

A Simulation of an Incentive-Based Human Flow Navigation in Cities

Ko OSHIMA^{a,1}, Daishi SAGAWA^a, Tomoki INOUE^b, Michael DZIOMBA^b and Kenji TANAKA^{a,c}

^a*School of Engineering, The University of Tokyo, Japan*

^b*GRID INC., Japan*

^c*Institute for AI and Beyond of the University of Tokyo, Japan*

Abstract. There has been a growing interest in transdisciplinary approaches to improve the added value of cities, such as smart cities. To add value to a city, not only the hard infrastructure but also the soft systems are important. Systematic distribution of incentives such as the holding of events and the issuing of coupons is significant as a means of creating liveliness in cities. This paper proposes a system that supports effective incentive selection using a human flow simulator. A part of the city, including a station and commercial facilities, is reproduced on the simulator by modeling the customer behavior based on actual data. We simulate the behavioral paths of individual customers with different incentives. The list of the incentives is proposed and the result of the simulation suggests insights for the selection of the appropriate incentive to improve sales and the liveliness of the city as a whole.

Keywords. human flow simulation, smart city, incentive design, digital twins, model curation

Introduction

Methods that add value to cities, such as smart cities, are attracting attention. For example, sharing mobility and energy management systems have the potential to make life more convenient, stimulate the local economy, and increase the population. This requires not only a hard approach, but also a soft approach to managing the flow of people, goods, and energy. Among these, managing the flow of people is important in creating a lively city. One of the soft approaches to managing human flow is to navigate the flow of people by providing incentives.

In particular, issuing incentives to attract customers in commercial areas within a city is important because it is directly related to the sales and the liveliness of the local economy. Incentives for commercial facilities include issuing coupons, holding events, and installing new facilities such as children's playgrounds.

It is difficult and time-consuming to verify which incentives are effective to issue and where by implementing multiple measures in the real world. Compared to it, it is efficient to build a simulator and use it to verify the effectiveness of issuing different incentives.

¹ Corresponding Author, Mail: oshima625@gmail.com.

1. Previous studies

Research on the simulations targeting commercial facilities often focuses solely on building simulators close to reality and its utilization for the simulation to attract more customers is not fully examined. Yasufuku et al. constructed a shopping model of customer agents in a commercial facility based on the purchase history data of membership cards [1], but this model is not scalable to towns outside commercial facilities because its model can be only applied to where sales data can be obtained. Mizuta et al. used distributed parallel execution to handle a large number of customer agents moving through a shopping mall [2]. Liu et al. validated an interaction model between customers in a commercial facility using indoor positioning data [3]. Shenk et al. simulated customer behavior at a macro-regional level [4], but not the individual behavior of each customer.

The common usage of these simulators is for evacuation planning purposes. Han et al. used evacuation simulation software Pathfinder to simulate the evacuation behavior of a commercial facility in Xi'an [5]. Bottlenecks were identified and improvements were proposed and verified.

Studies that have attempted to induce people flow have mainly been done by issuing coupons, and multiple incentive options have not been fully explored; Wang et al. proposed a system to issue discount coupons to balance customer flow within commercial facilities [6]. Ieiri et al. defined store attractiveness values and conducted a demonstration experiment using a street walking application that distributes points and money coupons so that the store attractiveness values of each store in a shopping district remain balanced [7].

The purpose of this paper is to construct a system to support the determination of which incentives should be issued and where, in order to revitalize a town centered on commercial buildings. The approaches to achieve this are 1. construction of a simulator using GPS data, and 2. simulation of navigating people flow through incentives. To construct the simulator, not retail data as in the past study but GPS data is used. This can be used to determine the number of people passing places other than commercial facilities, such as train stations, and will have scalability to the entire city, starting from commercial facilities.

2. Proposed Simulator

2.1. Data

The input data includes both GPS data and a map of the target city. For the case study in Chapter 3, we use point-based population flow data provided by Softbank Corp. This data is based on GPS and other location data obtained from smartphones, with confidentiality processing applied. The data consists of `user_id`, location information (latitude and longitude), and time. The user id is updated at 0:00 every day, so it is not possible to track users across days, but it is possible to track users' activities within a day. The average interval between acquisitions of location information is 6 minutes. The user destinations that can be acquired are not complete.

