Retailers Location Choice Based on the Shopping and Land Prices

Balac Milos
Ciari Francesco

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Abstract

For the success of a retailer, stores location is considered as one of the most important factors. In the evaluation of a location, contextual to the opening or the relocation of a shop, different aspects should be considered like accessibility, land price, applicable prices in the area, competition, etc. The work reported in this paper extends a previous effort which integrated an agent-based module of retailers’ location decision into the multi-agent transport simulation (MATSim). The module tries to find a constellation of stores which increases the number of customers and turnover for the retailer, based on the different shopping and land prices in the simulated area. The functionality of the module has been demonstrated on the “Greater-Zurich” scenario, where real grocery retail stores of the area are modeled. The results obtained show a significant increase in both number of customers and turnover. Finally, possible limitations and necessary improvements of the developed module are presented.

Keywords

Keywords, in English, language
1 Introduction

In retail science it is commonly accepted that the geographical location of a store is one of the most important factors of its success (Zentes et al. (2007)). Not surprisingly, a vast literature spanning over several decades, deals with store location methodologies (Hernandez and Bennison (2000); Wood and Browne (2007); Rogers (2007); Hotelling (1929); Craig et al. (1984); Brown et al. (1992)). Such methodologies are aimed to maximize aggregate returns by planning and adjusting a portfolio of stores. They range from extremely simple and not very scientific – sometimes simply based on intuition and experience – to complex, computer assisted approaches. Even the more advanced of these methodologies, however, tend to ignore the complex interactions between the different actors of the system, the customers and the businesses. A possible answer can be found in a different vein of the scientific literature, the one of land use and transport planning. Several tools combining land use modelling with traffic simulations have been developed over the years (Putnam (1983); De La Barra et al. (1984); Heppenstall et al. (2006); Schenk et al. (2007); van Leeuwen et al. (2007)). Some of these works specifically focus on retail markets (Heppenstall et al. (2006); Schenk et al. (2007); van Leeuwen et al. (2007)) but they tend to have rich descriptions of the travellers, but the other actors in the urban system are normally abstracted into market clearing mechanisms. In this sense they are not achieving the goal of a detailed representation of the interplay among customers and businesses. The only exception is probably the work of Arentze and Timmermans (2007) where an agent-based approach is used to describe in a fairly detailed way the behaviour of both retailers and customers. In fact this type of approach - agent-based modelling - is particularly suitable for the description of complex systems and other scientists have already observed that they could find a natural application in marketing science (Rand and Rust (2011)). The work reported in this paper presents ongoing work on optimal retail stores locations and is also an example of agent-based modelling applied to retail markets. It builds on a previous effort (Ciari and Axhausen (2012)) where a retailer location choice module was developed as part of an existing Multi Agent Transport Simulation (MATSim, Balmer et al. (2009)). The main improvement over the already existing version is accounting for additional dimensions in the search for optimal locations. Previously, optimal locations were chosen based on the number of potential customers, which was determined using catchment areas for the candidate store locations. The key feature of the module was its ability to evaluate how convenient a location might have been considering travel time to candidate locations for potential customers.

The work presented here adds another important aspect: how the location choice of the retailers depends on the areas where the candidate locations lie. It is assumed that in different areas (central, urban, suburban) a) land price is different and b) different price levels might be applied for the goods sold in the stores. While the only goal of the previous work was to generate an
increase of the number of customers, the current work investigates if the relocation will produce
profit for retailers in the long run, looking at the trade-offs between various factors - relocation
costs, land prices, applicable prices, etc. This is a substantial advance because it captures a
part of the complexity of retailers’ choice which was previously ignored, making the whole
representation much more realistic. The ”Greater-Zurich” scenario is used as a test case. This
includes the current locations of actual retailers operating in Switzerland. The remainder of the
paper is organized in three chapters. Section two provides a description of MATSim and the
implementation of the retail agent. Section three discusses the results obtained using a large
scale scenario representing the metropolitan area of Zurich, Switzerland, showing the behaviour
of customers with different price levels at different locations. In another set of experiments it
was looked at the behaviour of retailers assuming that land prices were different at different
locations. The final section presents the limitations of the current approach and addresses the
future work.

