Policy Simulation Trials of an Intelligent Shop-Around Agent Model

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Abstract

Since 2005, the authors have been working on a research and development project named ASSA (Agent Simulator of Shop-Around). ASSA is based mainly on a cognitive science approach and the layer-decomposition of downtown visitor behavior through data analysis, including redundancy analysis, of a series of shop-around surveys we had conducted. ASSA is activity-based and has dynamic scheduling but the agents are adaptive, behave with bounded-rationality and learn. The authors have already reported several findings from our project experiences. In this paper, as the final phase of this ASSA project, the authors have analyzed the Osu survey data of 2003 using ASSA ver.3, and have given visual verification and validation, before addressing the results of three different scenario policy simulation trials undertaken to examine ASSA's potential as a policy simulator and to explore revise strategies of the overall ASSA project. we conclude that ASSA has the potential performance for ensuring policy analysis.

1. Introduction

The shop-around behavior model is also known as the MultiPurpose-MultiStop (MPMS) model and since the 1980s the model has been developed and studied in such fields as geography and urban planning, not only for its practical interest, e.g. downtown revitalization and town center management, but also for its theoretical interest in the field of spatial analysis (Kelly, 1981, Borgers and Timmermans, 1986). In the 1990s, by applying a combination of the logit model that enables data-fitting based on utility-maximization approximation and the'Markov-chain assumption' that makes up transition probability, OD-matrices LLPM were established (Arentze et.al., 2001). However, from our detailed surveys of downtown visitor behavior we began to explore new approaches, and discovered limitations to the Markov properties, as they ignored the cognitive aspects of downtown visitors.

In agent modeling research the daily activity-travel model took the lead in such fields as transportation planning. Albatross (Arentze et.al., 2001) is formulated as a rule-based system that guarantees data-fitting by employing a data-mining tool to generate heuristic rules (binary tree). Aurora (Arentze et.al., 2005) is formulated as a utility-based theoretical model that generates a schedule by combining each activity (errand) that has nonlinear S-shape utility and employing genetic algorithms; in addition, in response to an unexpected event such as congestion, the model carries out re-scheduling.

However, when the shop-around behavior model is compared to a daily activity-travel model that has the same MPMS structure, its characteristics can be found in humanlike planned actions and the improvised actions of downtown visitors are shown; therefore, as a theme for research, the shop-around behavior model faces a higher degree of difficulty. There are few existing studies (except Kurose and Borgers, 2001, Dijkstra, Timmermans, de Vries, 2009).

From the results of our investigations, we can observe visitors frequently switch planned actions and improvised actions. So, based on the results of the data analyses, we have newly devised ASSA (Agent Simulation of Shop-Around, Yoshida and Kaneda, 2007, Yoshida and Kaneda, 2012, Kaneda and Yoshida, 2012). ASSA is a kind of activity-based model and deals with agent's spatial behaviors while on shop-around excursions in downtown areas. In ASSA, each agent makes and remakes their schedule to visit shops based on time constraints and shop preferences, chooses alternative visits when they fail in an errand, and makes impulse stops at shops and detour actions when they have sufficient time. A chain of such activities on one day affects their plans for the next visit and so on. In this context, our agent is “naturalistic and wise”; in short, they behave with bounded rationality in the short term, but intellectually in the long term, by devising and implementing planning (dynamic scheduling/rescheduling), learning and adaptation functions.

For this model, we have already prepared and conducted a framework of verification and validation: analysis of aggregated behavior, analysis of statistics, similarity of visit sequence, and so on (see Yoshida, 2010, Yoshida and Kaneda, 2012). Then in this paper, we report the results of the verification and validation using a much more intuitive visual presentation, instead of simply showing the metrical results.

In this paper, firstly we refer to existing research and briefly explain the features of ASSA, especially focusing on the decomposition of the shop-around behaviors and the system components. The final version ASSA ver.3 attempts a dynamic simulation of naturalistic and intelligent shopper behavior. Then, we discuss its verification and validation by showing the simulated results of the Osu shopping district case. Lastly, we attempted policy simulation using 3 scenarios as we explore the potential to develop our model into a supporting tool for practical planning.