A City map consists of agent-generating locations like stations, corridors and buildings/parks along which the agents move.

2.2. Modeling of human behavior

2.2.1. Generation of agents

Agents are generated from the station according to the time of day. The number of agents generated per time is determined from GPS data. Based on the latitude and longitude of the station area, the time at which each user first passes through the station area is tabulated. The simulator generates agents according to the ratio of the number of people in each time.

The generated agents can have attributes such as gender and age, as well as multiple destinations for their actions. Attributes are set based on the demographics of the target area. Planned destinations of visits are determined based on the distribution of the number of buildings visited per day and the number of people visiting based on GPS data. Agents move and visit the allocated planned destinations sequentially.

2.2.2. Move of agents

Each agent has a list of planned destinations at the time of generation. Each time a agent generated at the station reaches a parting of the ways, it chooses a path based on the relationship between the next planned destination and its current location. The agent chooses a path that is not the one it has walked on before and that does not move away from its planned destination. If two or more paths satisfy this condition, one is selected from them at random.

2.2.3. Entering the building

In the case study, human behavior is simulated in an area of town that includes a commercial facility. There are two major patterns of customer entry behavior: one is planned entry, in which customers enter a building with a purpose, and the other is unplanned entry, in which customers enter a building based on their interest when they wander past the store [8].

Each time an agent passes through the entrance of a building, it makes an entry decision. If the building it passes is the first building on the target visit list, the agent enters the building. Upon entering the building, the building is removed from the top of the planned destination list.

If the building is not at the top of the list, the agent determines whether or not to make an unplanned entry. Whether to make an unplanned entry for each building is determined by the entry judgement value E below.

$$E = S_{entrance} + S_{weather} - TimeValue * T_{stay} - Fatigue * T_{area} - Revisit \quad (1)$$

$S_{entrance}$: Score to enter and shop at the building

$S_{weather}$: Score when they enter the building while it's raining.

$TimeValue$: The value of time of each agent per hour

T_{stary} : The length of time when each agent stay at the building

$Fatigue$: The fatigue score agents accumulate per hour and get unwilling to enter building

T_{area} : The length of time that has passed since the agent was generated

Revisit : The extent of unwillingness that agents have when they have already visited the building on that day.

When entry judgement value E is larger than 0, the agent makes an unplanned entry to the building. After entering a building, the agent stays in the building for 15 minutes. After exiting the building, the agent starts moving toward the next planned destination.

2.2.4. End of movement

After visiting all planned destination stores, the agent moves to the station as the last destination. Upon arrival at the station, the agent terminates the action.

2.2.5. The measurement of the result

The results of the simulation will be measured by the number of visitors to each building and the total number of visitors to all buildings in the entire city. A higher number of visitors to buildings means that the city is more active, which can lead to an increase in sales at commercial establishments.

2.3. Incentive based human flow navigation

2.3.1. Simulation of different types of incentives

Inducing people to flow through incentives is important for creating a bustling town or revitalizing commercial facilities. There are various types of incentives. Figure. 1 shows a summary of incentives by the incentive issuer and area of influence that considers the ripple effect.

