An Adaptive-Agent Simulation Analysis of a Simple Transportation Network

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Abstract— **In general, transportation system consists of many drivers who choose the route, learning based on their experiences and information provided. In this study, drivers are assumed to reason and learn inductively based on their experiences. We develop an agent-based transportation system simulation model. In the model, the agent learns which route to choose based on his experiences. We shall call such a learning agent an adaptive agent. We examine the behavior of agents and network flow through the simulation. The results of the numerical experiments can be summarized as follows: 1) the system converges to Wardrop equilibrium; 2) the grades (the number of times of choosing the fastest route) are various among agents; 3) the difference of the grades occurs contingently; 4) agents who choose the route randomly deteriorate the system's stability excessively.**

1. Introduction

These days Intelligent Transportation Systems (ITS) are developing rapidly. In Japan, Vehicle Information and Communication System (VICS) has been introduced, and 8.4 million VICS units are used. Many drivers take the information provided by VICS into consideration and choose the route and decide departure time. Thus, there is a great demand for traffic information.

Providing information is said to be useful to alleviate traffic congestions, but it is not easy to evaluate the effect or influence of it. This is because how drivers who obtain the information behave is not sufficiently clarified. Also, the transportation system itself is a complex system, and the properties and mechanisms are not completely analyzed. A driver chooses a route and decides his departure time by himself based on his experiences and information. The transportation system consists of such autonomous agents. Furthermore, the driver learns how to choose the route, accumulating the information and experience. We have to consider driver's learning, build a model of drivers as an adaptive agent, who learns based his experience and information. We shall call this learning agent an adaptive agent.

In this study, we assume that individual driver is an adaptive agent, and develop a simulation model of transportation system with simple network as a multi-agent agent. Then, we examine the transportation system through simulation experiments.

One of the authors already studied the transportation system using agent-based simulation [1, 2]. The agent in the previous studies has limited information. In this paper, we shed light on complete information. As written before, evaluating providing information is very important. As a first step for assessing providing information, we assume that the agent has complete information and can know which route has been the fastest.

2. Induction

Driver's reasoning is not a deductive reasoning in which abstract and normative rules are applied [3]. Rather, faced with problems, drivers seek regularities and build hypotheses, verify them as rules, and apply them [4]. That is, drivers reason and learn inductively. Drivers are therefore assumed in this study to reason and learn inductively.

An example of induction in route choice behavior follows. Suppose a driver has experienced repeatedly that a route was not the fastest the day after it had been the fastest. This driver would then start anticipating, after experiencing that the route is the fastest one day, that the route will not be the fastest the next day. In this case experiences are generalized and a hypothesis is formed, which is then stored as a piece of knowledge and applied when a similar situation arises again. This cognitive process is induction.

Holland et al. [4] proposed a computational framework of inductive reasoning. It is basically a production system [5], which is a compilation of if-then rules for problem solving, in which the rules are revised by applying genetic

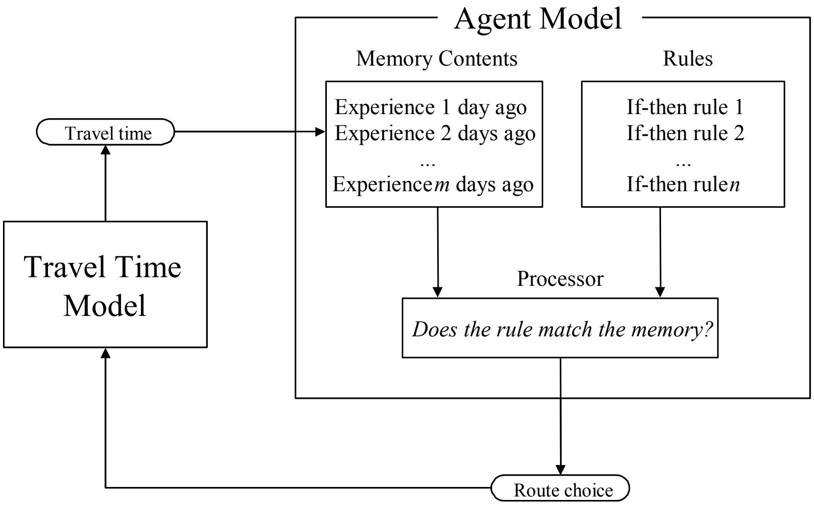
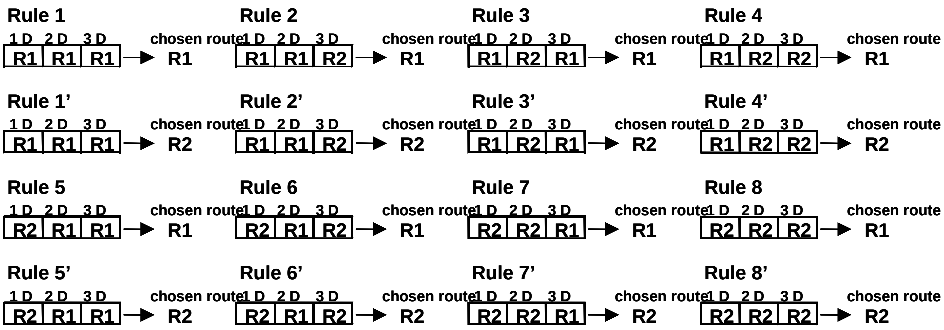


