence or employment not only increases people's choices for consumption, but also encourages walking (Forsyth, Hearst et al. 2008, Rundle et al. 2007; Hoehner, Ramirez, and Elliott 2005), reduces urban energy usage (Newman and Kenworthy 1999; Zegras 2004; Frank and Pivo 1994; Krizek 2003), fosters social cohesion (Jacobs 1961) and generates local jobs. Many city planning departments have adopted policies to encourage pedestrian-oriented retail clusters. But influencing the retail location pattern of a city requires complex policies, since 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 changes in one cluster are likely to affect others or how a district-wide system of retail centres could be improved as a whole, accessible tools and models are needed for planners.

This paper introduces an extension to the Huff (1963) model of retail interdependencies, where the patronage of each facility or cluster is proportional to its size and inversely proportional to its accessibility to potential patrons. We propose an additional distance decay term in the model that relates 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 customers make, we show that households with better access to retail centers visit the centers more frequently.

Our main focus lies on exploring how the spatial arrangement of stores with respect to a fixed pattern of customers can increase the patronage of retail centers. While according to this dependent variable it might seem that a more efficient location and size allocation of retail center would benefit stores, maximizing retail patronage is not a zero-sum game where the gains on behalf of stores come at the cost of customers. Every household is assigned a probability to visit each one of the retail centres around their house depending on two factors — the attractiveness of the center (we use size as a proxy) and the spatial accessibility of the center. Keeping the overall retail area constant, patrons' visits to retail centers vary according to their sensitivity to both center size and travel distance. This means that placing numerous small stores closer to customers does not necessarily increase customer visits, which depend jointly on access and store size. Similarly, a single large center might not be preferable if customers are sensitive to travel costs. The location and size pattern of centers that maximizes store visits therefore benefits both store revenues and improves customer welfare.

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 spatial relationships between customers and retail destinations are captured along actual circulations routes. This makes the model more precise and opens up interesting applications of the Huff model in dense and complex urban environments.

The model is implemented as part of the Rhinoceros 3D urban Network Analysis Toolbox plugin, which freely available for download. Implementation of the tool as part of the Rhino platform shortens the lengthy feedback cycle between design and analysis, where drawings from one software need to be exported to GIS or other analytic platforms for evaluation, and results eventually returned to design software for new placement iterations. Having the tools in Rhino allows a planner to evaluate a specific plan or development proposal within seconds, incorporating patronage analytics into a fast and iterative 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 clusters so as to maximize overall shopper utility. Both one-off estimations and automated simulations can be integrated with existing retail developments, whose sizes and locations remain unaltered. The tool can therefore be used to analyze incremental changes to well-established and distributed shopping environments, such as found in Cambridge MA, as well as newly and centrally planned shopping clusters in upcoming urban developments.

The paper is structured as follows. First, the literature review introduces the Huff model and some 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 the case-study of the Punggol New Town in Singapore.

Literature

The most widely-utilized retail patronage model was introduced by Huff (1963). The Huff model assumes that the probability of a consumer to make purchases at a given commercial destination is a function of the distance to that destination, its attractiveness, and the distance and attractiveness of competing sites around it. Since each consumer allocates a certain proportion of trips to each retail centre, an interaction ensues between all consumers and all centres. 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 same procedure is then applied to all available retail destinations around the consumer. 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. The Huff model is formulated as follows:

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

Equation 1

, where:

P_{ij} is the probability of a consumer i to shop at centre j,

W_j is a measure of the attractiveness of each centre j,

D_{ij} is the distance from consumer i to centre j, and

β is an exponent applied to distance to achieve an exponential decay for more distant sites.

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.

The distance decay exponent should be empirically based from observing the shopping habits of patrons from different distances. The attractiveness attribute of each destination centre (W) can describe any kind of feature that has a positive effect on consumer patronage. In practice, the size of destinations or Net Leasable Areas (NLA) is often used as a proxy for the choice of merchandize at the 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.

Individual consumers are aggregated to groups, typically at the census tract or block-group level, where demographic information is available. The probability of each polygon can be 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. At the neighborhood scale, using centroids of census polygon as demand origins can substantially distort the actual distribution of retail demand.

Most applications of the Huff model also utilize straight-line distances between consumer polygons and retail destinations. This simplifies the calculation, but it can misrepresent the true distances required to get to destinations over spatial circulation networks, especially at the finer-grain neighborhood scale.

