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Simulating spatial market share patterns for impacts analysis of large-scale shopping centre on downtown revitalization

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Abstract

The decline of downtown has been observed in many cities across the world. In response, many small cities in Japan, for example, have been taking regeneration efforts including development controls upon large-scale shopping centres (B-shops). It is extremely useful to analyze potential effects of relevant planning policies before implementation. We developed an urban planning support tool, a multi-agent simulation (MAS) model called Shopsim-MAS, to investigate the impacts of some downtown revitalization policies through consequent spatial dynamics of shops' market shares. We discuss methods to model household behaviour and to understand the market area dynamics of shops. The Shopsim-MAS developed in this project proves to be a useful means to analyze the impact of downtown revitalization policies in Japan. It is also expected to be further expanded for impact analysis of similar or more sophisticated urban policies in other parts of the world.

Keywords: Downtown decline, urban planning, geographic simulation; household, shop-choice, transportation mode.

1 Introduction

Many cities worldwide are experiencing decline of their traditional central business districts (CBD). In Japan, for example, the decline of downtowns has been such a problem that many local governments have developed all kinds of city center generation policies to restrain this trend and to revitalize CBD's commercial environments. To strengthen the commercial competitiveness of city's central area (CA, hereafter used interchangeably with downtown), local authorities have been making a series of planning policies. For example, through policy instruments, large scale shopping centers (hereafter B-shops) are encouraged to locate at CA rather than urban fringe or suburbs; park-and-ride facilities are planned to relieve congestion problem in CA. Nevertheless, it is difficult to tell in advance whether, and to what extent, these policies can effectively reach the planned goals. Indeed, it is difficult to evaluate the potential impact of current or planned policies on the future of a city due to the inherent complexity within components of the urban system and sophisticated interactions among them. Therefore, it is extremely useful to develop methodologies and tools that can shed lights on potential impact of planning policies in an urban system.

Prior studies have demonstrated that multi-agent simulation (MAS) models are powerful in exploring the innate complexity of urban systems. The MAS technique can provide detailed, decentralized, and dynamic views of an urban system and can serve as a virtual laboratory for urban planning policies analysis (e.g. , Kii and Doi, 2005; Chabrol, et al, 2006). MAS modelling is a popular means for representing autonomous, heterogeneous, and disaggregated decision-making processes such as urban residential dynamics (Li and Liu 2008; Loibl, Toetzer, 2003; Benenson 1998). Recently, a few studies are seen to use MAS to analyze the phenomena of downtown decline. For instance, Yosuke Ando et al (2005) studied city centre vacancy by simulating the emergence and agglomeration of vacant buildings and the effect of empty space on commercial space using agent based model.

This paper presents a methodology and a simulation modelling tool named Shopsim-MAS to study potential impact of city center revitalization policies. In this paper, the policies specifically refer to development regulations concerning the locations of B-shops and relevant transportation policies in a city. These regulations have generated much research interests because shifting shop locations from downtown to outskirts has been postulated one of the major reasons for the decline of downtown in many Japanese cities.

In agent-based modeling of urban systems, inhabitant agents (such as households, residents, customers, etc.) of the simulated city are fundamental components of the system. Prior studies emphasized heterogeneity of consumers to be consistent with reality (Suarez et al, 2004). However, most of previous studies only consider heterogeneous distribution of social-economic characteristics in households but simply assume uniform or random spatial distribution of these agents. Such assumptions have major drawbacks for several reasons. First, it neglects the fact that the spatial distribution of households is heavily affected by urban planning regulations such as zoning constraints (Frew 1990). Secondly, it pays no attention to the interdependence of households' geographic location and their social-economic characteristics (e.g. Brueckner, Thisse, and Zenou, 1999). Thirdly, such assumptions limit the usefulness of these simulation models for investigating the urban dynamics through individual-level interactions. To overcome these limitations, our study allocates household agents with consideration of land use zoning constrains and household location patterns by income level. More importantly, our model considers interactions among agents. Another special concern in this study is the impact of transportation policy, which is an important integrative component of CA regeneration policies.

The remainder of the article is organized as follows. The next section presents the design of our methodology and discusses how our MAS-based approach fits into, and extends from, the existing body of knowledge. Section 3 validates the model and conducts sensitivity analysis of policy parameters and model parameters. Section 4 analyzes the impact of interactions among agents. Section 5 tests the validated model with real city data. The article concludes with a summary of findings and discussions of future research avenues in Section 6.

2 The Design of Shopsim-MAS

2.1 Initial simulation conditions

Planning information and regulation

Some previous urban simulation studies, such as CityDev (Semboloni et al. 2004), model planners and developers as agents in order to investigate the dynamics of planners and developers in response to changes. Because the focus of this study is on the spatial choice behavior of urban residents in response to specific urban planning decisions, it is necessary to keep the planning information intact during the simulation. Therefore urban planning information is set as initial and static conditions of simulation in Shopsim-MAS. The urban spaces are represented as grid cells, each of which is assigned a land use zoning type. Table 1 lists the twelve standard land use zoning types and associated characteristics (or constraints) specific to each type. HUR stands for housing-use ratio and its values are designed based on the study of Kidani and Kawakami (1996). The variable Max HUR is the respective maximum values defined by the local government. The variable HFAR defines the maximum number of households in the area of a cell, or the household-capacity of a cell. The maximum floor area ratio (Max. FAR) of the zoning type is the planning value decided by the local government. To be consistent with the spatial distribution of population density in real Japanese cities, we assume that the values of HUR and HFAR in CA cells are higher than those in other UPA cells, as shown in Table-1. Because UCA has mixed-use areas of agricultural and urban land use, the HUR values in UCA cells are set as 50% and the HFAR is either 1 or 0 with equal probability based on the study of Kidani and Kawakami (1996).

Table-1. The zoning constrains for the UPA

Code	Land use zoning	Max.HUR (%)	Max. FAR (%)	CA HUR (%)	CA HFAR (%)	OutsideCA HUR (%)	OutsideCA HFAR (%)
H1	1st low-rise exclusive residential district	100	200	100	2	80	1
	2nd low-rise exclusive residential district	80	200	100	2	80	1
H2	1st mid-high-rise exclusive residential district	100	300	100	3	80	2
	2nd mid-high-rise exclusive residential district	80	300	100	3	80	2
H	1st residential district	70	400	90	4	70	2
	2nd residential district	70	400	90	4	70	2
	Quasi-residential district	60	400	80	4	60	2
C1	Neighborhood commercial district	60	400	70	4	50	2
C2	Commercial district	60	1000	50	10	30	5
I1	Quasi-industrial district	50	400	70	4	50	2
I2	Industrial district	15	400	30	4	15	2
I3	Exclusive industrial district	0	400	0	0	0	0

2.2 Agents in Shopsim-MAS

Shop Agents

There are two types of shop agents in the system: B-shop agents and S-shop agents. S-shops refer to downown shopping areas occupied by small and medium-sized shops, while B-shops refer to large scale shopping centers. Hereafter the simpler term *shop* is used to refer to either a shopping center (B-shop) or a downtown shopping area (S-shop).