2 Modeling Framework

This section introduces the modeling framework used in this work and describes each of its parts
in detail.

2.1 MATSim

MATSim is a fast, dynamic, agent-based and activity-based transport simulation. It is able to
simulate a synthetic population in a virtual world. The synthetic population is based on the
census data, while the virtual world represents the road network, available transport modes, land
use data, possible activities and their locations. The population consists of agents, each with a
daily plan (an agent can have multiple plans, from which one is chosen for execution). Each
plan consists of all daily activities an agent performs and also with which transport service it
reaches those activities. Each plan starts and ends with a home activity. Every agent tries to
optimize his daily plan based on a predefined utility function. As a general rule, performing
activities increases the utility while traveling decreases it. Traffic simulation is an iterative
process, through which each agent tries to find the optimum daily plan. Before the start of each
iteration, a fixed number of agents are allowed to change some part of their plan (their modes
of travel, location of shopping or leisure activities, departure times and routes) in order to try
to increase their utility. The simulation terminates when cumulative score (which is based on
the utility function) of all the agents is not significantly increasing. The final set of plans is an
approximation of what real individuals would do in the real world.
2.2 Retailer Agents

In a previous effort, the location behavior of retailers was introduced into the MATSim framework and a retailer agent was defined. Here is given only a brief description of this agent type. Further information can be found in (Ciari and Axhausen (2012)).

In the MATSim framework, agents perform their activities at facilities. The retailer agent is represented as an entity having control over a certain number of stores (facilities). Each store in turn has its location and opening times. Moreover, the retailer agent has knowledge of the number of customers visiting his store at each iteration of the simulation, of the location of the competitors’ stores, price level and land prices. An additional fact, which is known by the retailer agents and used in the relocation process, is the location of primary activities of all individual agents in the scenario. That is, their home, work and education locations. Moreover, only land suitable for commercial use is allowed as a potential location for a new store. The main objective of a retailer agent is to maximize number of customers or profit.

The technique used by retailers is the market support analysis (Birkin et al. (2002); Rogers (2007)). Despite its simplicity, it is a technique which is still used by practitioners nowadays. With this technique a caption area of every store is estimated along with the population in it. Competitors of each store are also taken into account in the model. Using this information along with the shopping and land prices potential locations are evaluated and the best are chosen.

2.3 The Retail Relocation Module

The retailer relocation module is implemented as a part of the MATSim framework. It tries to find the optimum number of customers/profit for a certain retailer agent. However, it is not part of the main MATSim loop in which demand is optimized, but it uses this demand to modify the supply side. Having this information, the module tries to find a better location for the stores. After the relocation, a new scenario is produced which is then simulated again with MATSim to obtain the final simulation results. The figure representing this process is shown in Figure 1.
2.4 Store Relocation

The relocation of just a few stores, picking up from a predetermined set of possible locations, can be evaluated with MATSim without the retailer relocation module, and the outcome of this move can be precisely estimated. However, if the retailer wants to find a better location for several stores within the possible predetermined locations, because of the large number of combinations, this simple approach is not suitable. Therefore, genetic algorithm – a particular type of evolutionary algorithm - was used in the module to find the best possible locations for stores based on the available information. The possible locations for stores are fixed before the simulation and the relocation of stores is controlled by a genetic algorithm (GA). GA tries to find the constellation of stores, based on the prices and accessibility, which maximizes the number of customers/profit.

The genetic algorithm will operate like this:

1. Find new locations for the stores using current stores locations and additional possible locations.
2. Evaluate the number of customers with the current locations of stores based on the fitness function.
3. Exit if the exit criterion is met (reached maximum computation time, global optimum reached, predefined number of generations reached etc.), go to 1 otherwise.