Even though the Huff model was formulated several decades ago, only fairly recently have its application reached a wide audience with software and data applications. ESRI's ArcGIS Business Analyst[1] package 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, which applies the traditional Huff model with straight-line distances between origin and destination locations.[2]

Lakshmanan and Hansen (1965) have developed a version of the model, which estimates the total sales at each of the centre based on the Huff probabilities for consumers to visit each of the centres. The total sales at centre j by consumers from zone i, is given as:

$$S_{ij} = C_i * \frac{\left(\frac{W_j}{D_{ij}^{\beta}}\right)}{\left(\sum_{k=1}^{n} \frac{W_k}{D_{ik}^{\beta}}\right)}$$

Equation 2

, where:

S_{ij} is the sales at shopping at centre j by consumers from zone i,

C_i is the total consumer retail expenditure of population in zone i,

W_j is the size of retail centre j,

D_{ij} is the distance for consumers from zone i to centre j,

D_{ik} is the distance for consumers from zone i to a competing centre k, and

β is an exponent for an exponential decay in the effect of distance.

There are two key differences from Equation 1. First, Lakshmanan and Hansen's consumer probabilities on the right hand side are multiplied by the total consumer retail expenditure of population in each zone, which allows the model estimate sales rather than patronage. Second, the Lakshmanan and Hansen formulation only treats competing centres on the denominator of the index, whereas the Huff formulation includes both competing centres and the centre in question in the denominator. Our application of the model uses the Huff formulation.

Weisbrod and Parcells (1984) and Di Pasquale,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 regressions 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 Huff model has so far been rarely used by urban designers and physical planners 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 or how much expenditure the new location could potentially obtain. 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 analyzed. 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 how patronage is likely to be affected by each configuration.

Further, the effects of the spatial circulation network – sidewalks, streets, local transit networks – are currently absent from available market potential models. Yet, we know that the way streets and access paths are configured can improve or hinder access to a store. This is especially important in newly planned areas, where the street network could potentially be planned with district centres and shopping streets in mind so as to foster access to commerce.

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 route in terms of distance.[3] This makes the patronage estimates more precise to the actual context of each shopping destination. A straight-line distance can misrepresent distances even in the most connected gridiron street patterns, as shown in Figure 1. Network-based distances correctly account for uneven densities in the street network (e.g. small versus large blocks), discontinuities (e.g. *cul de sacs*) and barriers, such as highways or rivers. 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.

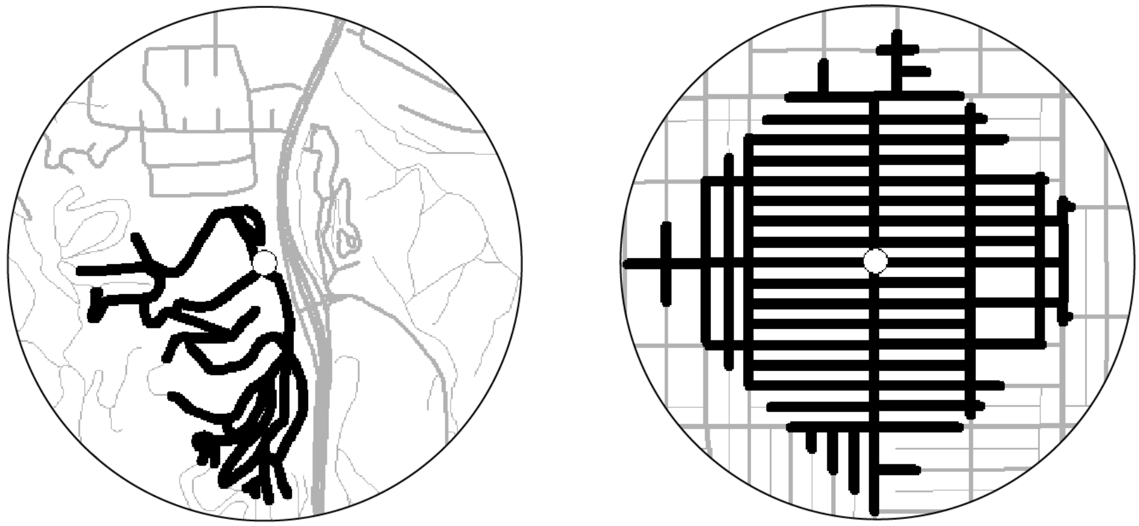

Figure 1. Comparison of straight-line and network walking distances at a neighborhood scale. The outer circle is drawn with a radius of 600m from the centre. The actual walkshed along the street network in the same 600m radius is shown inside the circle.