Many Japanese city authorities believe that locating B-shops in the outskirt of a city has drawn away many downtown shoppers and consequently has contributed to the decline of downtowns' commercial environment. This study aims to investigate the impact of B-shops on market shares, particularly in different transportation policy scenarios. Users of Shopsim-MAS can interactively set up a new B-shop at different locations to later observe emerging effects of each. Some S-shops are set up randomly in the commercial areas in the initialization stage but no new S-shop will be created in the middle of a simulation process. In addition, S-shops are assumed to have homogeneous attributes, i.e. they have similar floor spaces, goods, and prices. B-shops, however, are free of this assumption.

In a real city, every new shop faces competition from existing shops. Assuming the only way to keep customers is by providing competitive pricing for any product of equal quality, shop managers will try to offer competitive prices allowed by distance (transportation) advantages or shop size advantages due to economies of scale. Our modeling strategy of price considers competitive impacts of both shop size and location, as expressed in Equation (1).

$$P_n = Ke^{-b*dn} + R_{nd}\, f\,(S_n - S_e) \qquad (1)$$

where P_n is the price of goods in the new B-shop; parameter K is a constant, equal to the price of goods in downtown S-shops; parameter b is the price decline index, which is given as 0.01; variable d_n is the distance of the new B-shop from the city center; R_{nd} is a random number with mean of 1 and standard deviation of 0.5 generated by the computer following the normal distribution, which embodies the uncertain nature of influence from shop sizes. The other factor is the size difference between the new B-shop (surrogated by floor space S_n) and existing S-shops (surrogated by the average floor space, S_e, of existing S-shops). The coefficient f is a conversion constant set to 1

Japanese EN/500m^2. This scaling constant represents the relations between shop floor area and goods' price.

Household agents

Household agents may have different socioeconomic characteristics in Shopsim-MAS. The system's interface allows a user to load urban space data, land use zoning data and population data in various income categories. The initialization process then randomly allocates household agents under the constraints of such planning and population information with consideration of income-location pattern of households.

2.3 Shop-choice model

In the past several decades, a large body of literature has accumulated in the area of modeling consumer choice behavior for retail planning. Often a mathematical model is constructed to predict the consumer choice as likely outcome of factors such as consumer characteristics, transportation-related attributes, and policy measures. The models can be generally classified into the family of spatial interaction models and the family of random utility models. In review of the evolution of spatial interaction and spatial choice models, Fotheringham and colleagues (2000) point out that the earlier spatial interactions models are constructed either as social physics (which is analogous to the gavity model in physics) or as statistical mechanics following Wilson's pioneer work (Wilson 1967;1975).

More recently, random utility models (RUM) have been developed in the theoretical framework of random utility theory for choice-making from a finite set of alternatives (discrete choices) by individual consumers (Domencich and McFadden 1975). Becuase RUM has been designed in the framework of disaggregate (individual) modelling (Ortúzar and Willumsen 2001), it is much more suitable for simulating behavior of individual agents. In the model, utility refers to the benefit or well-being that an individual obtains from choosing an alternative . The RUM is not only a popular form of economic model for consumer choice behavior, it also has its way in other related disciplines (Marley, 2002) such as marketing (e.g. Baltas et al. 2001, Benati and Hansen, 2002; Suárez et al., 2004) and transportation planning (e.g. Cascetta et al., 2002; Cascetta and Papola, 2001). In the case of consumer choice research, many research efforts have been made in theoretical developments and innovative applications of RUM. A noteworthy example is a collection of research work by Timmermans, Arentze and their colleagues. For instance, Arentze et al. (2005) extended the RUM approach for multipurpose shopping behaviors. Particularly relevant to this paper is their work of agent models with the use of RUM. These studies include those of activity-travel behaviour and trip flows (Veldhuisen, Timmermans, and Kapoen 2000), pedestrian movement, and dynamics of land use development (Arentze and Timmermans 2004).

The Shopsim-MAS adopts the RUM approach to modeling shop-choice behavior. Our study is different from the previous studies in two ways. First of all, because we want to investigate the effect of planning policies on market shares of B-shops and S-shops, our research does not focus on separated individual shopping activities but instead it concerns the households' general shopping choices that might be repeated regularly. Secondly, our model considers interactions among agents so that the shopping choices may change dynamically in the simulation process, which is consistent with the dynamics in the real world.To focus on the impact of B-shops, we make the following assumptioms to avoid possible influences of other factors.

(1) The distribution of goods in all shops are homogeneous, i.e. the household can buy the same goods at all the shops.

(2) Each household has a constant demand for goods. When the total demands of all household agents are satisfied, the simulation process will end.

(3) In each simulation iteration, a household wants to buy one unit of demand.

(4) A household only considers shops within a threshold travel distance γ.

2.3.1 Utility Function without consideration of interactions

Significant progress of RUM has been made to account for the heterogeneity among variables' influences. The random parameter logit (RPL) approach (Lijesen, 2006), the latent class logit (LCL) approach (Boxall and Adamowicz, 2002) and the mixed logit (ML) model (e.g. Frew 1990) are three appealing improved RUM methods and are proven to be able to forecast equally well (Provencher et al., 2004). The ML model allows the coefficients of observed variables to vary randomly for different people. Considering the heterogeneity of household agents in our study, we adopt the framework of the ML model to design the decision rules of household agents. However, as shown in Equation (2), we modify the model to make sure that while accounting for variations among individual preferences, the households in the same income group also show general similarity.

$$U_{ijg} = \sum_{n=1}^{n} \mu\beta_{ign} X_{ijn} + \varepsilon_{ijg}, \quad \varepsilon_{ijg} = a - b(ln(-\,ln(\theta)), \theta \in [-\theta_g, +\theta_g] \qquad (2)$$

Equation (2) defines the utility function of household *i* of income group *g* shopping at shop *j*. X_{ij} is a vector of observable explanatory variables describing attributes of household *i* and the shop *j*. These variables include travel cost which depends on travel mode, urban amenity variables, price of goods, floor spaces of shop j, and others. The subscript *n* refers to the dimension of the vector (number of variables). The symbol $\mu\beta_{ig}$ is a vector of respective coefficients to the variables. The coefficient vector has two components, as defined in Equation (2). One is β_{ig}, the vector of average coefficients for the g^{th} income group. The other is a vector of random values reflecting individual deviation within the group, μ, which is generated following normal distribution with mean of 1 and standard deviation of 0.5.

The element ε_{ijg} in Equation (2) represents unobserved random contribution to the utility, which is used to compensate for the inherent uncertainty of shopping behaviors. This random element follows Gumble distribution and can be generated using a random number θ_g following uniform distribution. The pre-defined range of θ_g represents the maximal magnitude of possible internal differences within the income group *g*. The parameters *a*, *b* in Equation (2) are set as 0.5 and 2 in this study. After obtaining the utility measures from household *i* to every shop alternative, the probability that *i* shopping at shop *j* can be calculated from Equation (3).

$$P_{ij} = exp(V_{ij}) \,/ \sum_{k=1}^{J} exp\ \ (V_{ik});\ \ j,k \in J \qquad (3)$$

where J is the collection of all shops.