2. ASSA (Agent Simulator of Shop-Around behavior) – Its system design and components

The first feature of the downtown visitor behavior that was modeled was the function of time allocation or scheduling of visits to shops under a given time constraint (time-budget). Implementing the scheduling function in itself was an antithesis of the Markov model, even if it does emphasize time constraint, and was an application of the intelligent planning function in the agent. Shop-around behavior, as referred to here, has been explained in cognitive science (Hayes-Roth and Hayes-Roth, 1979). The second feature dealt with was dynamic updates as part of the agent’s behavior, including mainly rescheduling. This also relates to intellectual functions like adaptation and learning. Data-fitting oriented evaluation was the third feature of the agent behavior developed.

Next, the shop-around behavior to downtown Nagoya was investigated using 12 different survey results. As part of the survey, visitors were asked about their walking routes, shops visited, and whether visits to the shops were planned in advance. According to the redundancy analysis, the shop-around behavior within a survey area, including the routes taken and the distance traveled, were found not to be necessarily optimized (Arakawa and Kaneda, 2002).

It was thus decided to decompose shop-around behavior into planned and improvised action. Improvised action was decomposed alternative-visit, impulse actions (Table 1). Planned action was an action performed according to a schedule. Alternative-visit action, which is defined as an improvised action, is the action of visiting a shop that was not part of the original plan because the planned errand was not completed in the shop visited. This concept was not specifically differentiated in the Markov-type shop-around behavior model.

Table 1. Layer-decomposition of shop-around behaviors.

Agent's Action		Information Processing		On Schedule Plan
		On Shop-Visit	On Path	
Planning & Decision Action		Planning a Visit-Order	Planning Path	Forming
Planned Action		Visiting Planned Shop in turn	Following Planned Path	Keeping
Improvised Action	Alternative-Visit Action	Choosing Same Category's Shop when Failed Errand	Modifying Path	Inserting
	Impulse Action	Impulse-Visit (Stop) Action: Dropping in Non-Planned Shop if Time Available	Impulse-Detour Action: Walking Non-Shortest Path if Time Available	Re-forming

The basic structure of ASSA had been designed as a component consisting of several modules as seen below in Fig 1. The merits of such modular systems are the result of piecemeal updating. ASSA ver.1 deals only with Planned Action and Alternative Action (task completion / failure is represented as a fixed probability for each errand). The re-scheduling module (SPM) is called up in the case of a failure to complete an errand. Moreover, the tight assumption presupposes that all of the ‘path planning’ is always optimized by Dijkstra’s algorithm.

In ASSA ver.2, we implement Impulse Visit Action. Each occasion of Impulse Visit Action is determined probabilistically when there is enough time, based on the so called street appeal, the sum of the shop preferences along the street, and time remaining by the e-greedy method (for details, see Yoshida and Kaneda, 2008).

ASSA ver.3 adds two kinds of Detour Actions: one is the relaxation of the optimality of path planning, and the other concerns taking a detour on impulse. The former is dealt with by using‘subjective length’ as a weight set at each street. These weights are also to be updated through experience by using a similar algorithm as in shop-preference updating. In Impulse-Detour Action, several studies had appeared such as Dijkstra, Timmermans & de Vries (2007), but no study deals with the issue of time-constraint. We newly devised an algorithm similar to that of Impulse Visit, this time, the softmax method using a Boltzmann distribution was used to model this behavior.

The ASSA concept also considers dynamic updates within agents. In the order of shortest update cycle to the longest, (1) rescheduling (from 0 to several times per visit to an area, implemented in ver. 1), (2) reinforcement learning of store utility (every time after visiting an area, implemented in ver.1), (3) updating a mental map (every time after visiting an area, the current version assumes complete knowledge), and (4) updating visiting frequency and time budget (once every few visits to an area, fixed in the current version). Another implementation possibility includes the decision making principle (especially stance against risks and uncertainty) of an individual agent (Kaneda and Yoshida, 2012).