Second, our 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.[4] The tool also allows an aggregated estimation of demand from zones (e.g. census tracts instead of individual houses) when desired.

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 NLA doubles, attractiveness 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. The exponent over the attractiveness parameter allows a diminishing rate of utility, which has been observed with many destination characteristics and should be empirically specified for each context.

And 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:

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

Equation 3

, 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 Hanesn (1959), but the transportation costs in the denominator are modeled as e to the power of beta times network distance instead of a simple exponent. This alternative specification for distance decay has been found to approximate pedestrian trips more precisely than the exponent used in the original Huff model (Handy 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:

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

Equation 4.

Having assigned a visiting probability from each origin 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:

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

Equation 5.

, 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 4.

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 too far to visit that centre.

In Equation 5 above, 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 ten people on the demand side, then the sum of patronage across all stores is also ten. 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, people do not necessarily patronize stores with the same frequency when they face different transportation costs while going to stores. When we study the frequency of Starbucks coffee shop visits, for instance, patrons who live in a building right above a Starbucks may visit the coffee shop significantly more frequently than customers who come from a ten-minute walk. The former face almost zero transportation costs in getting their coffee while the latter spend $5 on each round trip on walking time[5]. For the latter customers, transportation costs can even exceed the cost of coffee itself.

Survey data from a thousand households in Singapore's HDB towns, shown in Figure 2, confirms that the frequency of visits to HDB retail centers declines when residents have less access to the 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 based on each respondent's home location and the location of the respective town, neighborhood and precinct centers they reported to typically patronize, using the gravity access measure shown in Equation 3, but keeping the enumerator as "1", which makes the measure effectively based only just the proximity to the center and ignores center size.[6] Pearson's correlation suggests that accessibility to retail centers explains 42% of the variation in 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, who make 6.8 visits per week on average.

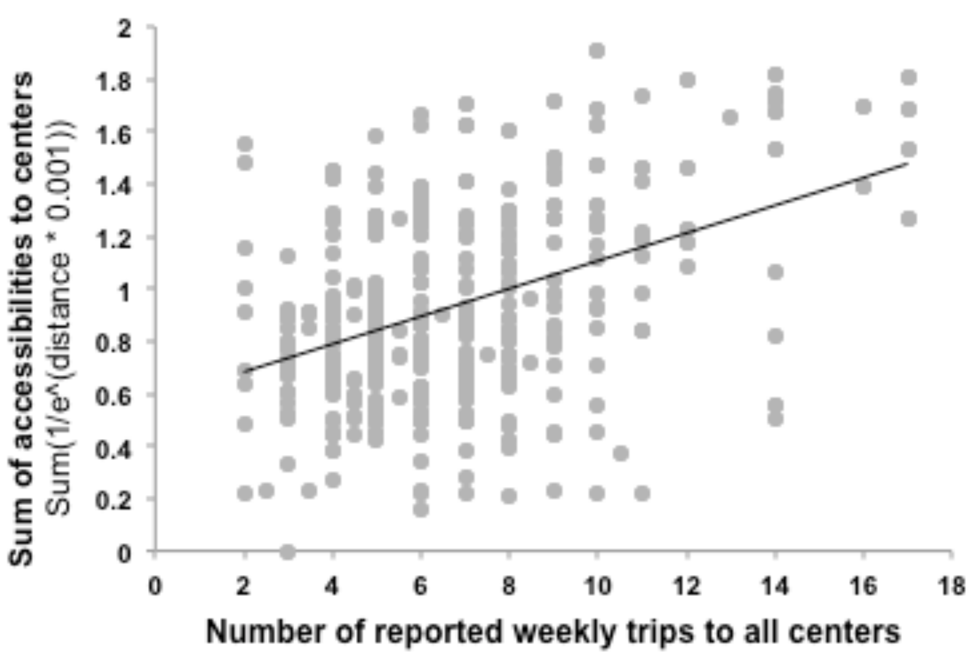

Figure 2. Relationship between households' reported weekly visits to retail centers in their town and their spatial accessibility to these centers. Pearson's correlation = 0.41.