2.3.2 Interactions among agents

Equation (3) expresses shopping choices at the individual level without consideration of interactive influences among agents. We model the combined effects of two types of interactive influences, the peer impact among neighboring household agents and information delivery from shop agents to household agents.

The peer impact concerns the influence from the shop choices of neighbors who are defined as those in the 9-cell neighborhood area around the cell where the household is located. The utility of a *t* type shop (say, S-shop) can be promoted by the peer impact from neighbours who go shopping at the same type of shops (any S-shop).

The information delivery type of interaction considers information of shops (such as prices, types of goods, shopping environment, etc) being delivered from the shop agents and spread among the households. The spread of such information may attract shoppers who were previously patrons of other shops. In this study, a surrogate variable of this conceptual construct is built upon the numbers of different types of shoppers in a search area around each target shop. The utility of a *t* type shop (say, S-shop) can be promoted by spreading information to households who are currently patrons of a different type of shop (e.g. any B-shop), thereby these households may be potentially attracted to the *t* type of shops.

Equation (4) models the additional component of utility (termed interaction utility) contributed by interactions among agents. The interaction utility of household *i* in income group *g* shopping at shop *j* is denoted as INT_{ijg}. It consists of the peer impact I_{ijg} , the information delivery D_{ijg}. In the equation, subscript *t* refers to the type of shop that *j* shop belongs to. In this study, there are obviously only two types of shops, namely the S type and the B type.

$$INT_{ijg} = I_{itg} + D_{itg}, \quad t \in \{S, B\}, \qquad j \text{ is type } t \text{ shop} \tag{4}$$

The peer influence I_{itg} and information delivery D_{itg} are measured in Equation (5):

$$\begin{aligned} I_{ijg} &= k_g (N_{itg} - N_{iog}) / N_{ig} \\ D_{ijg} &= d_g (N_{iogd} - N_{itgd}) / N_{igd} \end{aligned} \tag{5}$$

where N_{itg} is the number of i's neighbors who are in gth income group and shop at t type of shop, and N_{iog} is the number of those who shop at the other type of shop. N_{ig} is the total number of i' s neighbours in gth income group. The equation for information delivery has similar notations with the additional subscript d which is the distance between household i and shop j. A notation with subscript d means the respective number is counted within the search area of radius d around shop j. The parameter k_g is a scaling factor reflecting household agents' subjective reaction to such influences, which is a constant. In short, the impact of the number of any type of shops in a neighbourhood contributes to the interaction utility in two opposite ways through I and D respectively and thus makes the total interaction utility changing in a wave form.

After considering interactions among agents, the utility function defined in Equation (2) should be modified as Equation (6). At the beginning of simulation, utility values are initially calculated from Equation (2). Then interactions are believed to start acting and so Equation (6) is used in subsequent iterations of simulation.

$$U_{ijg} = \sum_{n=1}^{m} \mu\beta_{ign} X_{ijn} + \mu INT_{ijg} + \varepsilon_{ijg}, \quad \varepsilon_{ijg} = a - b(ln(-\,ln(\theta)), \theta \in [-\theta_g, +\theta_g] \tag{6}$$

2.4 Modelling transportation mode in the shop-choice model

Household agents may take different transportation modes to shopping. Actually the availability and cost of different transportation modes will strongly affect an agent's shop-choice decisions. For this reason, there is room for transportation policy instruments to leverage market shares of different shops. A traveler's choice of transportation mode and route can be influenced by many factors (Ortúzar and Willumsen 2001). An early empirical study found that the combination of time and distance alone can account for about 60% to 80% percent of the variations in route choices (Outram and Thompson 1978). In this study, we use generalized cost as defined in Equation (8) to incorporate time, distance, and monetary cost of a shopping trip. In the equation, $TMCost_m$ refers to the generalized cost for transportation mode m. The notation D is the travel distance, C_m is the unit monetary travel cost for mode m, s_m is the average speed associated with the travel mode, and T_m is parking fee. The notation h is a weight used as a scaling factor, which follows normal distribution with mean of 1 and standard deviation of 0.5. Equation (7) defines the utility function for travel mode choice. The random coefficient $\mu\beta_{igm}$ in Equation (7) is aimed to account for variations among household agents, in which μ is generated following normal distribution with mean of 1 and standard deviation of 0.5 and β_{igm} has different values based on the g^{th} income group and different travel mode m. There is also a random element γ_{img} to account for variations due to other unobserved factors. It follows Gumble distribution generated as independent and identically-distributed random element. In the equation,

$$U_m = V_m + \gamma_{igm} = \mu\beta_{igm}X_{ijm} + \gamma_{igm} \tag{7}$$

$$X_{ijm} = TMCost_m = DC_m + T_m + \frac{hD}{S_m} \tag{8}$$

$$P_m = exp(V_m) \,/ \sum_{m=1}^{M} exp\ (V_m); \tag{9}$$

A household agent makes shop choice based on the utilities of shopping at alternative shops and makes travel mode choice decision based on the utilities of generalized travel costs at alternative travel mode. The processes are illustrated in Figure-1. In the figure, the travel mode choice probabilities (P_1, P_2, P_3 and P_4) and the shopping probabilities

(P_b and P_s) are simulated by the mixed logit (ML) model (e.g. Frew 1990) based on utility values.