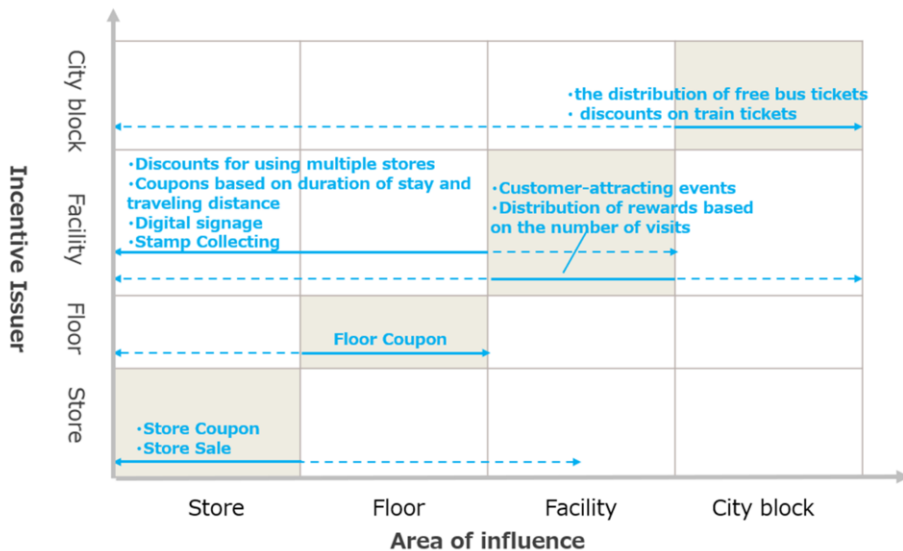


Figure 1. List of incentives for navigation of human flow

The most typical incentive is the issuance of coupons by individual stores. Coupon discounts are used to induce customers to visit specific stores. The typical incentive by a facility is the holding of customer-attracting events. This is expected to have a ripple effect not only on this facility but also on individual stores and the entire city block. At the city block level, incentives such as the distribution of free bus tickets or discounts on train tickets could be employed. These are expected to have a ripple effect on individual facilities and stores, and even if these measures are costly on their own, they are likely to be economically viable when the ripple effect on stores is taken into account. The first item to be examined is which of these various types of incentives should be selected in consideration of the ripple effect.

In the case study, three cases are compared: one in which there was no incentive, one in which coupons were issued at individual buildings and added to the agents' planned destination list, and one in which rail discounts were offered and the number of visitors increased. Simulation with other incentives will be performed in future work.

The simulation is performed under the following assumptions. The effectiveness of coupons is different depending on the contents and message. One of the most successful coupons is the one that offers free distribution of sampling goods. In a case study, its redemption rate is 16.78%. [9] We assume 16.78% of visitors will visit the target building as their destination with the issuance of the coupon. We also assume train discounts increase the number of agents generated by the station by 20%..

2.3.2. Simulation of incentives for different locations

We examined the effect of the same type of incentive in different locations, comparing the number of visitors to each facility when the coupon issuance is conducted in Building 1, near the station, and in Building 6, away from the station.

Simulations are conducted under the following assumptions. It is assumed that agents visiting the city have a 16.78% probability of visiting the target building due to the effect of the coupon.

By comparing the change in the cumulative number of visits to each building in the city, a study was conducted on the impact of different incentive issuance locations on the total number of visits to the city as a whole.

3. Case study and result of the simulation

3.1. Assumptions of the simulation

The target of this case study is the area around station X in Japan. The target area includes the station, the central park, and the commercial facilities from Building 1 to Building 6 surrounding the central park. Each of the buildings from Building 1 to 6 has several tenants in it. There are various ways to visit the area around the station, such as by train, bus, bicycle, and on foot. Focusing on visitors who come to the area by train, which is the most common mode, agents are set to get originated from the station.

GPS data was provided by Softbank Corp. Simulations are performed assuming a sunny holiday; data for all Saturdays, Sundays, and holidays in November 2020 were used.

Users meeting the following conditions were selected to calculate the distribution of the number of people who first passed through the station at different times of the day and the number of visits to the building.

1. passing through the station area after 9:00 AM
2. Staying in one of the buildings 1~6 area

Figure 2. shows the distribution of the time of the first appearance at the station. Agents are generated based on this distribution in the simulation. Figure 3. shows the distribution of the number of the destination. This is used to determine the length of the planned destination list. A planned destination is assigned to each agent at the point of its generation based on the distribution of visitors at each building.

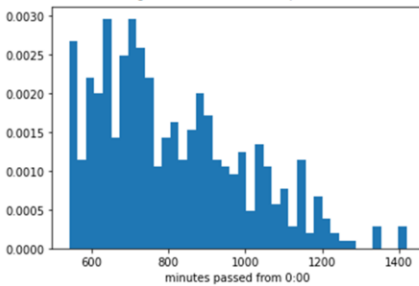


Figure 2. Distribution of the time of the first appearance at the station.

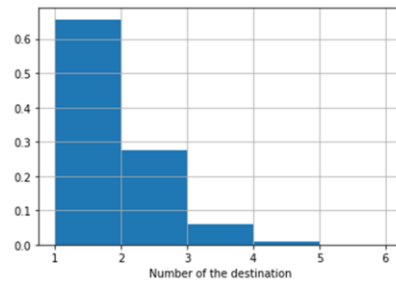


Figure 3. Distribution of the number of the destination.