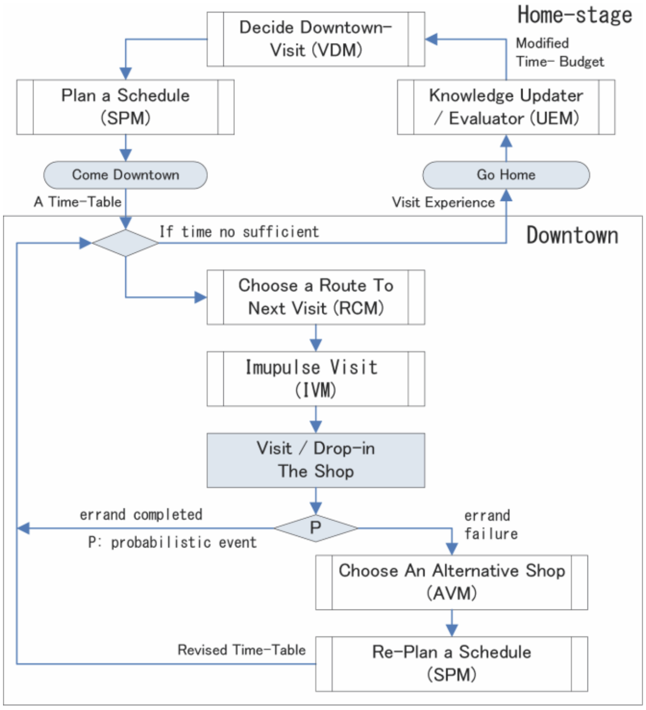

Fig.1. Module components of ASSA.

3. Implementing the Osu shopping district case – Its spatial representation, verification and validation

3.1. Framework

To evaluate the characteristics of the above designed model, ASSA ver.3 has been analyzed taking into account the following five aspects (Yoshida and Kaneda, 2012).

(a) General evaluation
- 1) Analysis of aggregated behavior (validation)
- 2) Analysis of statistics (validation)

(b) Individual function evaluation
- 3) Illustration of agent's individual behavior (verification)
- 4) Analysis of similarity of visit sequence (validation)
- 5) Analysis of redundancy (validation)

In this paper, we first give 3) as the verification examples, and then show mainly graphically 1) and 2) as a part of the validation results. The results of other metrical analyses such as 4) and 5) were discussed in Yoshida and Kaneda (2012).

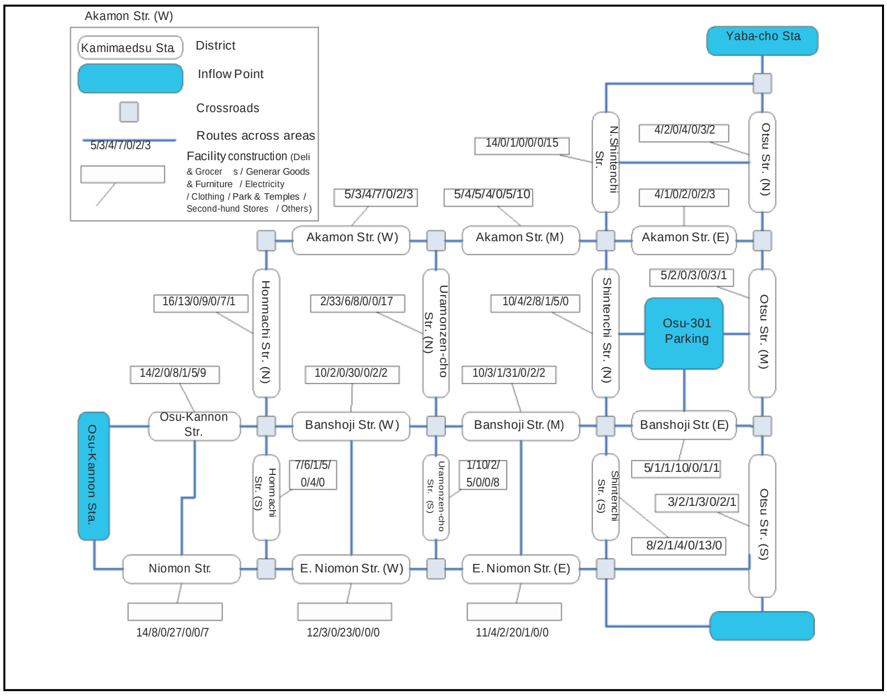

Fig. 2. Shop configurations in the Osu district case.

In this paper, we study the Osu district, a shopping street complex district with 685 shops and facilities falling into 8 categories (cafes and restaurants, grocers, household goods, electric appliances, clothing, parks and temples, second-hand goods, and others). This district is modeled as a network with 36 street-nodes (includes 4 nodes for entering and exiting the area) as seen in Fig.2. Detailed data for both cases are obtained by a survey that had conducted on autumn holidays in 2003 (Oiwa et al., 2005). Visitors were categorized by gender, three age groups and other attributes such as location of domicile and visit frequency. In the Osu Simulation Case, the performance data of 2,500 agents taken over 120 days were recorded, and after discounting the initial 10 days, the remaining data was used.