In order to account for the accessibility differences between customers, we add an optional third element to Equation 5, which discounts the patronage allocated to each store by the same inverse distance decay function as used in the Gravity model. Since the store attractiveness is already accounted for in finding patronage probabilities in Equation 4, this decay effect only focuses on an inverse distance effect, with a "1" on the enumerator. Customer i's patronage of a store j is thus given as function of a) demand point's weight, b) its probability of going to j and c) its distance from j:

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

Equation 6

Due 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 enumerator and factoring in only proximity on the denominator ensures that the overall patronage across all stores is always less or equal to the 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 the location of stores 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, depending on what alpha and beta parameters are used to dampen 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 one thousand households in nine HDB towns, administered in fall 2014.[7] 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 936m, 228 and 146m respectively, with considerable deviations among households. When a couple of outlier responses were eliminated, then all trips were less than 3,000m long. We thus used 3,000m as the limiting radius in the analysis of retail catchment areas below.

Each of the destination centers was matched up with a known net leasable floor area (in square meters) in GIS and accessibility to the said centers was calculated from each household's location using the gravity metric from Equation 3 and walking distances along street networks.[8] This enabled us to compare the actual and estimated number of trips from each home to town, neighborhood and precinct centers that respondents visited. Based on Equation 6, the estimated number of trips from a home *i* to a center *j* was determined as:

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

Equation 7

, where W_i is the size of the household and P_{ij} is estimated probability for each center from Equation 4.

Solver in Microsoft Excel was used to find 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 explained 38% of actual trips to these centers. If the additional decay term ($\frac{1}{e^{\beta D_{ij}}}$) was dropped from the model, testing the traditional Huff model, then the correlation between estimated and actual trips dropped to 30%. Note that these trip estimates ignore most destination characteristics, such as the choice, age or quality of stores, yet still the destination size and proximity explain over a third of the total trips.

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 2 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. Due to the idiosyncratic variations in visit frequencies, 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 7 and actual percentage of trips was 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 in a particular city – cities with dense retail patterns, such as London, make a longer commute unusual.

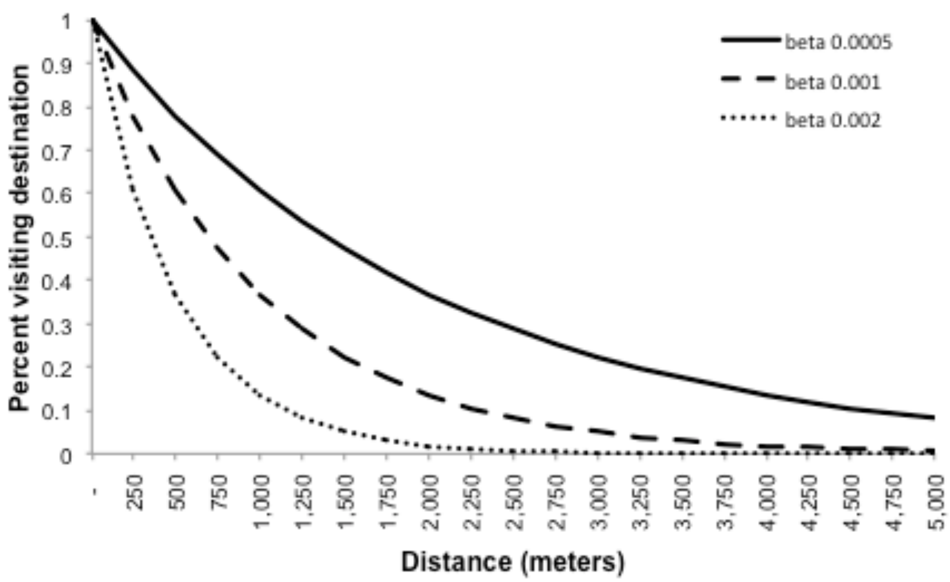

Figure 3. Distance (metres) effect on patronage, with a coefficient beta = 0.001.

A beta coefficient of "0.001" suggests that patrons who are within a hundred meters from a retail center are more than 90% likely to visit it, but for those that are 700m 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 3 and keeping the distance in the denominator constant, we see that as a destination’s size doubles, accessibility increases 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 that 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 the location of retail centers is more critical for HDB residents in Singapore (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, location plays an important role.

Punggol New Town

In this section 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. At the time of the study in 2014, about half of the town was built. In addition to housing, the government of Singapore also provides public transit, commercial and recreational facilities for the residents. 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. Though 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.