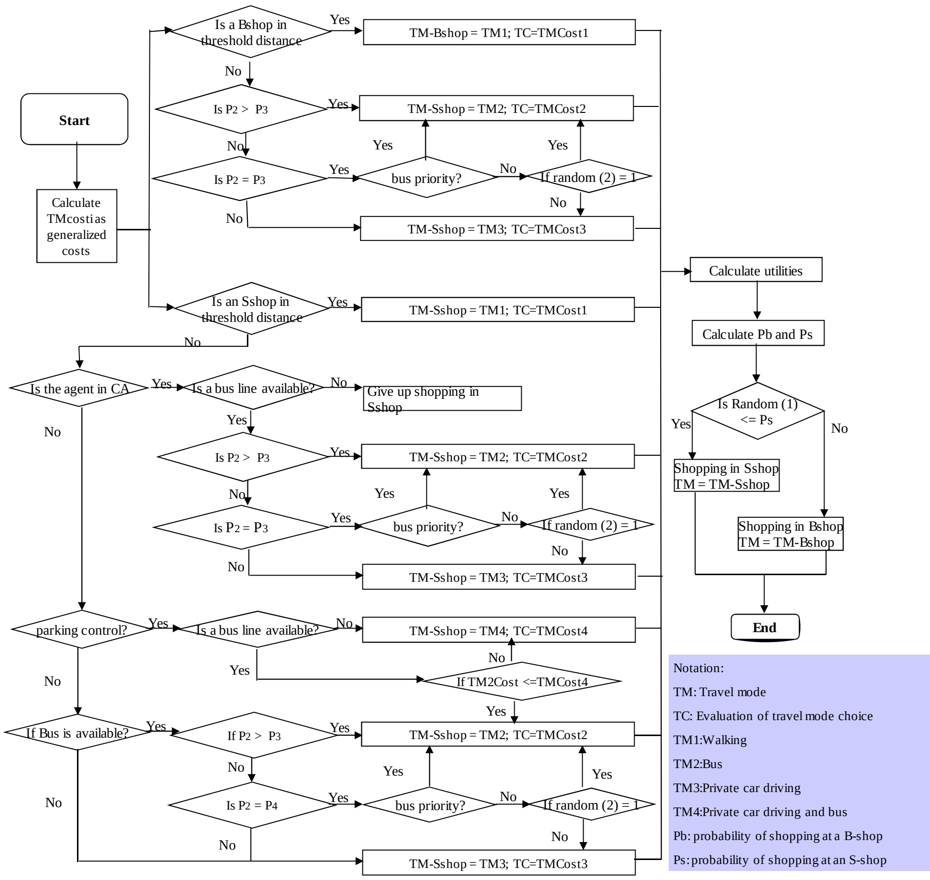


Figure-1. The process of a household agent making shop and travel-mode choices

3 Model Development, Validation, and Sensitivity Analysis

Figure 2 shows the interface of the Shopsim-MAS which was developed in Netlogo. In this section, we use a hypothetical mono centric city to evaluate the validity of the model and to analyze the sensitivity of policy parameters and model parameters. This hypothetical city has the characteristics of a typical Japanese city which has a traditional commercial centre located in the central area (CA) of the city. The entire city under the planning authority is divided into two concentric areas, an urbanization promoting area (UPA) and an urbanization control area (UCA). The UPA is the inner circle containing CA, while UCA is a donut area surrounding UPA. CA is the core area of UPA. Figure 3(1) displays a graphic illustration of this structure.

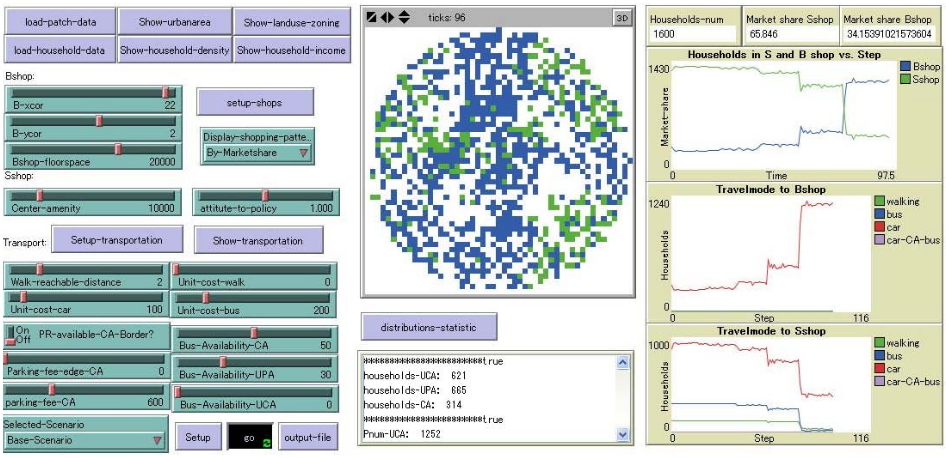
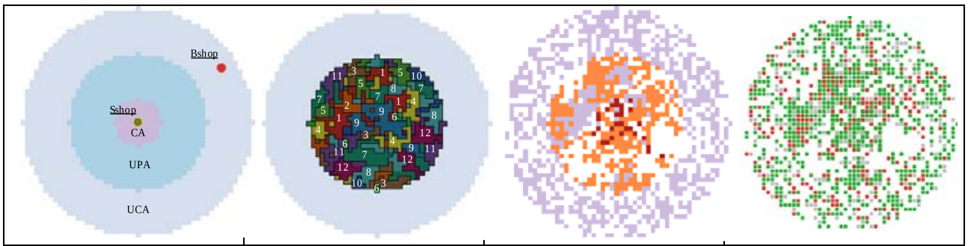


Figure-2. The simulation tools in the Shopsim-MAS

3.1 *Setting the Stage - Initialization*

There are 1600 household agents living in this virtual city. The household locations conform to land use zoning and residential suitability restrictions. Households are grouped into three income levels: Rich, Middle Class, and Poor. In the hypothetical city, we assume that percentages of population in the three income levels are 20%, 60%, and 20% respectively. We also assume that all households have cars. Figure-3 shows land use and household distributions in the virtual city. As noted in Table-2, parameters in the study of virtual city are configured according to prior studies of real Japanese cities.

There are seventeen existing S-shops in CA and one existing B-shop in the UCA. The floor space of the B-Shop is set as 20000 m^2 initially, which is in the range of the B-shop floor spaces stipulated in planning regulations. In National Survey of Price (www.stat.go.jp), the floor space of a small scale shop is under 450 m^2. Here, the S-shops in the city center are set to have a floor space of 300 m^2.



(1) Urban area	(2) Land zoning	(3) Household density	(4) Household income

Zoning type:

1---1st low-rise exclusive residential district
2----2nd low-rise exclusive residential district
3----1st mid-high-rise exclusive residential district
4----2nd mid-high-rise exclusive residential district
5----1st residential district
6----2nd residential district
7----Quasi-residential district
8----Neighborhood commercial district
9----Commercial district
10----Quasi-industrial district
11-----Industrial district
12------Exclusive industrial district

Household density:
Household-num >= 4
Household-num >= 2
Household-num = 1
Household-num = 0

Income level:
Rich
Middle
Poor

Figure-3. Spatial structures in the hypothetical city

Table -2. The parameters utilized in shopping model

Shop utility		Average of group βing			x_{ijn}	
		Low	Mid	High	In B-shop	In S-shop
Shops	Goods price	0.146000	0.0730000	0.014600	JP200	JP 300
	Floor space	0.002446	0.0122300	0.012230	20000	300
	Urban amenity	0.005738	0.0286900	0.028690	0	10000
Travel modes	Parking fee				0	600
	Bus cost	-0.038443	-0.0192217	-0.003844	JP200	JP200
	Car cost				100	100
	Walkable Distance	-	-	-	2*500m	
	Bus availability	-	-	-	50%(CA), 30%(UPA) and 0%(UCA)	
Household interaction	Impact of neighbour	0.023675	0.0236746	0.023675	Dynamic	Dynamic
	Impact of information delivery	0.023675	0.0236746	0.023675	Dynamic	Dynamic
Attitude to policy		1.000000	1.0000000	1.000000	-	Dynamic
ε_{ij}		-11.102000	-11.1020000	-11.102000	10000	10000

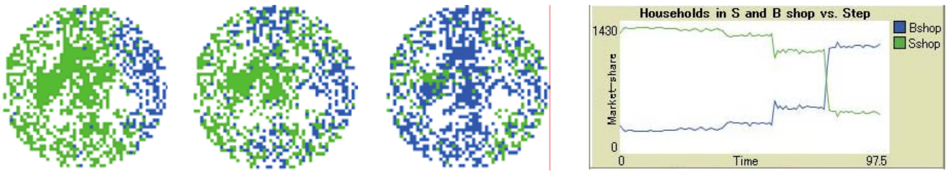
Note: 1. Parameters regarding shops and travel modes are set according to Y.Muramachi, et al (1990) and K. Hanaoka, et al (2000).