3.2. Verification – Examples of agent performances

Individual behavior results were extracted for each agent, and then graphically represented on a map. There are two focal points: shops visited and walking routes. For shops visited, attention is paid to the following four variables: location, visiting order, planned or unplanned visits, errand completion or failure. Based on the observations made, each of the following designed functions was verified as working: validity of a plan drawn up by an agent in the downtown visit decision; implementation of the plan in the planned actions; occurrence of alternative visits; and occurrence of impulsive visits. Walking routes were assessed mainly by whether agents deviated from the shortest route, by checking the initial planning and implementation of a planned route, and the occurrence of detours from the planned route. Here, we will explain the performance of a typical four agents to illustrate each elemental function we had devised.

3.2.1. Sample A

Fig. 3 shows the tracked movements of <Agent A>. This agent represents a female senior who lives in the <far area> and uses trains to visit. She planned to visit a secondhand shop, complex <A>(1), a clothing store <B>(2), and a restaurant <C>(3), and she visited these facilities as planned. The simulation shows that she was able to complete the errands in each store before going home. This indicates that in this simulation the model's planning function was executed as desired.

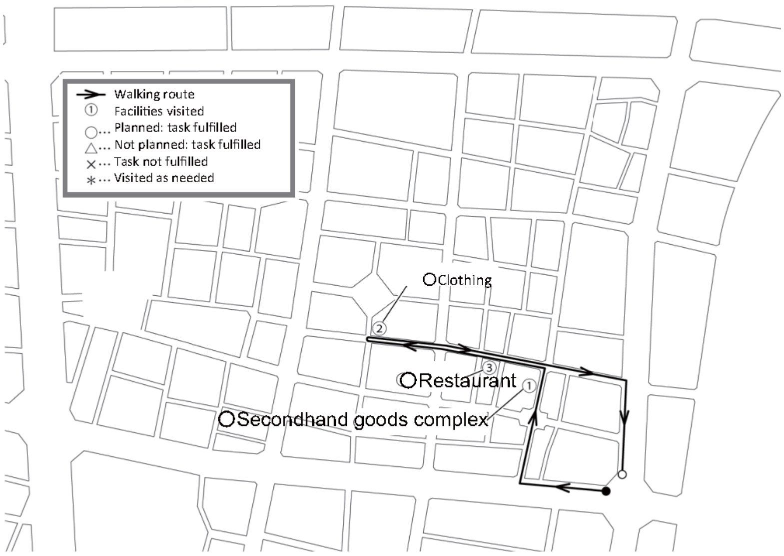

Fig. 3. Planned action in Agent-A's performance.

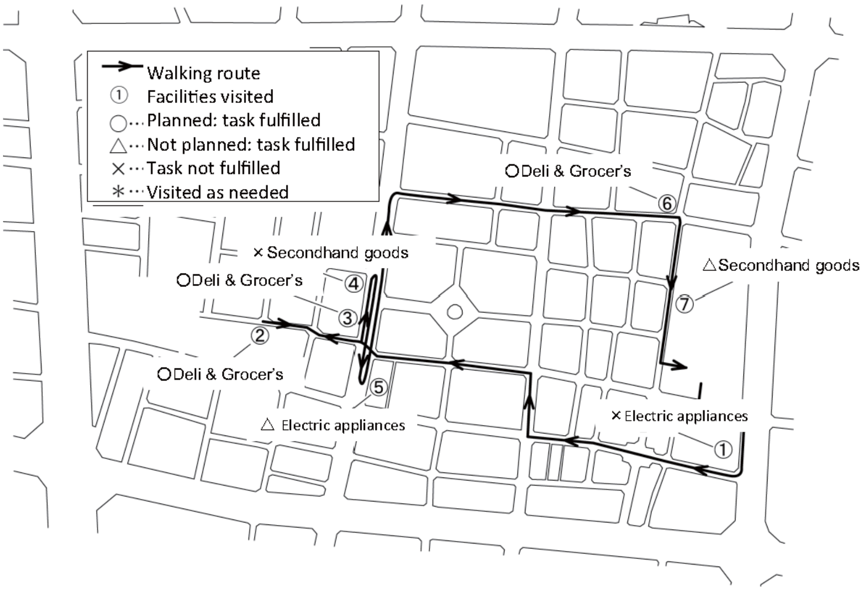

Fig. 4. Alternative visit and re-scheduling in Agent-B's performance.