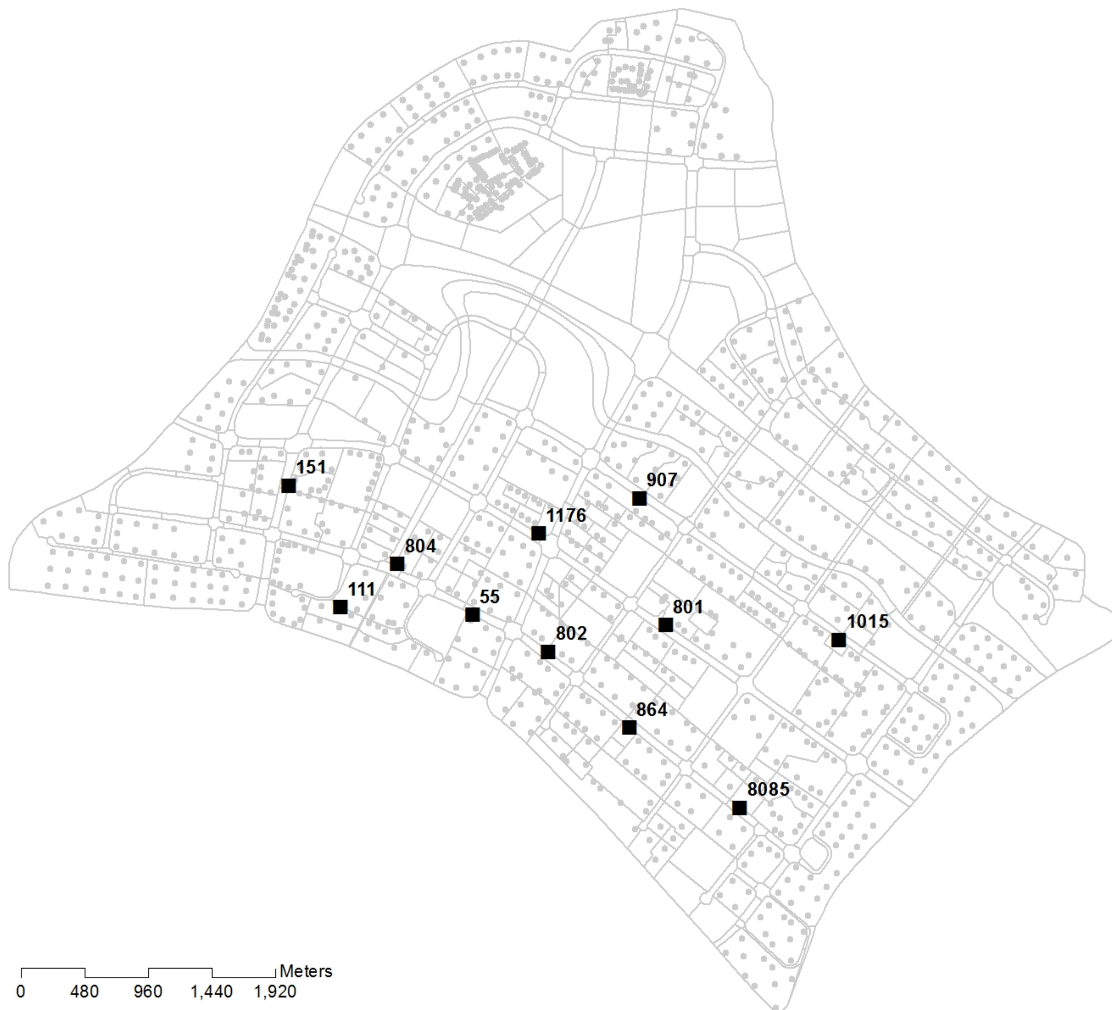

Figure 4. Punggol town layout with its street network, building locations and existing commercial centres. Numbers indicate the Net Leasable Area of each existing commercial cluster.

Figure 5 shows the predicted patronage of each of the centres according to the traditional Huff model (using Equation 5), calculated with a network radius of 3,000 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 3,412 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.

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

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

Figure 6. Estimated store patronage with existing stores in Punggol using a distance decay effect introduced in Equation 6. Total patronage in town = 33,211 households. Beta = 0.001; Search radius = 3000m; Alpha =0.37.