Fig. 1. Outline of simulation



1 D means the fastest route one day ago, 2 D the one two days ago, 3 D the one three days ago

Fig. 2. If-then rules

algorithms [6, 7].

In this study, we also adopt if-then rule system as the same as Holland et al, but for simplicity, we try to model an agent using as the small number of rules as possible, and avoid to use genetic algorithm.

2. Simulation Model

The simulation model of this study is developed for the case where agents travel daily from a fixed origin, O, to a destination, D, and the only decision element is route choice. The model consists of an agent model and a travel time model as Fig. 1 shows. The former simulates each agent’s route choice and inductive learning, while the latter determines traffic flow based on agent’ route choices and evaluates the travel time experienced by each agent.

A. Agent Model

Suppose agents remember the fastest routes for the latest m days, for simplicity. In reality, drivers remember much more information such as the travel time they experience. In this study, they only remember the fastest routes for the latest m days. The agent chooses a route based on his memories, that is, he considers the history of the fastest routes only.

The agent model performs the following: 1) scan the agent’s memory and identify the if-then rules that apply (or, “activate”) to the fastest routes in the past m days, and select the route which the rule indicates, 2) if there are more than one if-then rule that activates, select that rule which has the highest “superiority” value (described below) and choose the route indicated by that rule, 3) choose a route randomly if there is no rule that activates, and 4) update rules and their superiority values by applying genetic algorithms.

B. If-Then Rule

It is assumed that the agent in the agent model can store the fastest routes in the latest m days in the memory. Suppose agents remember the fastest routes for the latest m days. The memory can be coded as a set of bits, x_i’s, where x_i refers to the fastest route on the previous ith day.

An if-then rule consists of a condition and an action. The action part of an if-then rule contains the route, y, which the rule instructs the agent to take. The condition part comprises a set of bits, x_i’s, where x_i refers to the fastest route on the previous ith day. This is the same structure as the memory described above. The condition implied by the x_i’s is checked against the data in the memory, and a rule “activates” if the m bits of the condition part which correspond to the m pieces of memory from the last m days. Fig. 2 illustrates all if-then rules in the case of 1 OD 2 route network (the network has 1 OD pair and the OD connects 2 routes) and m = 3. In this case, two pieces of if-then rules always activate.

Now, suppose that an agent have the memory that on the latest 3 days Route 1 was the fastest. In this case, the memory is coded as $[x_1, x_2, x_3]$ = [R1, R1, R1] and in Fig. 2, the condition parts of Rule 1 and Rule 1' are the same as the memory and these two rules are activated. If the superiority of Rule 1 is higher than Rule 1', the agent choose the route Rule 1 instructs, that is, he chooses Route 1. Reversely, if the superiority of Rule 1' is higher than Rule 1, the agent choose the route Rule 1' instructs.

How well each rule is performing is evaluated using the following superiority indicator. If there are more than one if-then rule that activate, it is logical to assume that an agent should apply the rule that has provided good instructions more often in the past. The superiority indicator is used to judge which rule should be applied. The indicator is a weighted average of the travel times experienced on the route instructed by the rule, and is defined by applying the following recursive relationship each time the rule is used:

$$f_j^{i+1} = c\, f_j^i + \delta_j^i \qquad (1)$$

where

f_j^i = the superiority of the if-then rule j on Day i

δ_j^i= if the route that the if-then rule j instructs is the fastest on Day i, δ_j^i takes $+a$; otherwise, δ_j^i takes $-a$.

t^i = the travel time the agent experienced on Day i

c = positive parameter ($0 \le c \le 1$)

a = positive parameter ($a > 0$)

The above equation means that the superiority increases if the route chosen is the fastest; otherwise, it decreases. The value of the parameter a does not make a difference if it is positive. In the simulation in the next section, the parameter a sets to be 0.5..

