Multi-agent Simulation for Evaluating Demand Responsive Transport System

Fumitaka Kurauchi\(^1\) and Akira Harao\(^2\)
Dept. of Civil Engineering, Gifu University\(^1\) and NEXCO-Central\(^2\)
1-1 Yanagido, Gifu, 501-1193, Japan
email: kurauchi@gifu-u.ac.jp

Abstract—Through recent developments in information and communication technologies, dynamic monitoring and control of transport systems are technically possible. These technologies enable constructing more flexible and cost-effective transport services which may vary based on demand. Since passenger demand for public transports has been declining in rural regions, DRT (Demand Responsible Transport), which provides transport service in response to the requests, is expected to have an important role as new public transport system to fill the mobility gap between taxi and bus. The route and departure time of DRT changes according to each reservation. Therefore passenger’s mode choice influences on the service level. On the other hand, the mode choice is also influenced by the experienced service level. One might not want to use the DRT service any more if travel time is too long to accept in one day. After all, one’s decision making influences on others through the DRT system. To explore these phenomena, this study attempts to develop a multi-agent social simulation considering passengers’ mode and departure choice learning to evaluate the DRT service.

I. INTRODUCTION

Mobility is often a vital problem for older and disabled citizens. If the transport services available to them are not adequate these groups might become socially excluded. Avoiding social exclusion is one of the key policies in developed countries. On the other hand, as the needs and preferences for mobility have been diversified, it has become difficult to maintain the high level of service of the public transport system necessary to satisfy all types of users. In recent years, therefore, the usage of private cars is increasing, and the number of passengers using public transport is decreasing. In order to change this situation, the public transport service should be made more attractive and convenient.

Through recent developments in information and communication technologies, dynamic monitoring and control of transport systems are technically possible. These technologies would enable constructing more flexible and cost-effective transport services which may vary based on booking requests. Such transport systems are often called demand responsive transport (DRT) services and DRT has been developed as special transport services (STS), especially in European countries. Since the demand is quite low if DRT is used as STS, demand is often assigned manually. Nowadays however it is expected that DRT can be used as unlimited public transport services. For this purpose, the service characteristics of DRT services such as; how much demand is affordable with specific demand patterns, or how many vehicles with how much size are needed for sufficient service for the specific demand levels, should be identified. To explore the effectiveness of DRT services, a passenger assignment algorithm for DRT transport is needed.

Demand assignment algorithms for DRT can be regarded as a derivative of the TSP (Travelling Salesman Problem, [1]) and are often called as ‘Dial-a-Ride Problem (DaRP)’. Much of researches have been done for obtaining the optimal or approximately optimal solution for DaRP, but not much has been carried out to evaluate the service level of a DRT system as an alternative to ordinary fixed-route bus services. Moreover, the success of DRT may heavily rely on the travellers’ choice whether to use or not, and their decision may be made depending on the past experience and interaction among passengers. The travel time to the destination may get longer when other passengers will share the vehicle, and the level of service of DRT may decrease for all passengers. Considering the passengers learning behaviour and interactions among passengers as well as between passengers and service provider, this study attempts to develop the multi-agent simulation system for evaluating the DRT service.
II. EXISTING RESEARCHES FOR DRT SYSTEM

A. DRT in the world

Some papers have reported about the implementation and its effect of DRT system. For example, Westerlund[2] explains Flexline in Gothenburg, Sweden, which has been in operation since 1996. Flexline is originally introduced as special transport, but is now available to everyone to reduce unit costs of the existing shared taxi service (FareService) for disabled and older people. Booking requests was assigned manually at first but later an automated booking system has been introduced. In 2002, about 25,000 trips are made by FlexLine. There are several other systems like London Dial-a-Ride[3] or Odaka e-machi taxi[4]. There are various type of DRT systems and for example Motoda et al. has classified them into 27 types according to the route flexibility, schedule flexibility and bus stop flexibility[5]. Nowadays DRT is getting popular, but most of the services aim at either providing special transport services or providing minimum mobility in rural areas.

B. Demand assignment algorithm

In general, the objective function can be described as the summation of operator-side cost and passenger-side cost. Many researches have been conducted about the DaRP, and they can be categorised depending on the definition of the objective function, the booking/assignment type, and whether the model considers dynamic assignment.