Note that in both estimations shown in Figures 5 and 6, we assume that shoppers start their trips from home locations (residential buildings). But shopping from home does not necessarily reflect the dominant pattern of visits. In Singapore's HDB towns, over 65% of residents use the Mass Rapid Transit (MRT) system for daily home-work-home trips.[9] 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. If residents could instead visit stores *en route* to or from MRT, they could do so at a lower cost. The distance decay element in Equation 6 suggests that reducing transportation costs can increase overall shop patronage.

In order to model retail demand that 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. 10m). If a building's original demand point weight was "100 dwelling units", for instance, it was located 1,000m from the nearest MRT station, and the distributed demand points are placed at 10m intervals along the walk, then we obtain 100 distributed demand point, 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, distributed points that are 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*, allowing the weights to be re-distributed on all routes that are up to 15% longer than the shortest route from homer to MRT.[10] As a result of re-distributing the original demand weights from buildings to MRT walking routes, the sum total of the weights does not change – it stays at 96,112, corresponding the number of original households in the area.

Figure 7 describes the redistributed demand weights, which have been placed on the estimated walking routes from each dwelling unit location to the nearest MRT and bus station.[11] 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). A typical Punggol resident would find trips to existing stores closer on walks to or from MRT than from their home locations.

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 = 3000m; Alpha =0.37.

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 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 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 official 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 is positioned at new locations, which maximize access from MRT and bus stop walking routes. Across both scenarios, we explored how the positioning and sizing of stores could impact overall retail accessibility and patronage.

In order to make the two scenarios comparable, we made sure that both contained one town centre (30,000m^2), seven neighborhood centres (9,000 m^2 each) and 29 precinct centres (1,500 m^2 each). The use of such hierarchical centre types (TC, NC, PC) reflects a typical 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 (MTI 2002). The overall quantum of retail space was kept at 136,500m^2, 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.[12] Thought the improvement resulting from slightly closer store locations is relatively small (1.7% increase), it can grow, when less stores are involved and bigger market areas are being served.

Figure 8. Existing build-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 136,500m2. Centre allocation: 1 town centre (30,000m^2), 7 neighborhood centres (9,000m^2 each), 29 precinct centres (1,500m^2

each). Total patronage in town: 38,243 households. Beta = 0.001; Search radius = 3000m; Alpha =0.37.