Genetic algorithms are stochastic algorithms that need test runs in order to get a feeling for the
algorithm and also experience to be able to set the parameters in the algorithm to the right values. In step 1 of the GA each genome of the initial population is created by mutating 5 times the initial solution (with original locations of stores) until the whole first generation is created. In each subsequent generation the number of elites that were kept from the previous generation was 30% (which was used based on the test runs) and number of mutants was 5%. The remaining 65% of the new generation is produced through crossover of the current generation. The crossover type used is Partially Matched Crossover (PMX) (Goldberg and Lingle (1985)) which produces two children from two parents. The population size used was 50, as suggested by Sastry et al. (2005). In addition to the already existing locations of stores additional links were chosen for placing the stores to create the set of available links for the GA. The criterion that additional links needed to satisfy was that the number of people living in 1.5km radius around the location should be larger than 600*number of shops already existing in that radius. The objective function used to evaluate the fitness of each constellation, computes the number of primary activities $c_i$ around each location $i$ within its catchment area and it is divided by the number of stores $k_j$ around it multiplied by a constant $\beta$ (Eq. (1)), having in mind that the stores with lower prices are stronger in attracting the customers which will be presented in the next chapter.

$$\max \left( \sum_{i}^{n} \frac{c_i}{\sum_{j}^{m} k_j \beta_j} \right)$$  \hspace{1cm} (1)

Here two different scenarios are investigated. One where the shopping prices are the same for every location, but the land prices differ, and another where the land prices are kept constant, but the shopping prices differ in the simulation area. In both cases the retailer’s module tries to maximize the number of customers and the profit for the retailer.

### 3 Test Scenario

The scenario used in this work is a ”Greater-Zurich” scenario. It is a subset of the Swiss scenario and it contains an area inside the circle with radius of 30km and with the center at ”Bellevue” square in the center of Zurich. The scenario is based on the year 2000 population census, the year 2000 workplaces and the national travel survey for the year 2005. The road network model has more than 236,000 directed links and more than 73,000 nodes. Population of this area is around 1,600,000. In order to reduce computation time we simulate 10% of the whole population (around 160,000). The network capacity is also scaled down to 10% (because of the scaling of the population) in order to have realistic traffic flows.

In the scenario, two retailers, with 28 and 18 stores, sequentially try to find the best locations for their respective stores. The initial locations of these shops are taken from real store locations of
two real Swiss retailers, leaders in the grocery market. The possible locations for relocation are chosen based on the population density around the location and number of stores around the link. In addition to these new locations, the current locations of stores are also included in the possible locations for placing the stores in the relocation process.

As we mentioned previously, MATSim allows five different types of activities, with shopping being one of them. In our scenario we assumed two different types of shopping, grocery and non-grocery shopping. Moreover, it is assumed that all retailer stores are grocery stores. Additional stores that allow grocery shopping were chosen randomly, so that about 30% of the total shopping capacity is made up of grocery shopping. This scaling down of number of shops was needed because as mentioned before, in the experiments 10% scenario was used, so the number of shops needed to be scaled down as well.

### 3.1 Shopping Scenarios and Results

In the existing scenario there is no differentiation between shopping at different stores regarding the shopping prices. However, to see the impact of prices on the behavior of people we created a circle of 5km radius centered at Bellevue square and we assume that expenditure for buying the same amount of groceries in the circle is larger by a certain amount than on the outside. This can be seen as having higher prices in the city center and lower in the outskirts, as some of the cities in Europe have. The results were obtained for 3 levels of expenditure difference. In Scenario I agents pay the same amount at every store for the same items. In Scenario II, the expenditure inside of the circle is increased by \( \frac{1}{4} \) hour working value, which is about 15CHF in Switzerland. Finally, for Scenario III the expenditure inside of the circle is increased by 1 hour working value, which is about 30CHF in Switzerland. The traffic simulation was run for 100 iterations before it reached equilibrium.

Table 1: Results for three shopping pricing policies.

<table>
<thead>
<tr>
<th>Results</th>
<th>Scenario I</th>
<th>Scenario II</th>
<th>Scenario III</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customers inside:</td>
<td>4061</td>
<td>3174</td>
<td>2354</td>
</tr>
<tr>
<td>Customers outside:</td>
<td>11728</td>
<td>12615</td>
<td>13435</td>
</tr>
<tr>
<td>Avg. distance travelled inside [m]:</td>
<td>3748</td>
<td>3093</td>
<td>2751</td>
</tr>
<tr>
<td>Avg. distance travelled outside [m]:</td>
<td>4791</td>
<td>4876</td>
<td>5042</td>
</tr>
</tbody>
</table>

From Table 1 it can be seen that as the expenditure in the circle increase, the number of agents...
making their purchase there is decreasing, as expected. Moreover, average distance travelled to the stores with higher expenditure is decreasing as this expenditure is increasing. This shows that people who were, before the increase of prices, shopping at these stores and travelled larger than average distances, decided to go to lower price stores.

