Dynamic Mode Choice of Commuters in an Agent-based Simulation Model with Inductive Learning Machines

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***Abstract* – This study attempts to apply an agent-based approach to modeling a transportation system. Utilizing the advantage of agent-based model of being validated at an individual level, a social dilemma situation of travel mode choice is modeled and viewed as a complex system. Inductive-learning's capability of travelers is used and combined with an evolutionary approach in order to simulate travelers' learning process. A user-equilibrium point as predicted by a conventional equilibrium analysis can be reached and stabilized. The stable situation is produced by interaction process among agents and by behavioral change process of each agent, without a central or external rule that organizes objective function of the system. The study also reveals some conditions that may produce other stable situations in addition to the user equilibrium point. An emergent situation combined with travelers' sensitivity to payoff differences is observed to be influential.**

Keywords: travel mode choice, social dilemma, agent-based approach, inductive learning machine.

1. INTRODUCTION

In transportation modeling, equation-based approaches dominate most of models. But they have some disadvantages that may be covered by another approach named as 'an agent-based approach'. The agent-based approach, which can be validated at an individual level by comparing model output with real system behavior, gives the benefit for understanding individual's way of thinking, making decision, and learning.

Shalizi [10] defined an agent-based model as a computational model, which represented individual agents and their collective behavior. An agent-based model steers us toward representing individuals, their behaviors and their interactions, rather than aggregates and their dynamics. Axelrod [1] stated the importance of agent-based modeling to build simulation model in social sciences.

Deadman [3] implemented agent-based modeling to model individual behavior and group performance in the tragedy of the commons. The work introduces and illustrates the potential of intelligent agent-based modeling and simulation as a tool for understanding individual action and group performance in common-pool resource (CPR) dilemmas. Yamashita, Suzuki and Ohuchi [11] also simulated a CPR dilemma by extending "The Lake Game" into a distributed social dilemma game called as "Multiple-Lake Game". His work is one of models that utilize a kind of inductive learning machine as a decision making rule.

Nakayama, Kitamura and Fujii's [8] and Nakayama and Kitamura's [9] works on route choice behavior are examples of agent-based approach in transportation modeling. Travelers are modeled to have bounded rationality, limited information and also capability to do cognitive learning. Klugl and Bazzan [6] also studied route choice behavior by using a simple heuristic model. In travel mode choice, the agent-based approach is not so widely studied by researchers. The inspiring work by Kitamura, Nakayama and Yamamoto [5] was on travel mode choice by using a simple bi-modal transportation system and cellular automata. Those studies have shown that agent-based approaches make possible many things that can not be observed in a conventional approach.

Our study focuses on travel mode choice behavior. Most modal-split models rest on the presence of equilibrium. A conventional analysis assumes rational choice and complete information. Many studies have assumed that travelers predict costs of transport modes and choose mode with the smallest cost. Actually, they do not necessarily minimize cost but may adopt a strategy, such as continuing to take the same mode or change to other modes periodically.

We model a social dilemma situation of travel mode choice by using a simple bi-modal transportation system, which consists of car and bus as choices of mode. In the dilemma situation, selfish behavior of people who use cars based on personal interest of minimizing travel costs, creates traffic congestion, and furthermore increases travel cost for both users of car and public transport.

By utilizing a behavioral model based on the inductive learning capability of commuters, we aim to provide an agent-based simulation model of travel mode choice in order to understand behavioral process of commuters. We attempt to observe complex dynamical processes of commuters' behavior by considering interaction among travelers to be influential. New findings are expected in order to gain an insight into the way of solving the social dilemma.

2. SIMULATION MODEL

Behavior of autonomous agents may represent behavior of travelers who choose mode of commuting. A multiagent simulation is utilized to model and to show a complex decision-making process of travelers. An agent behaves based on a behavioral rule embedded in a kind of inductive learning machine named as a finite-state machine (FSM).