3.2.2. Sample B

Fig. 4 shows the tracked movements of <Agent B>. This agent represents a middle-aged female who lives in the <far area> and uses a car to visit. The agent planned to visit facilities <A>(1), <B>(2), <C>(3), <D>(4), and <E>(6). She came to the commercial district by car. Observations show that the agent parked her car at parking lot "Osu 301" and then visited (1). She failed to complete the errand at (1), which prompted reactional behavior. As a substitute facility, the agent visited <X>(5). This altered the plan, and facility (5) was squeezed in between (4) and (6). After this, the agent visited (2), (3), and (4). She once again failed to complete her errand at (4), and a substitute facility <Y>(7) was selected. Subsequently, the agent visited (5) to complete the errand that was planned for (1), and then visited (6) and (7). The agent then went to parking lot "Osu 301" to exit the area and returned home. This simulation result shows that the agent substituted, according to completion or failure, to complete various errands at each location. The agent revised the plan as she wandered through the district.

3.2.3. Sample C

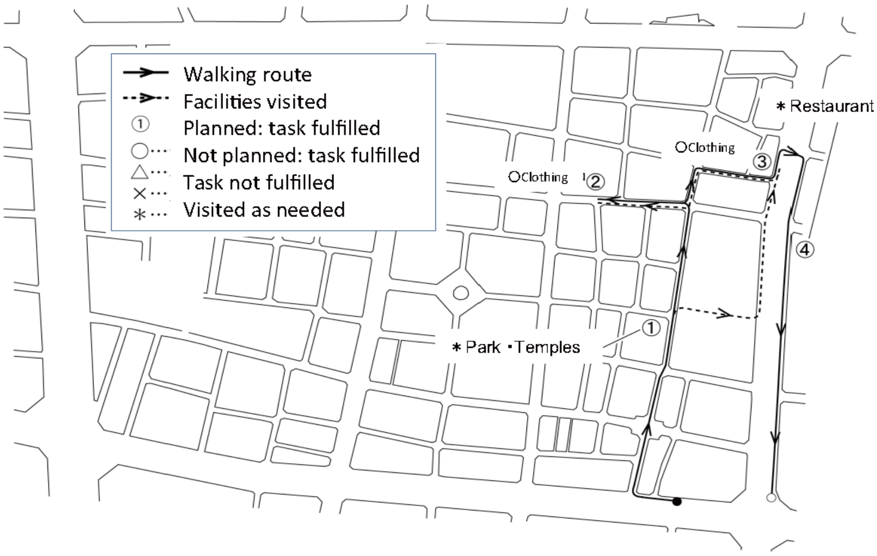

Fig. 5. Impulse visits in Agent-C's performance.

Fig. 5 shows the tracked movements of <Agent C>. This agent represents a male senior who lives in the <intermediate distance area> and uses trains to visit the district. The agent only planned to visit 2 facilities <A>(3) and <B>(2); however, he ended up visiting 2 additional facilities. The additional facilities were <X>(1) and <Y>(4). In addition, the sequence of visiting (2) and (3) were reversed from the initial plan because of visiting (1), which in turn altered the route. Taking a detour to visit (1) and (4) occurred unrelated to the 2 facilities in the original plan. Hence, visiting these 2 facilities occurred as improvisation behavior. The reversed sequence of visiting the facilities in the original plan can be explained when considering the fact that visiting (2) was time sensitive and could not be delayed. The agent honored the time restriction attached to visiting (2) by delaying the visit to (3). From this, we can see the occurrence of improvisation behavior, which altered subsequent visits.

3.2.4. Sample D

Here, we examine one more agent's behavior in the Osu Simulation Case whose behavior was of particular note (Fig. 6). <Agent D> was a <young woman> sample who came from the <intermediate distance area> by <train>. From her plan, it can be see that she intends to visit five shops: clothing shops <A>, <B>, <C>, <D> and an electric appliance shop <E>.