One of the earliest and simplest works is carried out by Psaraftis[6], who proposed a method to assign many-to-many trips onto one vehicle. Then, Jaw et al.[7] developed an algorithm to solve the advance-request, multi-vehicle, many-to-many DaRP. Advance-request means that booking requests are collected and users can notice the pickup time. A First-Request-First-Assignment protocol is applied and a heuristic solution algorithm is proposed. Because of recent progress in computer technology, researches for DaRP largely increased in the 90s. The extensions are mainly made to apply efficient heuristic algorithms ([8], [9], [10], [11]).

The formulation and solution for the DaRP are explored so far and many researches have been made in the field of operations research. It can be said that the tool for evaluating DRT is ready, but not much research has been carried out to evaluate the service level of a DRT system as an alternative to ordinary fixed-route bus services. Noda et al. [12] tried evaluating the profitability of a DRT system compared to a fixed-route service. However, the assignment model used in their research does not consider constraints of time window, which discards the main advantage of DRT services. Recently, authors have evaluated the service level of DRT system using passenger assignment model [13]. The proposed model assumes the First-come-first-serve system and considers the time window constraints. We have validated that it is possible to evaluate the capacity of the service by the proposed algorithm.

The limitation of the above two researches evaluating DRT system is that they do not consider the passenger preference. If the fare is higher, it may discourage the usage and the system may not work. For this reason, the authors have proposed the game theoretic approach to explore the interaction between passengers and service operator [13]. This model considers the passengers mode choice whether to use DRT or not under the given fare system and the DRT operator tries maximising its revenue to decide the service level (number of vehicles and the fare). Since this game theoretic approach assumes the simple rational behaviour for passengers’ mode choice, the result may not truly reflect the actual passenger preference. It is therefore important to develop a multi-agent social simulation considering passengers’ mode and departure choice learning to evaluate the DRT system.

III. CHARACTERISTICS OF MULTI-AGENT SIMULATOR

The characteristics of multi-agent simulator can be summarised as follows;

1. It is enough to model local interaction of agents (bottom-up approach).
The strong assumption of social relationship may not be needed for the simulation but may educe as a result.

2. It is possible to discuss the emergence phenomenon.
Since the multi-agent simulator does not require assumptions on the total system and models only localised interaction, the unexpected result of whole system might 'emerge'. This phenomenon can not be obtained by the conventional top-down approach.

3. It is possible to assume bounded rationality of limited information for each agent.
This assumption relaxes the strict assumption of rational behaviour.

4. Individual heterogeneity can be considered easily.

5. Dynamic process can be reproduced.
Not only the final output but also the ‘trajectory’ to reach there can be observed.

6. Learning and adaptation behaviour can be modelled.
IV. DEVELOPMENT OF MAS FOR EVALUATING DRT SYSTEM

In this study, we developed the multi-agent simulation (MAS) system for evaluating the DRT system. MAS assumes the simple behaviour for each agent but is said that through the interaction among agents the behaviour of complex system can be expressed. We assume two types of agents; DRT operator agent and passenger agents.

A. DRT operator agent

In the real world situation, DRT operator has numerous options such as starting/quitting service, the number of vehicles in operation, scheduling, routing of vehicles and so on. In our current simulation, we assume that DRT operator serves door-to-door Semi-Dynamic DRT system which departs designated depot at the designated time and offers door-to-door services in response to the passenger demand. The choice of DRT operator in the current simulation is routing vehicles and whether to accept/reject the booking request from the passengers. The current acceptance/rejection rule is very simple and the operator will accept the demand if there is enough capacity in the vehicle, and will reject if not. Therefore, passengers do not know the actual travel time since the DRT route may change according to the booking receiving after their bookings. Booking time will be closed before the operation, and the DRT operator will choose the minimum cost route.