Note that if the rule was used and instructed the route the agent took on Day i, the rule is updated according to Eq. (1) prior to Day $i + 1$. Namely, every day only one if-then rule is updated.

From its definition, it can be seen that a rule whose superiority indicator has a larger value has instructed a route on which the travel times have been smaller than on those routes instructed by rules whose superiority indicators are smaller. The larger is the superiority indicator, the better has the rule performed in the past. Induction implies that a rule that has performed well is judged as a good rule. Therefore, the rule which has the maximum superiority indicator value is adopted when there are multiple rules that have activated.

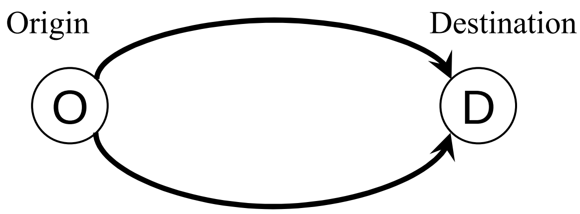


Fig. 3. Simulation Network

D. Travel Time Model

Route choices made by the respective agents in the agent model are aggregated and traffic volume is determined for each route. Travel time is then calculated for each route using the following formulation by the Bureau of Public Roads (BPR):

$$t(x) = t_f\,\{1 + \alpha(x/C)^{\beta}\} \qquad (2)$$

where t is the travel time to traverse a network route, x the traffic volume on the route, that is, the number of agents traveling on the route, C the route capacity, t_f the free-flow route travel time, and α and β are constant parameters. (This formula, which is in principle for a link, is applied to routes in this study as all routes consist of one link in the numerical analysis.)

The travel time model is simplified based on several assumptions. Most important is that the starting times of the trips made by the agents in the system are uniformly distributed over time. This study thus does not address the problem of departure time choice.

3. Simulation Experiment

The model system described above was applied to a simple transportation network as shown in Fig. 3. Some simulation experiments were performed assuming that a total of 200 agentss travel daily on the two-link network, making exactly one trip each day. It is assumed that all agents choose their routes independently without any knowledge of the other agents' choices. The number of days travel time information is stored in an agent's memory, m, is set to 3, and the number of if-then rules an agent has is 16. The parameter c in Eq. (1) represents the rate at which the superiority indicator is updated; the larger is its value, the faster does the superiority indicate change its value. When superior indicators change their values rapidly, so do the rules themselves. At the initial setting, the value of parameter c is given to each agent. It is uniformly distributed