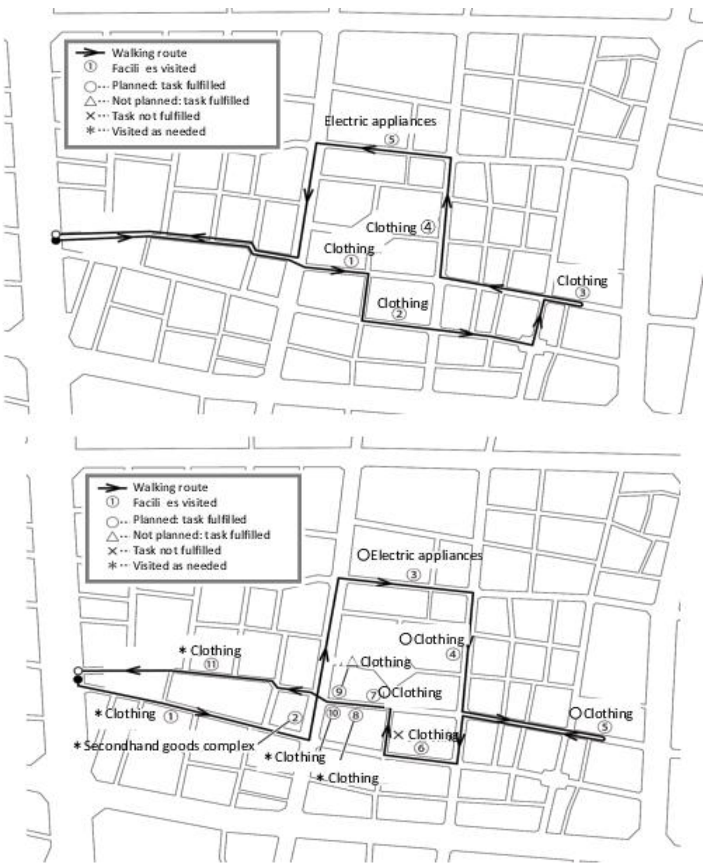

Fig. 6. Impulse detour action in Agent-D's performance (Above: plan, Below: performance).

Once this agent arrived in the district, she actually first visited a different clothing shop <U>(1). The agent walked by way of a street that is not the shortest route to shop <A>, the first planned-visit shop; therefore, it can be seen that the detour behavior function was working. Next, the agent visited a secondhand goods shop <V>(2), which again was not included in the plan, and as a result of these unplanned visits, the agent changed her plan yet again and went to shop <E>(3), which she had planned to visit at the very end of her trip. In the three shops (3) and the subsequently visited <D>(4) and <C>(5) the agent successfully fulfilled all her errands, but in <B>(6), she failed to complete her errand. As an alternative shop she chose

<W>(9). But before visiting <W>(9), she visited <A>(7), which she had planned to visit earlier, and then made an unplanned visit to another clothing shop <X>(8). In <W>(9) the agent completed the errand that she had failed to fulfill at <B>(6), and then made unplanned visits to yet more clothing shops <Y>(10) and <Z>(11), and finally went home. From these observed results, it is evident that each Agent Action shown in Table 1 was working in a complex way. In addition, the Impulsive-Visit Action of visiting several clothing shops in sequence is characteristic of the young women who actually visit this commercial district; this point confirms that the model is capable of rescheduling a set of behaviors unique to an agent's attributes.

3.3. Validation -- Comparison with survey results

Table 2 shows the comparison between the simulation results and the empirical data. Please note that the simulators used time distance expression, whereas the actual physical distance traveled was extracted from the route drawn on the maps of the surveys, making comparison between the two impossible. Therefore, the distance traveled is shown only as a reference. In the same way as the previous chapter, it is assumed the pedestrian's walking speed is 1.2m/s to 1.5m/s, the equivalent distance in the simulation is 1.35km to 1.68km. Observing other values, it is evident that the simulation accurately predicted the facilities visited and the facilities planned for visits. There is a discrepancy of about 10 minutes between the simulation and the actual data in terms of the duration of the stay in the commercial district.

Table 2. Comparisons of major macro indicators.

