Effects of Station Location and Capacity for Personal Mobility Sharing

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Abstract — In this study, we consider the sharing of standing-type personal mobility devices. Such devices have various advantages as a means of transportation, but their cost makes sharing more attractive than owning. Sharing personal mobility devices is expected to have social influences such as a modal shift; however, this is not yet apparent. Consideration of the effects based on a multi-agent simulation is useful, and in a previous study, we showed the preliminary results of such simulation. In this study, we extend the simulation and investigate the effects of the location and capacity of personal mobility sharing stations. The results suggest that a location change largely affects the traveling distance. Such a simulation will provide a basis for the future demand prediction and planning of personal mobility sharing.

Keywords — Personal mobility, Sharing, Simulation, Mobility robot

I. INTRODUCTION

One and a half decades have passed since the Segway Personal Transporter was introduced in 2001 [1]. In the meantime, other analogous mobility devices such as the AIST Micro-Mobility Device [2] and Toyota Winglet [3] were introduced. Their main usage is quite limited so far: touring for sightseeing or patrolling purposes. However, other applications of the personal mobility devices as means of transportation will emerge. They have certain advantages for urban use because they are efficient and environmentally friendly. In addition, their low speed contributes to the avoidance of fatal accidents. Furthermore, they are well suited to the recently advocated concept of compact cities [4], [5]. In this study, we simply refer to such standing-type, self-balancing personal mobility devices as PMs.

On introducing such PMs in the community, sharing is more probable than owning because it usually costs much less for both purchasing and maintenance. If PMs are introduced in a town, the human flow is changed and new behavior will emerge. PM sharing systems, however, have not yet been sufficiently studied.

In this study, we aim at considering the expected change in human behavior, especially a modal shift, by introducing a PM sharing system into society by means of a multi-agent simulation. As for the sharing of mobility, bicycle sharing has been studied [6], [7], [8] and has recently become popular in large cities. Vélib’ in Paris [9], Santander Cycle in London [10], and Capital Bikeshare in Washington, D.C. [11] are examples of successful systems. In both cities, bicycles are rented at sharing stations and can be returned to any station among many in the city. A PM sharing system is different from bicycle sharing in the following ways. PMs require charging time between uses. In addition, the efficiency of usage is important because providing PMs usually costs more than providing bicycles. The sharing of other mobility devices is studied in, e.g., [12], [13].

We have been studying the sharing of PMs and have conducted its simulation [14], [15]. In the hope of large-scale demand prediction and optimal planning of both location and capacity of PM stations, as well as the number of PMs, we have developed a prototype multi-agent simulator. The behavior of mobility decisions is modeled by the nested logit model [16]. The supposed scenario for simulation is the traveling behavior of employees of our institute (AIST) for business trips between AIST and the nearest train station.

We have developed a prototype simulator and conducted a preliminary simulation. In this study, we examine the effects of the location and capacity of PM stations. Such simulation will provide a basis for future demand prediction and planning of PM sharing.

II. PERSONAL MOBILITY SHARING SIMULATOR

A. PM Sharing

In this section, we review the simulator of personal mobility sharing in [15]. It was based on a multi-agent model with potential flexibility in its configuration for individual agents with different characteristics of walking speed, riding speed, and mobility preference attributed by age, gender, etc. Moreover, various behavioral phenomena arising due to the limited number of PMs and capacity of PM stations and their effects on renting and returning were naturally treated.

PM sharing is different from bicycle sharing in the following respects.

1) Charging time is required. When the mobility device is returned to a sharing station, depending on the riding distance or time of the previous user, some charging time is necessary before it is rented to another user.
2) Seamless PM riding between indoor and outdoor environments is possible. This can sometimes be useful for visiting shopping malls, museums, etc.
3) PMs can be carried easily in other transportation modes such as trains and cars. Such usage expands the PM’s range of operation.

4) Since PMs are equipped with information processing capability, assistance by an IT infrastructure will be easy.

A schematic of the overall framework, including behavior and decision models, is shown in Fig. 1. Photographs of the simulator are shown in Fig. 2.

The parameters of the behavior and decision models for the simulator were decided by experiments in the Mobility Robot Experimental Zone, in Tsukuba [17], and by a questionnaire. The simulations were conducted using these obtained values. Through the feedback of such information, the behavior and decision models can be refined. Once a simulator with these models is thoroughly developed with the geographic, traffic, and OD information of Tsukuba, presumably, the same approach can be applied to other cities by providing the relevant local information. Then, simulation can be conducted for the demand prediction or planning of the optimal assignment of PM stations.