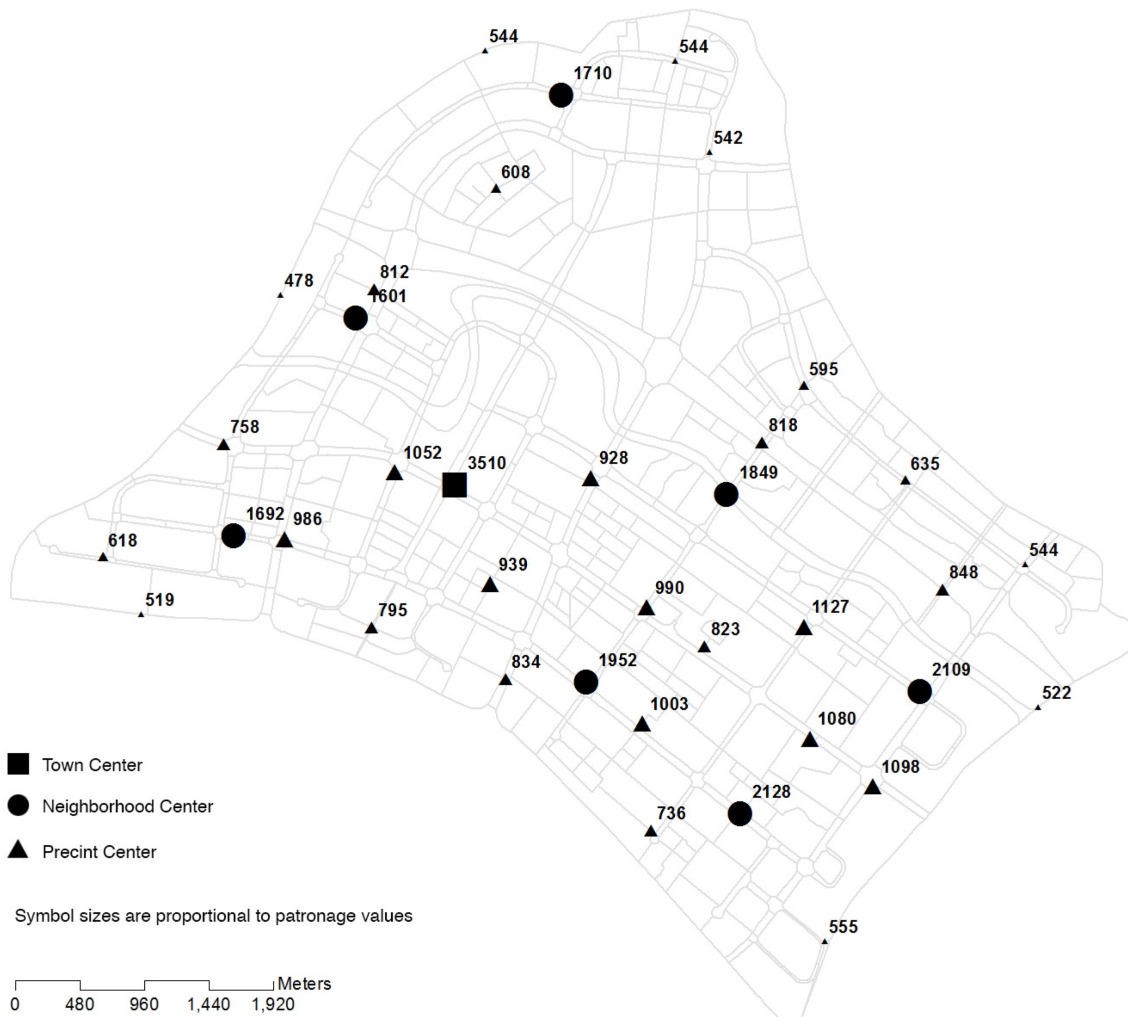

Figure 9. Patronage estimate for scenario two, where the same number and size of commercial centres is located deliberately closer to MRT walk routes. Total quantum of commercial space is 136,500m2. Estimated patronage across all clusters is 38,899 households. Beta = 0.001; Search radius = 3000m; Alpha =0.37.

Finally, another way to affect shopping patterns with a given set of locations is to vary destination sizes. In the example of Figure 9, we optimized retail destinations to be closer to MRT walking routes, but used a typical size allocation of HDB centres – 30,000m^2 NLA for a town centre, 9,000m^2 for neighborhood centres and 1,500m^2 for precinct centres. Could the overall patronage be increased with a different size allocation?

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 intervals – 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.[13] 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.

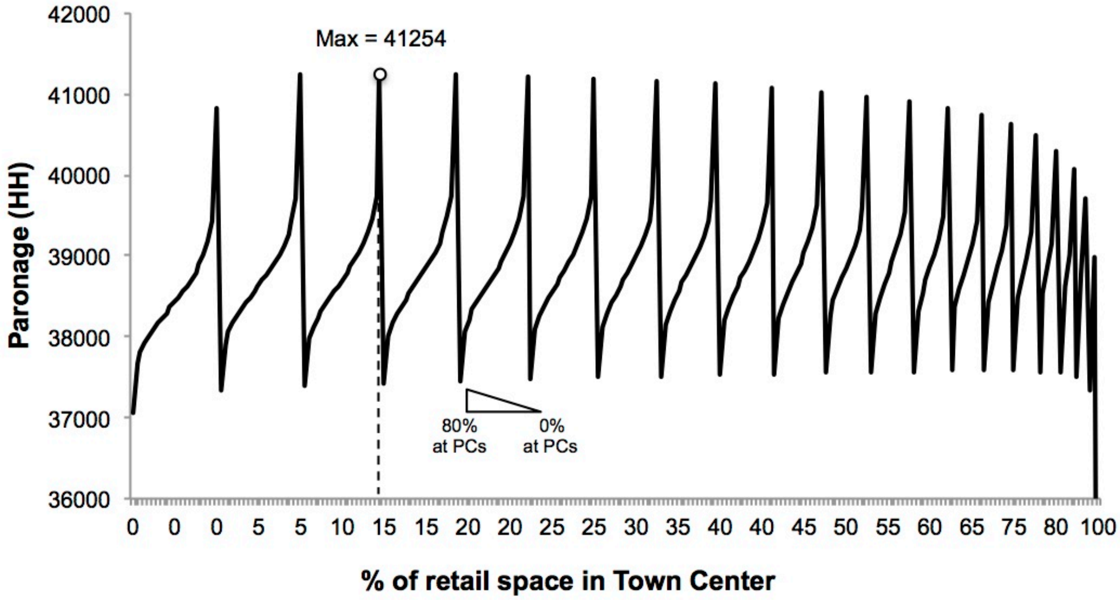

Figure 10. Patronage simulation results, where the total quantum of 136,500m2 was iteratively allocated to town, neighborhood and precinct types using allocation 5% steps. Maximum patronage is 41,254 households. Beta = 0.001; Search radius = 3000m; Alpha =0.37.