Our simulation model consists of two submodels, transportation model and traveler model (see Figure 1). In the traveler model, travelers decide the choice of mode guided by decision making rules. After all travelers decide the mode of commuting, then travel time is calculated in the transportation model. Generalized travel cost for each mode can be calculated and it returns to travelers as payoffs. Amount of payoff for each traveler depends on the mode he chooses. Day-by-day, the generalized travel cost of car and bus may vary dynamically, depend on the changes of travelers' choice. These processes are repeated for 10 iterations. After that, an evolutionary process to update travelers' FSMs by using genetic algorithm is

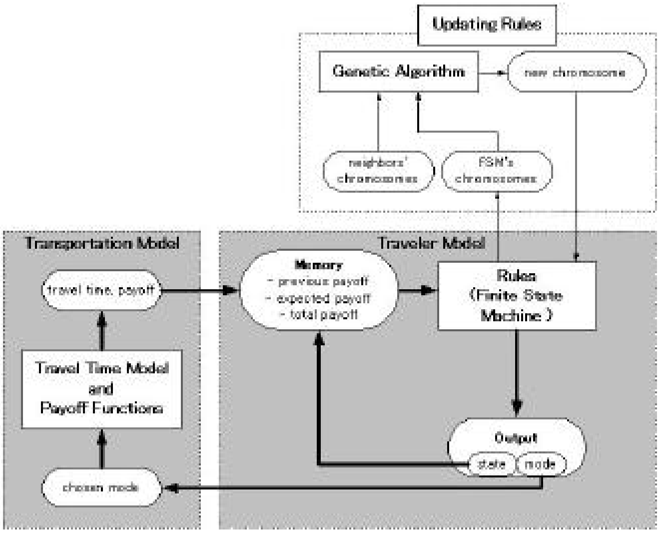

Figure 1: Multiagent simulation model utilized in order to acquire adaptive behavior.

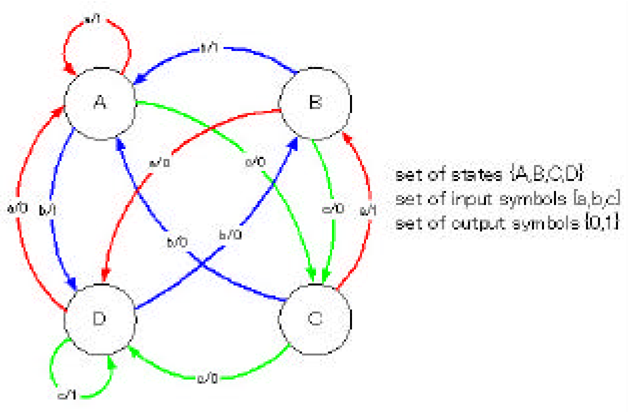

Figure 2: An illustration of an FSM

Table 1: A representation of an FSM in a table form

input symbol \ current state	A	B	C	D
a	(A,1)	(D,0)	(A,0)	(D,1)
b	(D,1)	(A,1)	(A,0)	(B,0)
c	(C,0)	(C,0)	(D,0)	(D,1)

2.1. Transportation Model

In order to understand basic travel mode choice that represents a social dilemma situation, we use a simple bi-modal transportation system that comprises private car and bus as choices of commuting. Both modes are assumed to be operated in the same lane, where there would be more interactions than being operated in exclusive lanes.

All travelers own cars so that they can easily change modes and they only know the payoff of mode they choose. Payoff received by a traveler is just a constant minus travel cost. Private car users are assumed to be solo drivers who drive alone. For public transport, bus operating frequencies and fare are adjusted so that bus passengers can pay the full cost of operating buses. For the transportation model, we derived equations and their parameters of generalized travel costs based on the work of Kitamura et al. [5] in order to represent the same social dilemma situation as in that work. But we have different methods and aims in our work.

2.2. Traveler Model

A finite-state machine (FSM) or finite state automaton (FSA) is an abstract machine that has only a finite, constant amount of memory (the states). An FSM looks like a mathematical logic that represents a sequence of instructions to be executed, depending on a current state of the machine and a current input.