	Simulation	Survey
Duration of stay	169min	148min
Walk Distance/Walk Time	18.7min	1.15km
Number of facilities visited	5.04places	5.00places
# of planned-visit facilities	2.17places	2.18places

Focusing on the traffic rate for each street and the number of facilities visited according to the simulation is shown in Fig. 7-below. Comparing the traffic rate with the empirical data shown in Fig. 7-above, we see that the traffic rate predicted by the simulation for Osu Kannon Dori ('Dori' means Street in Japanese), Niomon Dori, Honmachi Dori on the west side is below that of the actual data. Conversely, the traffic rate predicted by the

Fig. 7. Comparison of spatial distributions (Above: empirical data, Below: simulation data).

simulation for Kita Shintenchi Dori, Uramon Maemachi Dori was higher than the empirical data. The simulation also showed a higher rate of visiting facilities for those on the east side compared to the facilities located on the west. This can possibly be attributed to the lack of adjustment for agent preference of facilities within the simulation. Because there is no difference in preference for a particular facility, the facilities to be visited get selected by considering the distance from the entrance to the commercial district such as train stations and parking facilities. As such, it is understandable that the visits are more concentrated in the east side where there are more entrance points to the district. The challenges for this simulation would be putting less emphasis on the distance and improving facility and street preference parameters.

4. Policy simulation trials

As a simulation model application example, we will predict the changes to agent behavior according to hypothetical changes made in the district, and explore the possibility of the simulator contributing to revitalization of the shopping area. We chose the 3 scenarios described below.

1) Scenario A: Relocate a number of facilities.

Move a number of facilities from one street to other streets, and compare to the commercial district model in the base case.

2) Scenario B: Exchanging facility types.

Move all facilities of one type from street A to street B, and move all facilities of a different type from street B to street A, and compare to the commercial district base case.

3) Scenario C: Strengthening a particular type of facility and increasing the number of background personnel accordingly.

The number of facilities of a particular type on street A is increased compared to the base case scenario. Also, the number of background people is increased appropriately to reflect the increased number of facilities. We analyzed each case by comparing the traffic rate for each street and the number of visits to facilities between each scenario and the base case.

4.1. Scenario A simulation result

Based on Scenario A, 46 stores were moved from Uramon Maemachi Dori (North), which contains 66 stores of 6 types as shown in Fig. 2 to Honmachi Dori (North). Fig. 8-above shows the simulation results for traffic rate and the number of facility visits. Comparing the simulation results with the base case shown in Fig. 7-below, it is evident that the number of facility visits decreased in Uramon Maemachi Dori (North), from

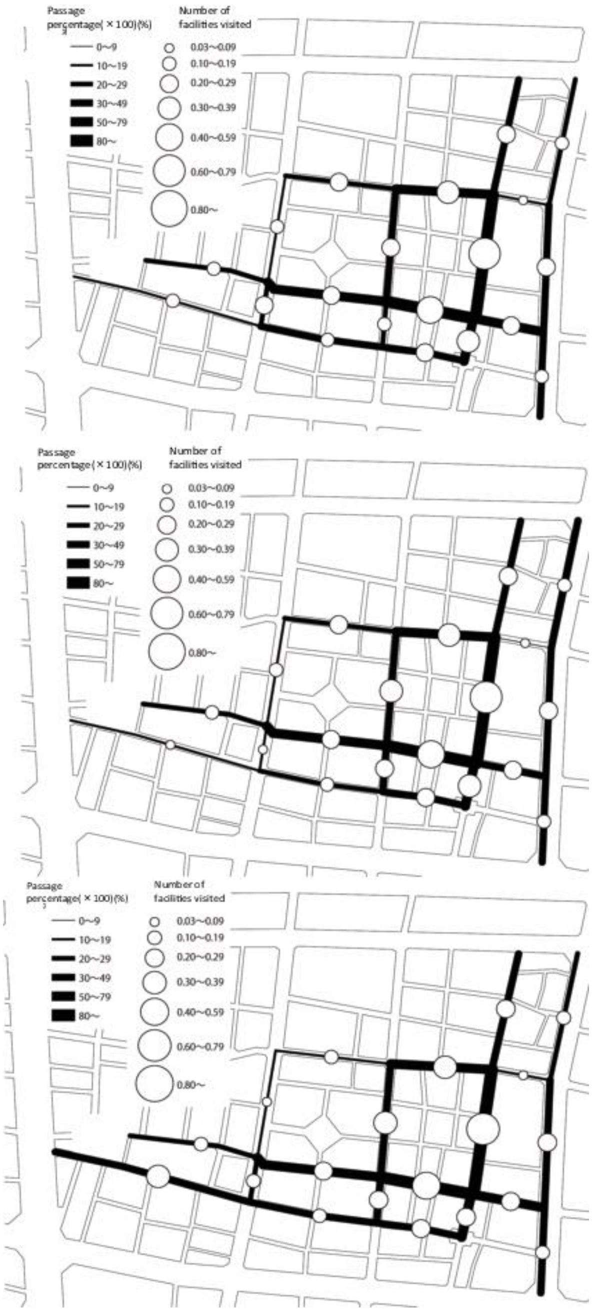

Fig. 8. Visitors' spatial distribution in each policy case (Above: Scenario A, Middle: Scenario B, Below: Scenario C).