2. "Dynamic" means that values change in simulation. Parameters of household interaction are added as average values of Mid class parameters.

3.2 Sensitivity Analysis of global parameters and policy scenario

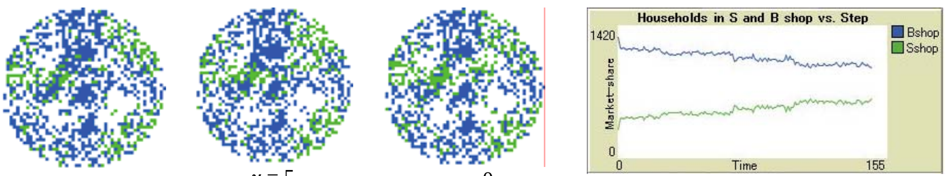
3.2.1 Travle cost, threshold travel distance

In Shopsim-MAS, a grid cell is considered the market area of a type of shops if more than half of the total trips by household agents in the cell are made at that type of shops. We examine the impact of some global parameters (those hold constant in the entire study area) on the market division. The global factors include unit travel cost (*c*), threshold travel distance (γ), parking fee, bus availability, and composition of population in various income levels. Limited by the length of the paper, we report the sensitivity analysis of the unit travel cost (by car) and the threshold travel distance in Figure 4. It shows that market area is very sensitive to the unit travel cost by car. The more expensive it is, the larger market area S-shops have. However, the market division is not very senstive to the threshold walking distance by travelers.



c = 1000 c = 300 c = 100 Unit cost of driving car from 1000 to 300 and100 (Japanese EN)

(a) Unit travel cost (c) and shop sales



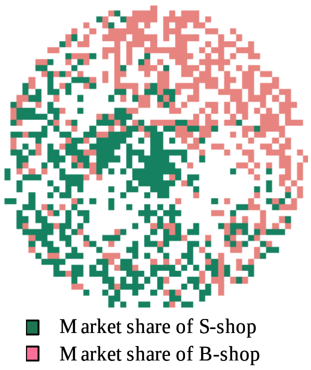
γ = 10 γ = 5 γ = 0 Walk distance from 10 to 7, 5, 3,0 (1 for 500m)

(b) Threshold travel distance (γ) and shop sales

Figure-4 Sensitivity of Parameters

3.2.2 Park-and-Ride travel mode and parking fee policy

Currently Shopsim-MAS considers four types of travel-modes for shopping trips: walking (TM1), bus (TM2), private car driving (TM3), and multi-modal mode which combines car driving and bus (TM4). The fourth mode is boosted by the so-called park-and-ride (P&R) transportation policy (P&R) in Japan. When this policy is enforced, traveling in downtown by car (TM3) is not permitted. Instead, people from outside can drive to the edge of downtown area and then take bus inside the central city. Figure 5 and Figure 6 compare simulation results of market shares before and after implementing the P&R transportation policy.

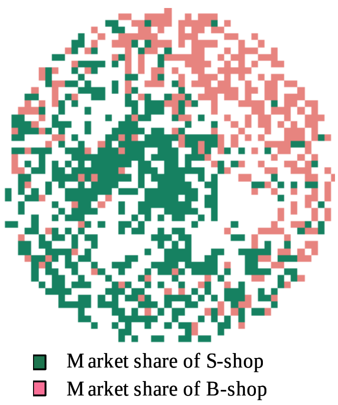


(a) Market spatial pattern

Market-share of Bshop	46%		
Market-share of Sshop	54%	TM1	4%
		TM2	14%
		TM3	36%

(b) Market statistics

Figure-5. Market shares without P&R mode (TM4)



(a) Market spatial pattern

Market-share of Bshop	33%		
Market-share of Sshop	67%	TM1	5%
		TM2	26%
		TM4	36%

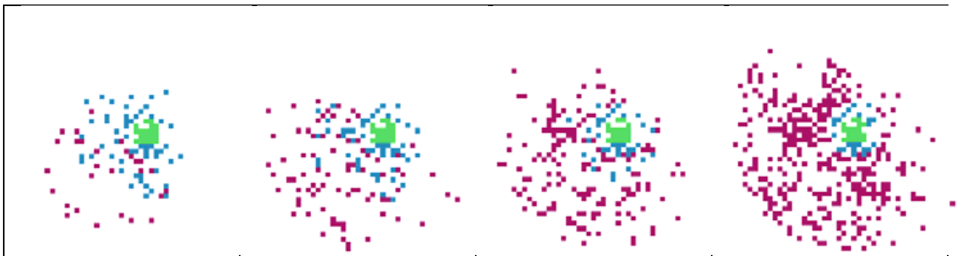
(b) Market statistics

Figure-6. Market shares with P&R mode (TM4)

After implementing the P&R transportation policy (TM4), as illustrated in Figure 6, the market share of S-shop expands from 54% to 67%. Our interpretation of the significant growth of market share of S-shop is that it is a result of the increase of shoppers who were otherwise not able to go shopping in S-shop by bus (increased from 14% to 26%). Now the share of the P&R travel mode (TM4) in Figure 6 equals the share of car driving travel mode (TM3) in Figure 5.

P&R transportation policy is closely associated with parking fee policy. It is very useful to gain insights into the effects of different parking fee policies. Usually there are different parking fees implemented in CA and in urban fringe, because land values at the two places are hugely different. In the simulation shown in Figure 6, the parking fee charged at urban fringe is set as zero and that in downtown is set as 600 Japanese En. Comparing to that in Figure 5, this simulation yields a 1% growth of households walking to CA for shopping might suggests that after implementing the integrated public transportation policies, CA environment is becoming more comfortable for walking, probably due to less traffic congestion and pollution caused by car.

Let's now focus on charging parking fee at the edge of downtown as it is an important measure to control car use in CA. Figure 7 shows simulation results of S-shops market area when different parking fees are charged at the edge of downtown, while holding other simulation and policy parameters unchanged. It reveals that the lower the parking fee the larger market share of CA shops is. This implies that parking-control policy can effectively restrict car to enter CA and consequently improve the shopping environment of central city. However, if the parking fee is too high, this policy may discourage many car-driving households from shopping in downtown and consequently accelerate downtown decline.