Table 1 shows the values for the storefront entry decision model. The value of $U_{weather}$ is 0 if it's not raining. The value of $Incentive$ is 0 if not coupons are issued. The value of $TimeValue$ and $Fatigue$ are different depending on the age group of each agent. Based on the visitor data, the agents' age group is determined randomly with the probability on the table.

Table 2 shows the value of $S_{entrance}$ for each building. Its value is assumed to be in proportion to the total floor area of each building.

Table 1. The values for the storefront entry decision model for each age group.

Age Group	Ratio[%]	$S_{weather}$	$TimeValue$	$Fatigue$	$Revisit$
Young	39.5	300(rainy) / 0(not rainy)	1500 ± 50%	$f \pm 50\%$	500 / 0
Middle-aged	53.9	300(rainy) / 0(not rainy)	2000 ± 50%	$2f \pm 50\%$	500 / 0
Old	6.6	300(rainy) / 0(not rainy)	500 ± 50%	$4f \pm 50\%$	500 / 0

Table 2. The score to enter and shop at each building.

Building Number	Calculated Total Floor Area	$S_{entrance}$
1	2769	$1.45u \pm 50\%$
2	1905	$u \pm 50\%$
3	14541	$7.63u \pm 50\%$
4	5103	$2.68u \pm 50\%$
5	21675	$11.38u \pm 50\%$
6	27351	$14.36u \pm 50\%$

3.2. Results of the simulation and validation of the simulation results

The number of agents was set to 200 and the hours were to be 9:00-18:00. Simulations are performed repeatedly with the different pair of values of f and u . f and u are set to the values in increments of 50 from 50 to 300.

The simulation results for each building were compared with data on the number of real visitors per building for the holidays in November 2021, which was provided by the commercial facility operators. Every time simulation is performed with a different set of f and u , the correlation coefficient was calculated. The best pair of f and u is $(f, u) = (100, 250)$ with the correlation coefficient being 0.785. Figure 4 shows the relationship between the number of visitors on the simulation and the actual number of visitors.

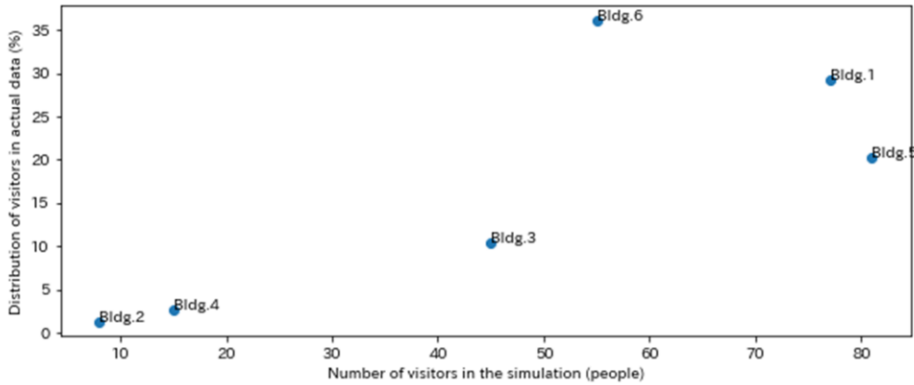


Figure 4. The relationship between the number of visitors in the simulation and the distribution of visitors in actual data.

Figure 5 shows the simulation in progress, and Figure 6 summarizes the number of people visiting each building in one day.

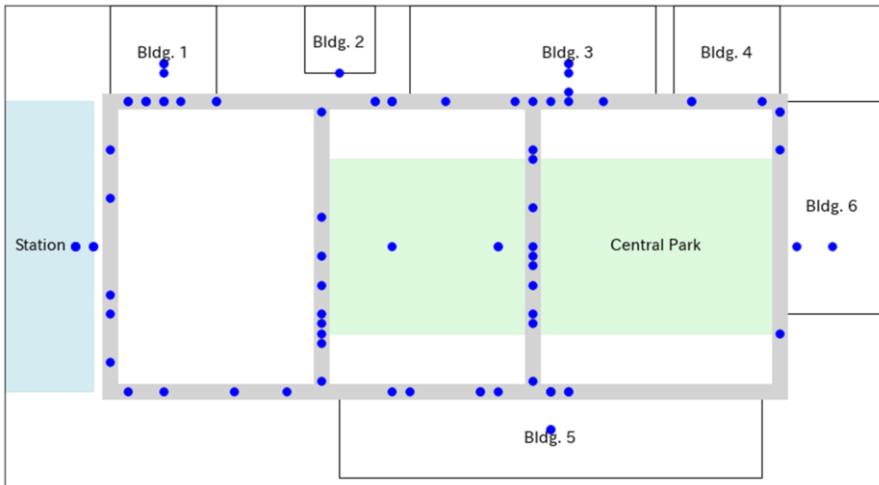


Figure 5. Visualization of the simulation.