Figure 10 illustrates simulation results, where the total quantum of 136,500m^2 of NLA was iterative allocated at 5% intervals to different centre types.[14] 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 at 136,500m^2 in each iteration, but areas are allocated differently 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 size 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. 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-size neighborhood centers and lots of small precinct centers.

But 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 75,500m^2 NLA town centre (55% of total) and seven 8,775m^2 NLA neighborhood centres, patronage reaches 40,896 households. No one centre 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 9,000-18,000m^2 NLA.

These particular town and neighborhood centre size combinations would maximize retail access with Punggol's town layout, but a different combination may work in other towns, depending on their layouts and customer densities. However, the most important determinants of the optimal size configuration are the alpha and beta values, which are based survey data that was combined from nine HDB towns throughout Singapore.

Overall, optimizing the sizes of retail cluster 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 both the location optimization that placed centers closer to MRT walking routes and the size optimization together, then 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 feasibility and 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 $500m^2$ to $3,000m^2$, accommodating 5-10 shops each. Our model suggests that a proliferation of precinct centers in Punggol does not benefit overall retail patronage as well as larger neighborhood centres would. Precinct shops receive rent subsidies from the government and are meant to please residents with convenience. But since the patronage of stores depends on both the proximity and size of a center, a fewer set of larger clusters 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 the simulations, largest estimated patronage was achieved when the bulk of a town's retail space was placed in medium-size (9,000 – 18,000m^2) neighborhood centres. Combining both location and size optimization for planned centers, a 10% improvement in estimated patronage was achieved over the existing baseline scenario.

This result can not 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. Further experimentation is also needed to understand the robustness of the alpha and beta coefficients we found as well as the sensitivity of the model outcomes with different coefficient values.

We have focused our attention on optimizing retail destination locations and sizes. But similar gains could be made by manipulating demand locations and access routes – housing layouts, residential and employment densities as well as transit locations. In planning new residential towns, it would make sense to coordinate the site plans of residential and commercial areas, 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 could impact patronage at the named, as well as competing clusters around it. This could inform policy makers on deciding where zoning alterations and policy incentives are best placed.

Among the shortcomings of the above analyses is the fact that we used a simplified proxy variable – destination NLA – as the only characteristic of destination attractiveness. 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.

A similar 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 an analogous patronage model, where the overall layout aims to maximize the accessibility and patronage of such spaces in a district. The placement of electric car chargers and shared bicycle stations face similar issues.

There are multiple other software tools available for computing Huff models. The model presented here is aimed for 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 environment. 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 store patronage. The simulation engine allows store sizes to be optimized through a high number of automated trials, which would be too labor intensive to undertake manually. Jointly, these features are meant to make computerized facility patronage estimation accessible to a wider audience of spatial planners and urban designers.

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[1] http://www.esri.com/software/businessanalyst (accessed Sept 10, 2016).

[2] https://www.arcgis.com/home/item.html?id=f4769668fc3f486a992955ce55caca18 (accessed August 25, 2016).

[3] 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 what are pedestrian only, with no crossings slowing pedestrians down.

[4] 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.

[5] Assuming that the 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] The Survey of Residents' Shopping Experience in HDB Towns (n=1,088) 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.

[8] 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.
[9] Source: Singapore Land Transport Authority's HITS travel survey, 2012.

[10] The survey was carried out as part of a class experiment with students at the Singapore University of Technology and Design, where respondents at 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).

[11] 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 statin was available within a 800m 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.

[12] 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 7 additional Neighborhood centre locations were optimized. In the final step, both he 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 400m from a PC. This resulted in 29 PCs.

[13] With a step size of "1" percent, this required 5,151 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

[14] A 1% allocation produces a similar result, but the visual graph includes a 100 instead of 20 humps, which visually harder to read.