These average distances travelled were then used to define the catchment areas of stores inside and outside of the "city-center". With the catchment areas defined as the average distance travelled to stores retailer’s module was ran for both scenario I and III and with the relocated stores another 100 iterations of traffic simulation were to observe the final results. Location of stores before and after relocation can be seen in Figures 2, 3 and 4.

Figure 2: Initial locations of retailer stores for both retailer agents (blue) and all other grocery stores (yellow).
Figure 3: Locations of stores after the relocation for both retailer agents in the scenario I.

Figure 4: Locations of stores after the relocation for both retailer agents in the scenario III

From these figures it can be clearly see that the module disperse the stores in both scenarios
in order to reduce the cannibalism among the stores and to avoid with the high competition in the city-center. Moreover, it can be seen from Figure 4 that there are two times less stores within the high price area compared to the Figure 3 where shopping expenditure was the same for the whole simulation area. This is expected as the purpose was to maximize the number of customers, and this is achieved by having more stores with lower prices. Results after running the traffic simulation after the relocation can be seen in Table 2.

Table 2: Results obtained for scenarios I and III before and after applying retailer’s module.

<table>
<thead>
<tr>
<th>Results</th>
<th>Scenario I Before Move</th>
<th>Scenario I After Move</th>
<th>Scenario III Before Move</th>
<th>Scenario III After Move</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of stores:</td>
<td>46</td>
<td>46</td>
<td>46</td>
<td>46</td>
</tr>
<tr>
<td>Stores moved:</td>
<td>-</td>
<td>42</td>
<td>-</td>
<td>44</td>
</tr>
<tr>
<td>Customers:</td>
<td>2900</td>
<td>4241</td>
<td>3220</td>
<td>5007</td>
</tr>
<tr>
<td>Inside stores:</td>
<td>18</td>
<td>5</td>
<td>18</td>
<td>2</td>
</tr>
<tr>
<td>Outside stores:</td>
<td>28</td>
<td>41</td>
<td>28</td>
<td>44</td>
</tr>
<tr>
<td>Inside customers:</td>
<td>1203</td>
<td>589</td>
<td>566</td>
<td>139</td>
</tr>
<tr>
<td>Outside customers:</td>
<td>1697</td>
<td>3652</td>
<td>2654</td>
<td>4868</td>
</tr>
<tr>
<td>Customers increase[%]:</td>
<td>-</td>
<td>46.2</td>
<td>-</td>
<td>55.5</td>
</tr>
<tr>
<td>Turnover[CHF]:</td>
<td>44,660</td>
<td>65,311</td>
<td>66,568</td>
<td>81,447</td>
</tr>
<tr>
<td>Turnover increase[CHF]:</td>
<td>-</td>
<td>46.2</td>
<td>-</td>
<td>36.4</td>
</tr>
</tbody>
</table>

The results show that in both scenarios increase of customers is substantial, over 46% for scenario I and 55.5% for scenario III. It is noticeable that in the Scenario III there is larger number of customers in both pre and after the move of stores compared to scenario I. This can be explained by the fact that original stores probably already have a very good locations and that the increase of pricing in the inner circle brings more customers to these stores. Moreover, by reducing the number of stores in the III scenario inside the high-price circuit the retailers are able to get more customers at the low-price locations. When the turnover of the retailer is considered couple of things must be stated:

1. Every customer spends the same amount of money in every store on the outside of the circle, while on the inside it spends 30CHF more for the average shopping visit.
2. Having in mind that the average expenditure in Switzerland on groceries is about 287CHF per month per person (BfS (2014)), and if we take into account that the number of grocery shopping activities per day per person is around 0.62 (BfS (2014)) we get a daily average expenditure of about 15.4CHF (which is an underestimate since not all persons in the
household perform shopping activities).