B. Passenger agents

We assume here that 1 passenger agent is living on each node, and he or she may make a trip with a certain trip generation probability. The destinations of passengers are assumed to be the same as the destination depot of DRT vehicle. We also assume here that the passenger has preferred arrival time and the scheduling cost is added as a penalty cost when he/she arrive earlier or later. The preferred arrival time is fixed through the simulation. Passengers have a freedom to choose DRT or not and they will use taxi when they decide not to use DRT. They know the scheduled departure time of DRT vehicle but the travel time for each DRT vehicle is not fixed and uncertain because of detouring. We assume the simple learning process for the passenger to forecast the travel time of DRT service.

\[
t_j^p \leftarrow t_j^p + \alpha(t_j - t_j^p)
\]  
(1)

Where \(t_j^p\), \(t_j\) and \(t_j^p\) are updated perceived travel time, previous perceived travel time and experienced travel time at this time, respectively. The learning parameter, \(\alpha\), represents how important the previous experience is, and takes a value between 0 and 1. Passengers learn travel time independently and information sharing among passengers is not assumed currently.

Based on the above perceived travel time, passengers will decide whether to use DRT as well as which service in terms of depart time to use. Based on scheduling cost, perceived travel time and fare, the mode as well as service of minimum generalised cost is chosen.

Passengers also have to decide when they make a booking since if the demand is high, the request might be rejected because of full capacity. To represent this, we assume a simple algorithm. The reconsideration of booking timing will occur every five days, and passenger will advance the timing if the rate of rejection is above a certain threshold, and recede the timing if the rate of rejection is below another threshold.

The overall interaction of agents can be summarised as Figure 1, and whole procedure of the simulation can be summarised as Table 1. The simulation is coded by one of the object-based RAD software, Borland Delphi®.

V. CASE STUDIES BY HYPOTHETICAL GRID NETWORK

A. Simulation setting

Case studies are carried out on 5 x 5 grid-type
network shown as Figure 2, where the DRT origin depot is located on the top left, and its destination depot on the bottom right. Travel time and vehicle running cost for each link is set to be 3 minutes and 100 yen, respectively. Three DRT services are scheduled every one hour at 10:00, 11:00 and 12:00. Preferred arrival time is same for all passengers and set to be 12:30. DRT operator uses only 1 DRT vehicle with the capacity of 4 persons. We iterate 500 days for each simulation run, and 50 simulation runs are carried out and the results are evaluated by the average of these 50 runs. Booking is only available from 7:00 to 9:30 in the morning, and travellers advance/recede booking time by 15 minutes. Learning parameter is set to be 0.2, and the penalty function is shown as follows:

\[
g(x) = \begin{cases} 
200x & x > 0 \\
0 & x = 0 \\
-10(x+10) & x < 0 
\end{cases} \quad (2)
\]

Taxi fare is assumed to be so expensive that passengers may only use when all DRT services are unavailable.

B. Differentiation of service share

We discuss here how DRT services are used under different demand setting. Trip generation probability is set to be 0.1, 0.5 and 0.9, respectively and the difference of DRT usage is discussed by the DRT service share calculated as follows.

\[
r_{ij} = \frac{t_{ij}^d}{t_{ij}^c} \quad (3)
\]

Where, \(t_{ij}^d\) represents the number of trips passenger \(i\) used the \(j\)th DRT service and \(t_{ij}^c\) is the number of total trips made by passenger (or node) \(i\). Figure 3a, 3b and 3c show the result of three demand cases. When the trip generation probability is low, since using DRT is cheaper than taxi, all passengers can move by DRT. The sum of service share is therefore 1.0 in this case. When the generation probability increases to 0.5 or 0.9, the DRT mode share declines. This is because some requests are rejected because of the full vehicles.

Judging from the figure 3b or 3c, it is interesting to say that passengers tend to be differentiated automatically especially to either 10:00 or 11:00 service. The spatial distribution of service share is further investigated. Figures 4a, 4b and 4c represent the spatial distribution of the service share for 10:00, 11:00 and 12:00 service, respectively, in the case when the demand generation probability is 0.5. It is clear that passengers living along the shortest route for DRT vehicle from origin to destination depot such as nodes 2, 6, 7, 13, 19, 20 and 24 tend to use the 12:00 service, and other passengers living outskirt of the area such as nodes 4, 5, 10, 16, 17, 21 and 22 are likely to use the 11:00 service, the earlier one. This may be because travel time may increase when DRT vehicle picks up passengers apart from shortest route, and the 12:00 service may not arrive before 12:30 when the vehicle picks up such passengers. This result seems to be similar to segregation model by Schelling [14], and may not be adequate as a public service.