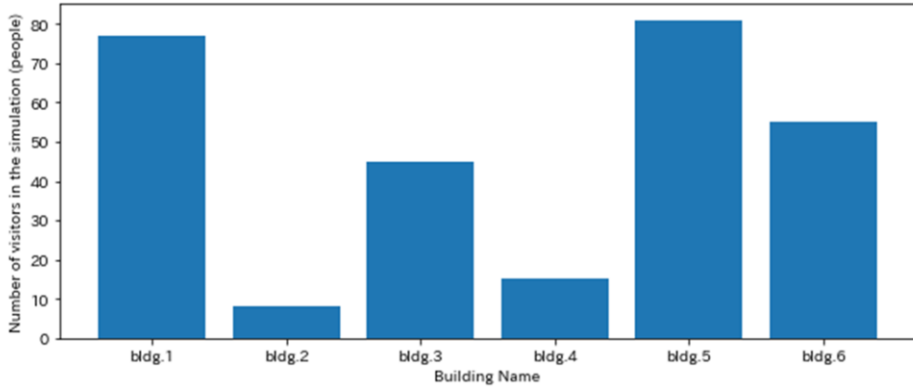


Figure 6. Number of the visitors for each building on the simulation.

3.3. Results of the simulation with incentive-based human navigation

As a comparison of incentive types, simulation was conducted for the case where coupons were issued in Bldg. 5 and a train discount was offered. The number of visitors per building is shown in Figure 7.

The train discount increased the number of visitors to each building except Building 2. The issue of the coupon increased the number of visitors to Building 5, but it also increased the number of visitors to other buildings in the vicinity, indicating a ripple effect.

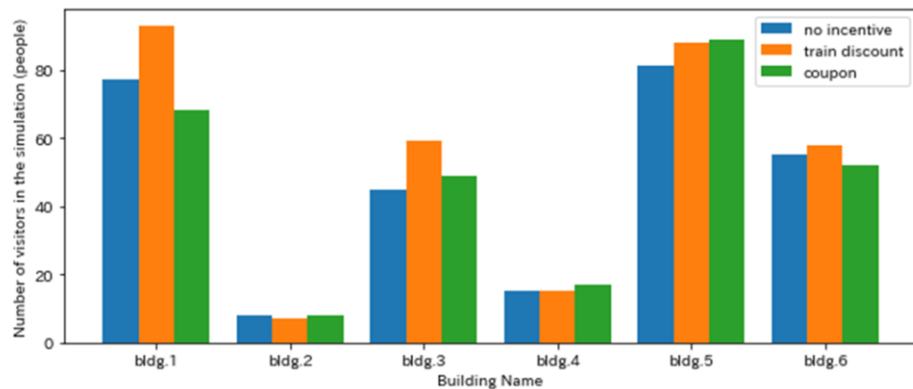


Figure 7. Comparison of the simulation results with different incentive types.

As a comparison of incentive issuance locations, coupons with a 16.78% response probability were issued in Bldg. 1 near the train station and in Building 6, the building farthest from the train station, and its difference were compared. The results are summarized in Figure 8.

The total number of visitors to the buildings in the entire city was greater when the coupon was issued at Building 6 than when the coupon was issued at Building 1. This is

thought to be because the coupons were directed to the further side of the building, away from the station, which lengthened the time spent by customers and had a ripple effect on the other facilities.