(a) Parking fee at the edge of CA = 1500	(b) Parking fee at the edge of CA = 1000	(c) Parking fee at the edge of CA = 500	(d) Parking fee at the edge of CA = 0

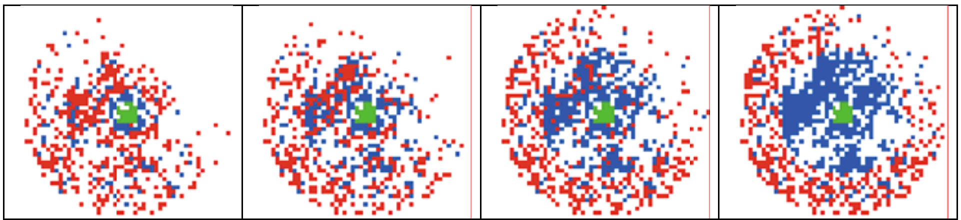
TM1 TM2 TM4

Note: TM1 (Walking mode), TM2 (Bus mode), TM4 (P&R mode)

Figure-7. Parking fees vs. market areas of downtown shops by travel modes

3.2.3 Bus availability

Another transportation policy, which aims to improve the availability of buses in the entire city, is also examined in this study. Figure 8 shows market areas of downtown shops by travel modes when bus availability in non-CA part of UPA (hereafter simplified as UPA) is improved to specific levels, while keeping bus availabilities in other areas (i.e. downtown and UCA) unchanged. It is found that with the increase of bus availability in UPA, the market area of downtown shops expands. It is also interesting to see that, as revealed in Figure 8, the growth of the market area of downtown shops is largely the result of the increase of shopping trips by bus. This suggests that with the improvement of accessibility, more households are attracted to shopping in downtown instead of going to the B-shop in the suburb.



(a) Bus availability of UPA = 30%	(b) Bus availability of UPA = 50%	(c) Bus availability of UPA = 80%	(d) Bus availability of UPA = 100%

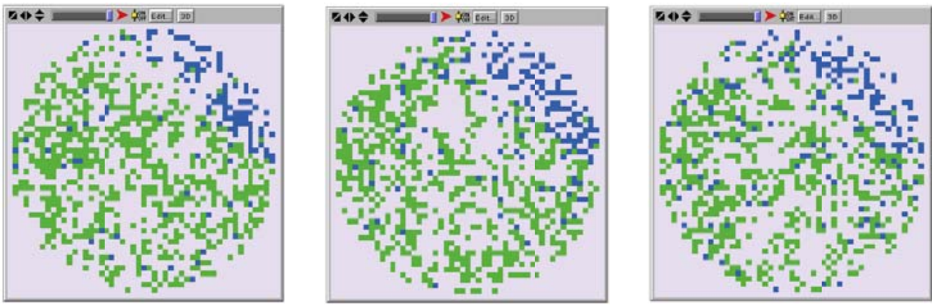
TM1 TM2 TM3

Note: TM1 (Walking mode), TM2 (Bus mode), TM3 (Car mode);
bus availability in downtown (CA) = 100%, bus availability in UCA = 20% in all cases

Figure-8.Bus availability vs. market share by travel modes

3.2.4 Composition of income levels

Figure-9 exhibits market shares of S-shops and the B-shop under three different compositions of income groups. Figure 9(a) shows the two market division when the composition of the three income groups is 10%, 60% and 30%. The market share of B-shop turns out to be about 17 %. When the composition changes in the direction of increased proportion of affluent population, as shown in Figure 9(b) and (c), the market share of B-shop increase accordingly. This seems to suggest that the market share of B-shop becomes larger increase when urban population become wealthier.



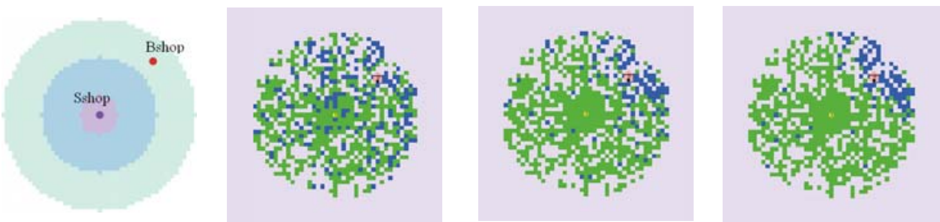
a) Rich: Middle: Poor = 0.1: 0.6: 0.3 B-shop share = 17%
b) Rich: Middle: Poor = 0.3:0.5:0.2 B-shop share = 23%
c) Rich: Middle: Poor = 0.5:0.4:0.1 B-shop share = 25%

Market share of S-shop   Market share of B-shop

Figure-9. The spatial pattern of shopping spatial market shares

3.3 Sensitivity analysis of random factors

Due to the random component in the utility functioin, the boundaries between the markets of B-shop and S-shops are indistinct and may be different in different runs of simulation. Figure 10(b), (c) and (d) are results from different random components, while all other parameters are the same. The R_s quantifies the scale of random component for S-shop, while R_b is that for B-shop. Consequently, the larger the random components are, the more random is the emgerging spatial pattern of the market shares. Becuase this study does not focus on the impact of subtle individual differences, we will choose small random component for clearer demonstration of general patterns. Hence, the random value is set as 500 for the utility model.



(a)B-shop and S-shop in different location

Market share of S-shop   Market share of B-shop

(b)Rs=5000,R_b=10000   (c)Rs=2000,R_b=2000   (d)Rs=500,R_b=500

Figure-10. The effect of random component parameter

3.4 *Sensitivity analysis of Interactions among agents*

The interactions among agents are theoretically in section 2.3.2 and are modelled in Equation (6). This study carries out simulation with consideration of interaction and interprets the results in this section. We investigate each type of interaction separately by controlling for the other type of interaction when the analysis is performed.

3.4.1 *Peer impact*

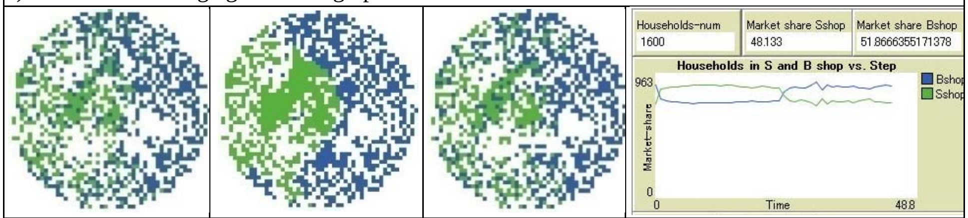
Figure 11(1) compares a few snapshots at certain timestamps in a simulation. In the figure, *tick* refers to the tick of time (timestamp), corresponding to the sequence number of iterations in a simulation. The parameter k_g is the scaling factor in Equation (6). The factors adjust the level of contribution of peer impact in individuals' choice making process. From Figure 11(1), it shows that when k is set to a higher value (30000) which means the household agents are very sensitive to peer impact, S-shop and B-shop patrons tend to become more clustered in the simulation space after many iterations of simulation (higher tick). When the k value is set lower (3000), however, the spatial pattern becomes more dispersedeven after a long time (higher tick).

3.4.2 *Information delivery*

Figure11 (2) shows the impact of information delivery. The parameter d_g assumes the similar role as k_g, according to Equation (6). The figure shows that when d is set at a lower value (3) which means the household agents are not very sensitive to information delivered from the -other shop agents, S-shop and B-shop patrons tend to become more dispersed in the simulation space. When the d value is set higher (18), the spatial pattern becomes more clustered. Now when the simulation proceed, because the market share of B-shop is larger, utility information of B-shop expand gradually and market share grows gradually too. Therefore, B-shop's market area keeps expanding with the increase of ticks.