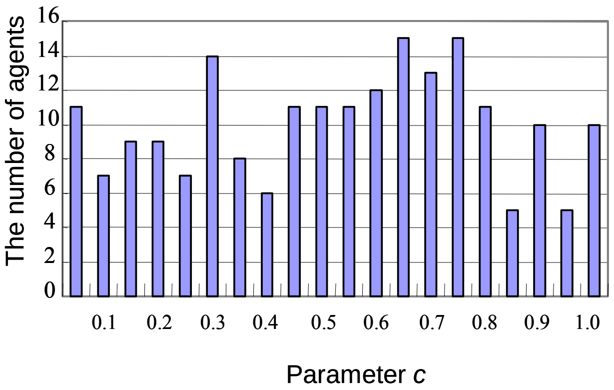


Fig. 4. The distribution of values of the parameter c

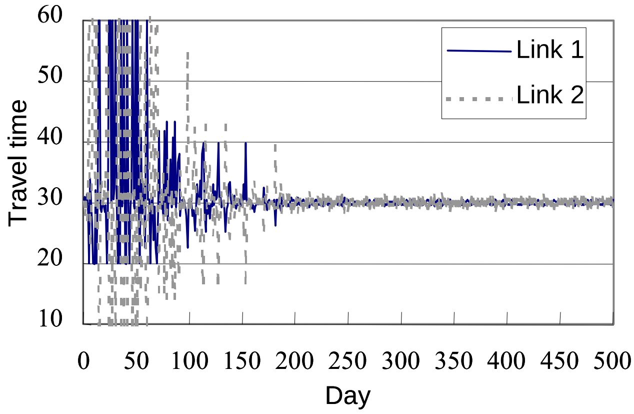


Fig. 5. The travel times through Day 500

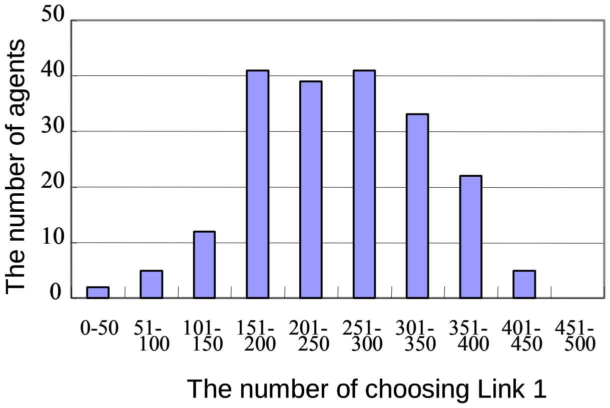


Fig. 6. The histogram on how many times Link 1 is taken

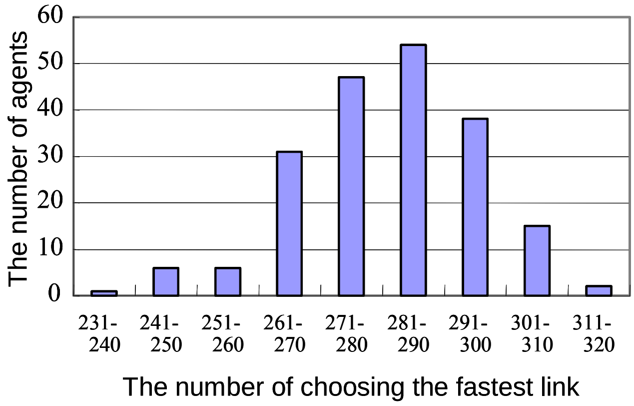


Fig. 7. The histogram of agents' grades

in the range from 0 to 1, and is generally different among agents. After the value is provided, it is fixed during the simulation. The distribution of values of the parameter c is shown in Fig. 4.

Fig. 3 shows the network in the simulation. The simulation network has one OD pair and the OD pair connects by two links. The travel time functions of links are as follows:

$$t_1(x) = 20\{1 + 2(x/200)^2\} \quad (3)$$

$$t_2(x) = 10\{1 + 2(x/100)^2\} \quad (4)$$

The network is simple and the number of agents is small. This simplified representation in the simulation analysis of this study is, however, considered to be sufficient as the objective of the study is to appreciate the behavior of the agent-network system. It is believed that making the model more detailed or realistic is not necessarily helpful in gaining insights into the mechanisms of complex systems. There would be cases where a model system which focuses on the most relevant factors while disregarding elements of lesser significance may better aid in gaining an understanding of the system behavior.

Wardrop's equilibrium [8] is the situation in which the travel times of both links are equal. In the simulation, both travel times are 30.0 at equilibrium and traffic volumes are both 100.

Fig. 5 illustrates the travel times of both links through Day 500. From the figure, we found that at the start of simulation the system oscillates ferociously because all agents have no knowledge of the system, but after Day 200, the system converges to Wardrop's equilibrium. This is because through learning, the agents try choosing faster link, and finally, the travel times of both links become equal. This is a kind of Nash equilibrium in game theory. Fig. 6 shows the histogram on how many times the agents choose Link 1 until Day 500. While there are some agents who choose Link 1 almost every day, there are some other agents who continue to take Link 2. Thus, which link the agents choose is various among agents. This represents agents' heterogeneity.