where the facilities were moved, but the number of visits increased in Honmachi Dori (North), to where the facilities were relocated. This result is rather intuitive. There was also a reduction in traffic in Uramon Maemachi Dori (South), an area that is near Uramon Maemachi Dori (North). We also see increased traffic in Honmachi Dori (South), which is right next to Honmachi Dori (North). Somewhat surprisingly, we also see increased traffic in Higashi Niomon Dori (West), which is not adjacent to either of the streets targeted by this simulation. This increased traffic can perhaps be attributed to pedestrians walking through the area as they head to the Honmachi Dori area.

4.2. Scenario B simulation result

Based on Scenario B, all 23 clothing stores were moved from Higashi Niomon Dori (West), the location of which is shown in Fig. 2 to Akamon Dori (West). Higashi Niomon Dori (West) has a total of 38 stores of 4 types. In the exchange, all 35 general and furniture stores were moved from Akamon Dori (West) to Higashi Niomon Dori (West). Simulation results are shown in Fig. 8-middle. Comparing the simulation results with the base case shown in Fig. 7-below, we do not see any significant changes to the traffic rate in either Higashi Niomon Dori (West) or Akamon Dori (West). We did see a marginal drop in the number of facilities visited in Uramon Maemachi Dori (South) and Honmachi Dori (South), surrounding areas of Higashi Niomon Dori, but the difference is negligible. The simulation indicates that as long as the overall composition of the stores within a district does not change, there would only be a marginal change to pedestrian behavior when a large number of stores of a single kind move out of an area.

4.3. Scenario C simulation result

Based on Scenario C, 10 more electric appliance type stores were moved into Niomon Dori as shown in Fig. 2, and the background population was increased by 250 people. Fig. 8-below shows the simulation results for the traffic rate and number of facility visits. Comparing the results with the base case shown in Fig. 7-below, it is evident that the traffic rate and the number of facilities visited increased in Niomon Dori where the store composition changed. In addition, traffic increased in Honmachi Dori (South) and Higashi Niomon Dori (West), areas adjacent to Niomon Dori. This is evidence that streets adjacent to the target benefited from the change as well. On the other hand, the traffic and number of facilities visited decreased in Akamon Dori (West) and Honmachi Dori (North). The reason for the decrease can be attributed to the fact that the main stores on Akamono Dori are electric appliance stores, resulting in increased competition from the relocated stores and an ultimately decreased number of customers. It first appears that there are no changes on other streets, but these numbers have reduced visitors to the commercial district. In actuality, the number of pedestrians and number of visits in all streets have increased because the average number of visitors to the commercial district has increased from 550.0 people to 640.0 people per day due to the increase in the background people. The above results show that this scenario not only positively affected the streets to which changes were made, but the positive impact was felt by Osu district as a whole. However, the impact may be negative for those facilities in streets that will experience increased competition, and thus some consideration will need to be given to this fact.

5. Conclusion

ASSA deals with downtown visitor shop-around spatial behaviors. From the viewpoint of a constructive approach of'human-like' agents, an integration of bounded rationality and feedback modifications of the agent's behaviors were explained as the key ideas of this ASSA study. Dynamic scheduling is one of the key features of ASSA, as well as the improvisation of the downtown visitor actions within the time-budget, as opposed to the existing Markov-type models.

The key essence of ASSA design are a layered-decomposition of shopper agent's behaviors and a formulation as constraint-satisfaction problem, in comparing with the existing approaches. When considering further research, we would like to refer to two topics. One is the relaxation of the 'completeness of the mental map', so in such cases, a utility function inside the shop-around agent would be required, though we have already devised a theoretical consideration by introducing fundamental consideration of decision sciences (Kaneda and Yoshida, 2012). Another is the parameter tuning problem. In our ASSA study, several of the parameters were tuned up in an ad-hoc manner. Artificial Intelligence aided statistical estimation methods are expected. The latter is our current largest weak point to be solved.

Through these revisions, we conclude that ASSA would become a more useful policy and planning simulation tool.

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