B. Decision Model

To model the user behavior, we needed to build some sort of decision model. We adopted the nested logit model [16], [18]. For this model, we assumed that the possible mobility candidates were PMs and two types of buses. Each candidate was assigned a choice probability, and depending on the probability, one of them was stochastically chosen as follows.

For each choice of mobility, its representative utility was calculated. It was defined by several aspects. As in the conducted experiment, we assumed only one type of agent with the same representative utility. We assumed a category of mobility $C = \{c_{bus}, c_{PM}\}$, and each category represented $c_{bus} = \{m_{AIST} \text{ and } m_{public}\}$, $c_{PM} = \{m_{PM}\}$. The utility function $V_{m|c}$ for mobility $m$ in category $c$ was assumed to be a weighted sum of factors such as distance, estimated required time, estimated delay time, and preference of main transportation mode:

$$V_{m|c} = \beta_1 x_{m|c,1} + \beta_2 x_{m|c,2} + \cdots + \beta_N x_{m|c,N}.$$  

The details of these parameters are described later.

Depending on the representative utility, the choice probability $P_{m,c}$ of mobility $m$ in category $c$ was defined as the product of the probability that category $c$ was chosen and the conditional probability that $m$ was chosen in category $c$ as follows:

$$P_{m,c} = P_{m|c} \cdot P_c = \frac{\exp(V_{m|c})}{\sum_{m'\in c} \exp(V_{m'|c})} \cdot \frac{\exp(\lambda I_c)}{\sum_{c'\in C} \exp(\lambda I_{c'})},$$

where

$$I_c = \ln \sum_{m\in c} \exp(V_{m|c}).$$

The actual parameters, $\lambda$ and $\beta_i$, for this model were obtained by conjoint analysis based on a questionnaire.

C. Behavior model

We adopted a simple behavior model. In the simulator, each agent is generated at some designated time with start and goal positions, and then each agent stochastically decides its behavior using the decision model. If the agent chooses a bus, for example, it walks to the nearest bus stop, waits and gets on a bus, gets off the bus at the bus stop close to its goal points, and walks to the goal. The free-flow speeds for walking and riding PMs are given; however, the actual speeds in the simulation decrease depending on the ratio decided by the attributes of the agent and the density of pedestrians on the same road segment. Buses are assumed to arrive on time, and only the expected maximum delay time is used in the decision model. Here, we assumed that each agent that is walking or riding PMs chooses the shortest path to the goal points or target PM/bus stations for the calculation of utility.
III. SIMULATION SCENARIO

The supposed scenario for simulation focuses on the traveling behavior of employees of our institute (AIST) on a business trip, traveling between AIST and the nearest train station. The distance is about 3.8 km. The road network is given as a shapefile. We assumed two types of buses: the AIST shuttle bus and a public bus, with capacities of 20 and 50 passengers, respectively. The actual fare (260 yen) of the public bus was also used. In the simulation, we used actual timetables of buses (the 34 and 59 routes for the AIST and public buses, respectively, during the simulation period) and actual locations of bus stops. We assumed five location candidates for PM stations, and in each simulation run, two of them were used to examine the effects of their location. These five locations, designated as A, B, C, D, and E, were located at nearly equal intervals. Location A (and E) were the nearest to Tsukuba station (and AIST, respectively). These locations are shown in Fig. 3.

We used the parameters in [15], obtained from actual data by outdoor sharing experiments in the Tsukuba Mobility Robot Experimental Zone, using a Toyota Winglet. In the decision model, two buses were in a single nest. The values for $\beta$ are shown in Table I and $\lambda = 0.785$. Here, the parameters from $\beta_1$ to $\beta_4$ and from $\beta_9$ to $\beta_{15}$ were used for the corresponding cases.

IV. SIMULATION

A. Simulation Settings

The main parameters of the behavior model are as follows. The free-flow speed of walking was 4 km/h. Getting on/off the PMs took no time. Moreover, we used a fixed time (15 min) for charging before a returned PM was rented to another user.