This case study suggests that the equity of DRT service may not be pursued, and public intervention may need to carry out equitable services. One of the possible reasons for this result is that we do not consider the fare of DRT service. By the strategic fare structure, this problem may be resolved.

C. Demand condensation by share-ride fare discount

Another case study to discuss the efficiency of strategic fare structure has carried out here. It is common to introduce such DRT system in the rural area. In these cases, not a capacity but empty seats of the vehicle may be a problem. It is therefore preferable to encourage passengers who do not have tight time constraints to shift to the service that other passengers may want to use. Then some of the services may be cancelled and the operation cost reduces. To encourage this condensation, we evaluate fare discount by sharing ride (share-ride fare discount) here.
either preferred arrival time of 10:30, 11:30 or 12:30 with the equal probability of one third. Penalty function of scheduled cost is calculated as follows.

\[
g(x) = \begin{cases} 
5x & x > 0 \\
0 & x = 0 \\
-5(x + 10) & x < 0 
\end{cases} \tag{4}
\]

The parameter for the penalty is very small in this example to encourage the temporal shift. We consider two fare structures. For the first scenario, the DRT fare is set to be 700 yen per person and unchanged even somebody share the ride. For the second scenario, the DRT fare is set to be 1,500 yen per service, and this fare can be paid by the passengers who share the ride. Therefore the fare will be cheaper than the scenario 1 if more than 2 passengers share the ride. Running cost for DRT vehicle is assumed to be 150 yen/km here to discuss the cost efficiency of this fare system. Demand generation probability is set to be 0.1 in this case study. 500 iterations are carried out. Taxi is assumed again to be so expensive to use. Since the service fare may change every day by the number of passengers, we assume that passengers also create the 'perceived' fare of each DRT service. Similar to travel time of DRT, the perceived fare is updated as follows.

\[
f_j^p \leftarrow f_j^p + \alpha(f_j^p - f_j^0) \tag{5}\]

Figure 3. Service share by different generation probability

Table 2 shows the comparison of two scenarios. For the first scenario, 827 services out of 1,500 (55%) have been operated, and operation cost per passenger

a. Demand generation probability = 0.1

b. Demand generation probability = 0.5

c. Demand generation probability = 0.9

Figure 4. Spatial distribution of service share (Trip generation probability = 0.5).
is 573.2 yen. For the second scenario, only 650 services are operated, and almost 20% of services have been cancelled. By this, the operation cost per passenger reduced to 512.7 yen (-10%). This result suggests the efficiency of proposed share-ride fare discount scheme.

Table 2. Calculation result for different fare strategy.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Number of operated services</th>
<th>Total operating cost</th>
<th>Operating cost per passenger</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed fare</td>
<td>827</td>
<td>710,200</td>
<td>573.2</td>
</tr>
<tr>
<td>Fare discount by share-ride</td>
<td>650</td>
<td>576,800</td>
<td>512.7</td>
</tr>
<tr>
<td>Differences</td>
<td>-177</td>
<td>-133,400</td>
<td>-60.5</td>
</tr>
</tbody>
</table>

VI. SUMMARY

This study developed the multi-agent simulation system to evaluate Demand Responsive Transport services. Main motivation of developing a simulator is to express the interaction of behaviour among passengers as well as DRT operator and passengers. The behaviour of passengers and DRT operator is assumed to be very simple but the interaction among them can be explored.

Through the case studies on the hypothetical network, the differentiation phenomenon that is similar to the segregation phenomenon was observed. The current simulation does not allow DRT operator to pick up preferable passengers for them (cherry-picking). Larger differentiation may occur if DRT operator can choose which passengers to pick up. It is therefore found that DRT service may be limited to the specific passengers, which is not preferable for public transport system. Another case study explores the effect of share-ride discount fare where the total fare for a service is fixed and the fare is divided by the number of passengers. The more the passengers are, the cheaper the individual fare is. As a result, it is expected that passengers may condense to the specific passengers, which is not preferable for Demand Responsive Transport services. Also the simulation result should be explored more in detail especially to explore the interaction of agents.

Running a simulation using practical data is of course a future challenge.

ACKNOWLEDGEMENT

This research is supported by the Ministry of Education, Science, Sports and Culture, Grant-in-Aid for Young Scientists (A), 2006-2008, 18686042.

REFERENCES