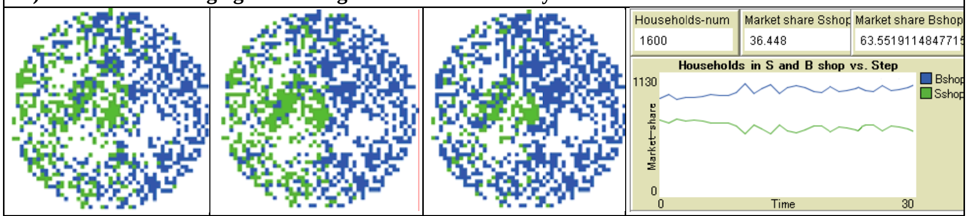
We further examine the influence of information delivery under different shop characteristics. We used *floor area* as an examplar type of shop characteristic information. As shown in the figure 11(2-2), when the floor space of B-shop is set as 30000, number of B-shop patrons grows gradually over simulation iterations. When the floor space is set as 1000, many patrons switch to S-shops gradually. For testing purpose, shop agents are programmed to change its floor space again to 20000 at tick 40 and it was found that the number of B-shop patrons grew again in the entire city. If price or other attributes of shops are changed, we can observe similar impacts through information delivery.

1)Interactions among agents through peer influence



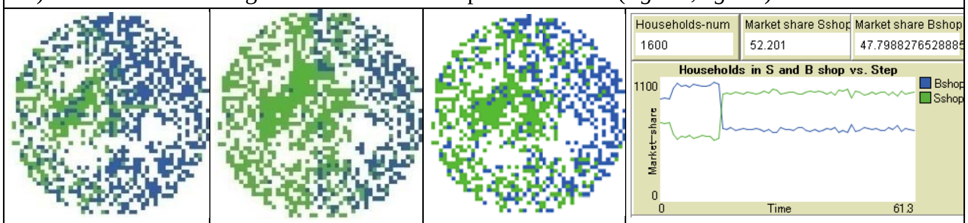
k_g =30000 tick=1	k_g =30000 tick=10	k_g= 3000 tick=20	Household agents in B-shop and S-shop

2-1)Interactions among agents through information delivery



d_g =3 tick=10	d_g =18 tick=10	d_g =18 tick=25	Household agents in B-shop and S-shop

2-2) Influence from changed floor area of B-shop in simulation (Kg = 0, dg = 3)



B-shop Fl. area=30000 tick=1	B-shop Fl. area=1000 tick=30	B-shop Fl. area=1000 tick=60	Household agents in B-shop and S-shop

Figure 11. Analysis of interactions

4 A case study of Kanazawa

To examine the usefulness of Shopsim-MAS, we test it with data of a real city, the Kanazawa city. In Kanazawa, the local regulations about B-shop development, as shown in Tables 3 and 4, have been in place since 2002. In the UPA of this city, restrictions on B-shops's location and upper limits of floor spaces are specifically stipulated for each planned zonning type by the Commercial Environment Planning in Japan, as shown in Table-4.

Table-3 Bylaw for B-shop's site selection and floor space in Kanazawa City

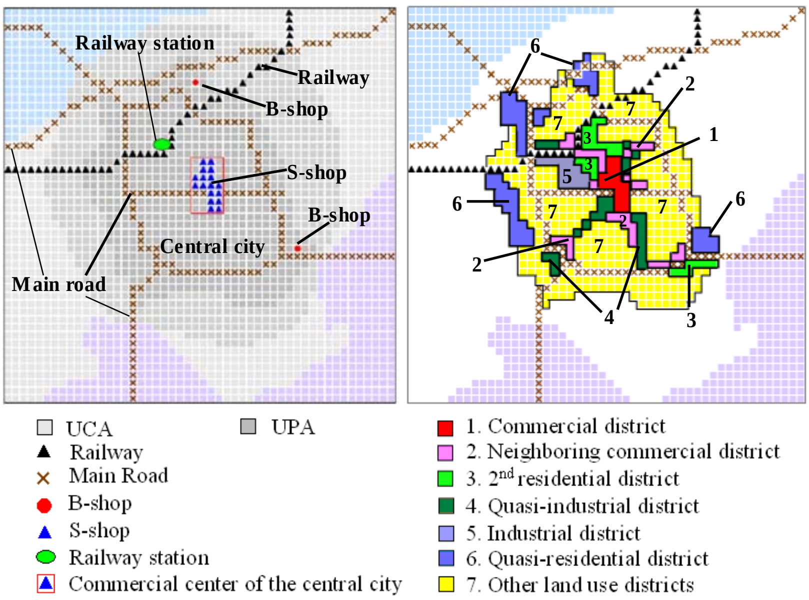
Area for candidate sites	Requirements on candidate sites	Upper limit of Floor space (m^2)
Central area	CBD	No limit
	Improvement areas along main road	20000
	Other improvement areas	3000
Railway Station area	Areas along the main road connecting to station and other major transport facilities	10000
Cultural preservation zone	Areas along main road	3000
	Other areas	1000
Sub central area	Areas along main road	5000
	Other areas	1000
Neighborhood commercial areas	Areas along main road	3000
	Other areas	1000
Residential areas	Areas along main road	3000
	Other areas	1000
Industrial areas	Areas along main road	3000
	Other areas	1000

Table-4 Planning regulations regarding B-shop locations

Urban planning area	Land use zone	Permitting State
Urbanization Promoting Area	1st low-rise exclusive residential district 2nd low-rise exclusive residential district 1st mid-high exclusive residential district 2nd mid-high exclusive residential district 1st residential district Exclusive industrial district	X
	Commercial district Quasi-industrial district Industrial district 2nd residential district Quasi-residential district Neighborhood commercial district	O
Urbanization Control Area	—	▲
White Land	—	O

X B-shops are not permitted to locate in these land zoning district
O B-shops can be permitted to located in these land zoning district
▲ In principle any development are prohibit in Urbanization Control Area.

Household distribution and households' shopping behaviour are simulated in computers. We need to examine if the simulated household distribution and shopping choices (and thus market shares) are consistent with real situations. To do this, we use Japanese Census Survey as ground-truth data for household distribution and the Commercial Statistics Survey for market share.



(a) Urban space (b) Land use zoning in UPA

Figure-12. The spatial structure of Kanazawa

4.1 Model test in Kanazawa city

The urban space in the case study is represented by 2500 cells with the spatial resolution of 500 meters . The model assumes that the central city has the typical characteristics of Kanazawa which means it has a traditional commercial center located in the heart of the city and an urban planning area of 1230 cells. The urban planning area is further divided into Urbanization Promoting Area (UPA) and Urbanization Control Area (UCA). There are pre-defined land use zones within UPA. The spatial structure of the city is shown in Figure 12. The first through the sixth types of land use districts in Figure-12(b) are zones where B-shops are permitted according to the abovementioned planning policies.