When there were no available PMs, users needed to wait for a PM to be returned. If any PM was not returned for a fixed amount of time (called maximum wait time), users gave up using PMs and chose another mobility mode (walking, in this case). The wait time actually affected the utility of PMs but estimating it in advance was difficult. Therefore, we conducted simulation several times (10, in this case) in one simulation run, with feedback of the resulting PM wait times. The following results are the average of ten simulation runs.

In this study, we focus on the effects of the location of PM stations. In our previous study, sharing stations were fixed so that each station was close to the origin or destination. In this study, we consider how the sharing of PMs is affected by both location and capacity of the PM stations.

Under such settings, simulations were conducted from 9:00 to 17:00 by changing the number of generated agents and PMs; the number of agents per hour was 5, 10, 25, and 50 in one-way travel (i.e., 10, 20, 50, and 100 both ways); the number of PMs assigned initially to each station was changed from 5, 10, 25, and 50 (i.e., 10, 20, 50, and 100 in total). Agents were randomly generated at the specified ratio in each simulation run. We assumed that the PM stations were large enough so that PMs could be returned to any station at any time.

In this simulation, the following parameters were fixed: the fare of the AIST bus was 0 yen (as is), the expected delay of both buses was 10 min, the maximum wait time for PMs and buses was 20 min, and the speed of a PM was 10 km/h.

Figure 3 is a snapshot of the simulations; the area shown is around Tsukuba Station, and circles represent moving

<table>
<thead>
<tr>
<th>Parameter</th>
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<tr>
<td>$\beta_1$</td>
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<td>$\beta_3$</td>
<td>preference to PM</td>
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<td>$\beta_4$</td>
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<td>walk and wait time (min)</td>
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agents.

B. Results

The resulting share of PMs is shown in Fig. 4 for various numbers of agents, PMs, and locations. We denoted the locations of PM stations by concatenating the location characters, e.g., locations AE denotes that PM stations are located at A and E. Note that we assumed that there were only sharing stations in each run and that returning PMs to the other three stations was not possible. The figure shows that PM sharing decreases as the number of agents increases. This drop becomes larger as the number of PMs becomes smaller. This phenomenon is due to the limited availability of PMs: agents will not likely choose PMs if they have to wait until one is available. Location also affects PM share. Among these locations, AE was the most convenient location, close to the origin and destination and covering most of traveling distance. Each of locations AB, BC, CD, and DE covered only about 25% of the overall route. At first glance, this graph shows that sharing does not increase even when a station location is inconvenient.

Figure 5 shows the average travelling distance of each PM unit in a single day under the same conditions. This figure shows the tendency that the average travelling distance of PMs increases as the distance between stations becomes increases, i.e., one trip requires a long distance and time. In many cases, the travelling distance for location AE is nearly double the travelling distance for short locations, such as AB, BC, CD, and DE. The results suggest that the appropriate location of PM stations is important for the efficient use of PMs.

V. DISCUSSIONS AND CONCLUSIONS

We presented a prototype multi-agent simulator for personal mobility device sharing and considered the effects of location and capacity of PM stations. Under this simple simulation setting, the locations of PM stations were characterized as the distance between the start and end stations, and as the distance increased, the usage was reduced. However, considering operational efficiency, one use for a long distance corresponds to multiple uses for a short distance, and operational efficiency over longer distance is more efficient. The results suggest that the appropriate location of PM stations is important for the efficient use of PMs.

One of the problematic aspects of sharing is that mobility device usage is not balanced and manual relocation is required. Some relocation methods have been studied [19], [20]. If we can introduce an autonomous driving capability without humans, such problems will be decreased: PMs will move to another empty sharing station in advance of anticipated demand. PMs are considered a good candidate for such capability because they are equipped with information capability and sensors.

There remains a significant amount of future work. First, the accuracy of the simulation is not clear, and the calibration of the results should be considered. Based on the calibration, refinements in both the decision and behavior models as well as in parameter values will improve the results.
We are currently conducting sharing experiments in a wider area with four PM stations. An extension to three or more PM stations reveals various potential problems corresponding larger simulation, which will make the research even more interesting. In this case, we will need to introduce other mobility candidates such as bicycles, trains, and private cars in the simulation. Unlike other means of transportation, PMs are suitable for moving around for pleasure. Such activity should be incorporated as well. Such a simulation will provide a basis for the future demand prediction and planning of sharing stations for a large scale introduction of PMs into society: the demands of PMs can be evaluated on the basis of more realistic assumptions, and the optimal planning of a PM sharing system will be envisioned.

REFERENCES