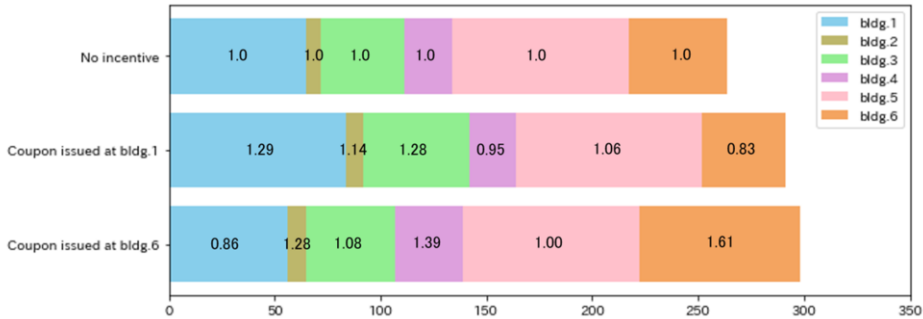


Figure 8. Comparison of the simulation results with coupons issued for different locations.

4. Conclusions and outlook for the future research

This paper proposed a method of constructing a human flow simulator for an area containing commercial facilities and a method of navigating human flow with incentives. The simulator was constructed based on GPS data. Its parameters were tuned to be correlated to reality. It was observed that the issuance of incentives had different ripple effects depending on the type of incentive issued and the location of the incentive. In particular, it was found that issuing incentives at more distant locations increases customer circulation and activates the entire city. This paper uses a transdisciplinary approach of multiple fields like multi-agent simulation, GPS data analysis, smart city and digital twins.

The simulator proposed in this paper can be used to verify the effectiveness of store layout and changes in the design of roads. One of the values of the simulator is that it is possible to see not only the results of the number of visits but also which paths the agents are moving along.

In this simulation, the simulator was built based on GPS data, and assumptions were made for data that was difficult to obtain. This year, it is planned to actually install beacons around Station X and issue incentives to conduct demonstration tests in this city. Based on the data that will be obtained, the assumptions of the simulation will be further refined and validated in the future. This case study only takes into account the age group of visitors but did not take other attributes and visitors coming from outside the station into account, but these factors will be taken into account in the future to build a simulator closer to reality.

Acknowledgement

The authors are grateful to Odakyu Electric Railway Co., Ltd., Softbank Corp. and GRID INC. for providing data and giving advices for this research. This research was carried out under the support of Institute for AI and Beyond of the University of Tokyo.

References

- [1] K. Yasufuku, Development of Data-Driven Agent Model for Consumer Shopping Behavior in Commercial Facility. *Advances in Intelligent Systems and Computing*, Vol. 1296, 2021, pp. 175–85.
- [2] H. Mizuta, Large-Scale Distributed Agent-Based Simulation for Shopping Mall and Performance Improvement with Shadow Agent Projection. *Proceedings of the 2017 IEEE Winter Simulation Conference*, Article 86, 2017, pp. 1–12.
- [3] Y. Liu et al. Indoor Mobility Interaction Model: Insights into the Customer Flow in Shopping Malls. *IEEE Access*, vol. 7, 2019, pp. 138353–63.
- [4] T.A., Schenk, et al., Agent-Based Simulation of Consumer Behavior in Grocery Shopping on a Regional Level. *Journal of Business Research*, Aug. 2007, vol. 60, no. 8, pp. 894–903.
- [5] F. Han, et al. Pathfinder-Based Simulation and Optimisation of Personnel Evacuation Modelling of a Shopping Mall. *Journal of Physics. Conference Series*, Jan. 2021, vol. 1757, no. 1, p. 012112.
- [6] L. Wang et al. Blockchain-Based Diversion-Point System for Balancing Customer Flow in Shopping Mall. *Symmetry*, Nov. 2020, vol. 12, no. 12, 1946.
- [7] I. Yuya et al. “Proposal on incentive design for activation of shopping street using city walk application, *Proceedings of the Annual Conference of JSAI*, 2018, <https://confit.atlas.jp/guide/event/jsai2018/subject/1B1-OS-11a-01/date>, accessed June 20, 2022.
- [8] J. Dijkstra, et al. Modeling Planned and Unplanned Store Visits within a Framework for Pedestrian Movement Simulation. *Transportation Research Procedia*, vol. 2, Jan. 2014, pp. 559–66.
- [9] P.J. Danaher, M. Smith et al. “Where, When, and How Long: Factors That Influence the Redemption of Mobile Phone Coupons. *Journal of Marketing Research*, 52(5), Feb 2015, pp. 710–725.