The factors of shopping utility and their parameters used in this case study are shown as Table 2. It shows that parameters employed in the study are adopted from those obtained in Muromachi et al (1990) and Hanaoka et al (2000)'s earlier studies. In the simulation, the unit travel cost is set as 20en, which is the average bus fare for one cell distance 500m. The threshold travel distance is set as 15000 m (30 cells). Shop data are obtained from Commercial Statistics Survey in 1985 through Digital National Information (http://nlftp.mlit.go.jp). Figure-13 (a) shows the spatial distribution of shops in Kanazawa in 1985. The cells with more than 150 shops are identified as the city center, which accommodates 2006 S-shops and 4 B-shops. The total floor space of S-shops is 192445 m^2 and that of B-shops is 26483 m^2. To simplicity, we cut down the number of B-shops and S-shops but keep their ratio of their total floor spaces the same as real data. As a result, the downtown of this central area is mapped into only one cell with 36 S-shops (the floor space of each S-shop is 300 m^2) and 1 B-shop (1500m^2). The ratio of total S-shops' floor space (10800 m^2) to B-shops' is 7.2, roughly the same as the real floor space ratio of S-shops to B-shops. The allocation of household agents is the same as that specified in the previous section. Figure 13 (b) shows the virtual shops' locations based on the real city on the left and the simulation results of market areas on the right. It can be seen that the market share of S-shops greatly surpasses that of B-shops because of their obvious advantages in quantities.

4.2 Accuracy Assessment

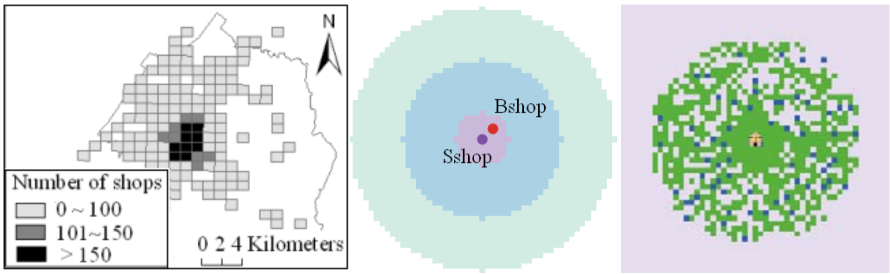
To evaluate the accurcy of simulated household distributions, Table-5 compares the percentages of households in the real city and in the simulated city by land use zoning type. In the initialization process, the same proportion of various land use zoning types are generated automatically according to the real city data. The comparison shows consistency by and large. However, significantly larger proportion of H2 and lower proportion of I1 are seen in the simulated city. This may be due to the fact that the simulation tool takes considerations of above-mentioned policies which did not exisit in 1985.

Table-5 Comparison of households in the real city and the simulated city

		UCA	UPA (including CA)							
			H1	H2	H	C1	C2	I1	I2	I3
Real	Households	21186	13341	21565	50249	8030	8818	14510	2917	436
	%	15.00%	9.50%	15.30%	35.60%	5.70%	6.30%	10.30%	2.10%	0.30%
	Subtotal %	15.00%	60.40%			11.90%		12.70%		
Simulated	Households	260	200	338	493	86	87	95	41	0
	%	16.30%	12.50%	21.10%	30.80%	5.40%	5.40%	5.90%	2.60%	0.00%
	Subtotal %	16.30%	64.40%			10.80%		8.50%		

Note: GOF (subtotal) is 90% and GOF (land zonings) is 80%.

Table-6 compares sales between that from real survey data and that from simulation result. The market share (proportions) of B-shops and S-shops are very consistent with real-world survey data. The sale amount is different from real data only because we cut down the number of shops proportionally to simplify the computation. This comparison result proves that Shopsim-MAS is a promising tool to simulate spatial patterns of market shares.



(a) The distribution of real shops in Kanazawa (1985)

Market share of S-shop Market share of B-shop

(b)Simulation results in the virtual city

Figure-13. Real shops' distribution and virtual simulation

Table-6 Comparison of sale amount in real and virtual center

Cell size	Shop(number)	Floor space (m^2)	Sale amount	Market share
Reality	S-shop(2006)	192445	186(billion en)	89%
($1km^2$)	B-shop (4)	26483	22.4(billion en)	11%
Virtual	S-shop (36)	10800	55475(demand)	90%
($0.25km^2$)	B-shop (1)	1500	6025(demand)	10%

5 Conclusions

This research presents a multiagent simulation approach to analyzing impacts of city center regeneration policies in the context of Japan. The developed system, Shopsim-MAS, proves to produce results that are consistent with real world data. The contribution of the study is three-fold. First of all, it introduces real urban land use zoning to constrain behaviours of various types of agents and it takes consideration of interactions among agents in the model. Secondly, the operational characteristic of the Shopsim-MAS is examined through parameter sensitivity analysis which allows researchers to investigate the nature and degree of impacts with various parameters. Finally, the developed MAS system provides a useful platform for planners and practitioners to gain better understanding of the potential effect of any new or existing policy in various scenarios.

Important empirical findings in the research shed lights on potential effect of relevant downtown regeneration planning policies. It shows that with the increase of bus availability and decrease of parking fee at the edge of a city, growth of shopping in downtown can be remarkable. This may be primarily lead by the increase of new downtown shop patrons who prefer to at least partly use private cars during their shopping-journey. Although impacts of public transportation policy and park-and-ride regulations have generally positive impacts on downtown regeneration, our study also indicates that this can only be achieved by carefully implementing planning measures. For example, one sensitivity analysis shows that very high parking charges may cause negative effect for downtown revitalization.

Although the multiagent simulation approach proves to be instrumental in planning policy analysis, there are still many opportunities for further improvement. We like to suggest a few possible research avenues in this regard. Firstly, the dynamic competitions among shops for market area should be considered. Shop characteristics such as prices of goods and shopping environment work with shop location cooperatively in the market competition. This research considers spatial location while assuming predefined shop characteristics. Modeling strategy of dynamic competition will help to simulate more realistically. Secondly, parameters of the choice models included in the system can be estimated in a more rigorous manner based on real shopping choice data of individuals. A related research challenge is to deal with large amount of data required by micro-scale simulation and calibration in MAS. A reasonably complete urban simulation system will need enormous amounts of detailed data including, for instance, not only land use, households and their characteristics, but also environmental and social-economic features. Further research on seamless integration of MAS and GIS may provide opportunities for more comprehensive and customizable simulation tools for urban planning policy analysis. Finally, an equilibrium solution is necessary when simulating social dynamics. Namatame (1998) suggested two types of solutions, the competitive equilibrium solution and the cooperative equilibrium solution. With the cooperative equilibrium solution, it is assumed that household agents make their choices cooperatively with shared information such as those about commercial environment and urban policy. We think this equilibrium solution makes reasonable assumptions for simulating the dynamics of shopping behaviours. Future research may introduce a modeling mechanism that regulates large-scale shop locations and shopping choices under cooperative equilibrium to the simulation system of urban policy decision-making.

Acknowledgements

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