Most agents continue to use one of the two rules which

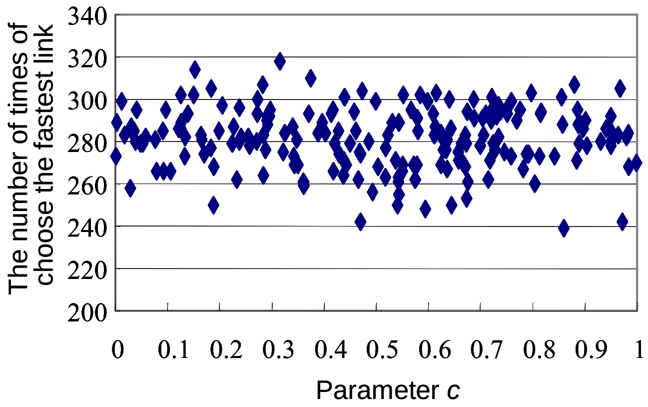


Fig. 8. The relationship of the grade and parameter *c*

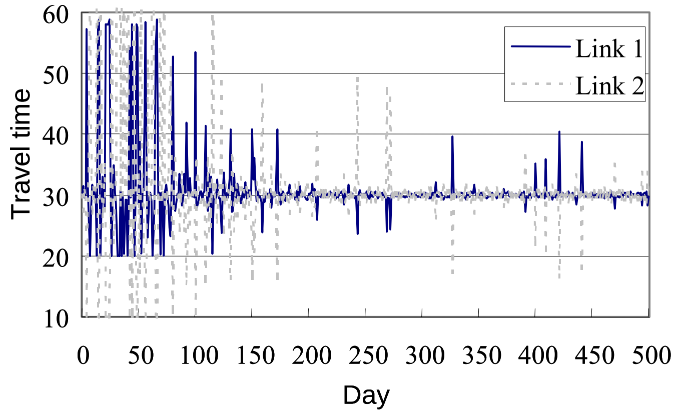


Fig. 9. The simulation with 10 noise agents

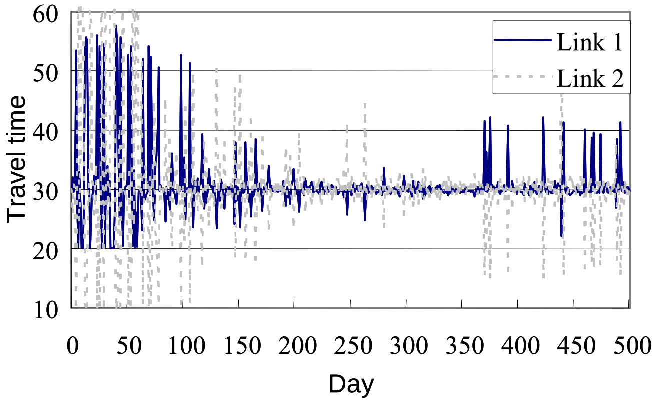


Fig. 10. The simulation with 25 noise agents

have the same condition part. But, the used rules are also various among agents and each rule is evenly used. Heterogeneity of agents seems to contribute to reach Wardrop's equilibrium.

The agents try taking the fastest link. The "grade" of agent is how many times the agent chooses the fastest link. Fig. 7 illustrates the histogram on how many times the agents choose the fastest link until Day 500. The average is 281.4, the minimum is 239, and the maximum is 318. The standard deviation is 14.2. The difference of the grades is not small. In this simulation, all agents can store the information for 3 days, and the capability is the same among agents. Also, the information, that is, which link has been the fastest, is the same. The differences among agents are the parameter c in Eq. (1) and the history of chosen links. Fig. 8 shows the relationship between the value of the parameter c and the grade. It is found that there is no correlation between them. We made another simulation where the value of the parameter c is the same among agents. In this case, the difference of grades among agent is not small like Fig. 7, too. This result means that even if the agent has the same information processing ability and have the same information, not a small difference of grade or result is made, and implies that even though people use the route guidance system or navigation system with the same ability, some can take the fastest route many times while some other take the fastest route less times.

We made the simulations with noise agents. Fig. 9 is the simulation where 190 agents are adaptive agents described above and 10 noise agents. The noise agents choose their links at random. Fig. 10 is the simulation with 25 noise agents and 175 adaptive agents. Compared with Fig. 5, in Fig. 9 and 10, the systems fluctuate much more largely after Day 200. Namely, the stability of converged steady states in the simulations with noise agents is much worse than the simulation without noise agents. The noise agents seem to deteriorate the system's stability. This could be very problematic from the standpoint of traffic management. Very a few noise agents deteriorate the system's stability. Imagine that in the future, most traffic is well-controlled by means of route guidance system with mutually communication or something. This result implies that it would be very difficult to manage the traffic stably if a little uncontrolled traffic exists.

4. Conclusions

Transportation system generally consists of many adaptive agents who learn based on their experiences and information provided. In this study, we developed an agent-based transportation system simulation model. In the model, the agent learns which route to choose based on his experiences. Then, we applied the simulation model to a simple transportation network, and examined the behavior of agents and network flow. The results of the simulation experiments can be summarized as follows: 1) the system converges to Wardrop equilibrium; 2) the grades (the number of times of choosing the fastest route) are various among the agents; 3) the difference of the grades occurs contingently; 4) agents who choose the route randomly deteriorate the system's stability excessively.

As a future work, we will have to incorporate departure time choice and predicted travel time information to the simulation.

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