3. Finally if Scenario III is taken as an example, turnover increase is calculated as follows:

\[
\text{turnover increase} = 139 \times (15.4 + 30) + 4868 \times 15.4 - 566 \times (15.4 + 30) - 2654 \times 15.4
\]

CHF turnover increase = 14,879 CHF

The average turnover increase for Scenario I is 46.2% and 22.35% for Scenario III. Having in mind the underestimate of the average expenditure per person per day, it is clear that the turnover is even larger.

### 3.2 Land Price Scenario and Results

To investigate the impact of land prices on the relocation of retailer stores we created an artificial scenario where the highest land prices are at the city center, at Bellevue, and they are linearly decreasing with the distance from Bellevue, with the lowest land price being 70% of the highest price. Here we try to maximize the profit of the retailer based on the number of customers and land prices. For the sake of simplicity it is assumed that the retailer had profit of 0 before the relocation of stores and that every person spends the same amount of money in stores (for instance the average expenditure across the whole population). Objective function that represents the fitness of the solution and that GA is trying to maximize can be represented with Eq. (2):

\[
\max \left( \sum_{i} \frac{c_i}{l_i} \right)
\]

where \( n \) is the number of stores, \( c \) is the number of potential customers for a given store and \( l \) is the land price for the store at a given location. Results before and after the relocation of stores can be seen in Table 3.

Table 3: Results obtained for different land prices.

<table>
<thead>
<tr>
<th></th>
<th>Without Relocation</th>
<th>With Relocation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customers:</td>
<td>2900</td>
<td>4094</td>
</tr>
<tr>
<td>Land Price:</td>
<td>( \mu )</td>
<td>0.93( \mu )</td>
</tr>
<tr>
<td>Stores moved:</td>
<td>-</td>
<td>42</td>
</tr>
<tr>
<td>Income:</td>
<td>( \mu )</td>
<td>1.41( \mu )</td>
</tr>
<tr>
<td>Profit:</td>
<td>0</td>
<td>0.48( \mu )</td>
</tr>
</tbody>
</table>

It can be seen that the relocation of stores significantly increases the number of customers while
it also reduces the land price for stores. This in turn produces a major improvement of the retailer’s profit which was the goal of the optimization process. The new store locations can be seen in Figure 5. It can be observed that stores have moved away from the high priced city-center which was expected since they try to avoid high land price areas and large competition that exists there (the yellow stores reported in Figure 2).

Figure 5: Location of stores after the relocation, with land prices.
4 Conclusion and Future Work

The results presented in the previous chapter are consistent with the expectations. Retailers succeeded in finding better locations in the metro area of Zurich for their stores, in order to increase their profit and number of customers, based on the shopping and land prices that are assumed implemented in the scenario. These locations differ based on the constraints that are used (different shopping or land prices) which was expected since they force the retailer to look at different aspects of income and expenditure.

The work in this paper provides a significant addition to the previous effort. The retailers’ relocation module now is able to use shopping and land prices while searching for better store locations. Even though it is done on a basic level, it still shows what usually can be seen in large cities across Europe, where in peripheral areas grocery stores apply lower prices and land price is also lower.

The results obtained show that this module can be an important and powerful instrument for policy makers and location planners. For location planners it is very important to have a tool that gives better if not optimal locations for retailer’s stores. Building on the previous effort, the quality, speed and convergence time of the genetic algorithm, that is the core of the relocation module, is significantly increased. With these improvements the module is able to find much better location for stores, further increasing number of customers and profit for the retailer. In the future work, special attention is going to be paid in integrating real data on shopping and land prices into MATSim, and also on agents shopping expenditures to be able to more realistically represent the location choice of retailers. For policy makers it is very important to have a tool which is able to predict the outcomes of a certain policy. For example with this instrument it could be tested how land regulation could affect retailers’ choices and, in the end, how this would affect the transportation system. An important aspect which is still lacking in the model is the bidding competition among the retailers for the available locations. Additionally, the scenario validation was done only based on traffic counts data. To have more realistic scenarios, however, it would be important to base the validation on the number of agents shopping at each location too, which can be easily done as soon as the relevant data is available. Finally, explicitly including other parties of the supply side - i.e. planners, legislators, etc. - would make the model much more complete.
5 References