Formally, an FSM is a 5-tuple: M=(Q, t, r, s, o) [4]. Where Q is a set of states, t is a set of input symbols, r is a set of output symbols, $s: Q \times t \rightarrow Q$ is the next state function, and $o: Q \times t \rightarrow r$ is the output function. A 5-tuple is to be interpreted as a machine that, if given an input symbol x while it is in the state q, will give output $o(q, x)$ and transition to state $s(q, x)$. Only the information contained in the current state describes the behavior of the machine for a given stimulus, while the entire set of states serves as the 'memory' of the machine.

Figure 2 illustrates an FSM with 4 finite states, 3 input symbols and 2 output symbols. An FSM can also be represented by a kind of table as Table 1. A pair of values in each cell is a pair of next state function and output function (s,o). For example, (A, 1) means that next state will be A and current output is 1. The number of states, input symbols and output symbols can be varied according to modeling needs.

In our simulation, each agent has an FSM that functions as a decision rule to choose mode of traveling. Each agent has an FSM with 4 states, 5 input symbols and 2 output symbols.

Past payoffs that are memorized as expected payoffs, are used to decide the input symbols for the next step. Expected payoffs of a traveler are calculated and updated based on a work of McFadzean [7]. A traveler receives payoff P_t^j of using mode j at time t. The payoff is then recorded and used to update its expected payoff. The expected payoff U_t^j is updated according to Equation (1), where A means automobile or car and B means bus.

$$U_t^j \leftarrow wU_{t-1}^j + (1-w)P_t^j; \quad j = \mathrm{A,B} \qquad (1)$$

Only expected payoff of the chosen mode is updated. When a traveler chooses car, his expected payoff of car is then updated. But expected payoff of bus is not updated until the traveler chooses bus.

Weight factor (w) ranges from 0 to 1. It depends on the traveler's perception of the influence of his payoff P_t^j on the expected payoff U_t^j. A traveler with high weight factor is resilient to his current payoff. On the other side, a traveler with low weight factor is easily affected by his current payoff.

A commuter, for instance commuter C, has an FSM as in Table 2. The five input symbols (x=1…5) represent choices of strategy for a traveler to decide which mode they use for the next trip. Each choice of strategy has a range of value to differentiate it with other choices of strategy. The range depends on the value of d, which represents travelers' sensitivity of the difference between payoff of car and payoff of bus. The higher the value of d, the less sensitive a traveler's consideration about payoff differences is.

As an initial condition, choices of mode (o) for x=1 are only car, and for x=5 are only bus. x =2 has 75% choices of car and x=4 has 75% choices of bus. x=3 has equal proportions of car and bus choices. In the beginning of simulation run, all commuters receive a random initial value of expected payoff of car (U^A) and bus (U^B) with range from 1 to 2. An initial value is

Table 2: An example of agent's FSM in table form

input symb. (x) \ current state	1	2	3	4
(1) $U^A - U^B > 2d$	(3,0)	(2,0)	(3,0)	(4,0)
(2) $d < U^A - U^B \le 2d$	(2,0)	(3,1)	(4,0)	(1,0)
(3) $\lvert U^A - U^B \rvert < d$	(3,0)	(1,1)	(4,0)	(2,1)
(4) $d < U^B - U^A \le 2d$	(4,1)	(1,0)	(2,1)	(3,1)
(5) $U^B - U^A > 2d$	(2,1)	(1,1)	(3,1)	(2,1)

needed to avoid premature convergence and inertia in early stage of a simulation run.

Decision making processes of commuter C in Table 2 starts with x=3 and s=1. Let us assume that initial values of U^A and U^B are 1.1 and 1.2, and w=0.9. Initial pair of state and output (s, o) is (3,0), which means that the decision is to choose car, coded as 0, and next state will be state 3. After all commuters have chosen a mode based on their FSMs, they receive a payoff of their decision. P^A is given to commuters who choose car and P^B is given to commuters who choose bus. As commuter C's choice is car, then he receives P^A and updates his expected payoff of car using Equation (1) ($U^A = 0.9x1.1 + (1-0.9)xP^A = 0.99 + 0.1P^A$). He observes that $d < (0.99 + 0.1P^A) - 1.2 \le 2d$, so that for next iteration, x=2. Based on x=2 and s=3, commuter C receives a new pair of state and output (s, o) from his FSM. The pair is (4, 0), meaning that the decision is to choose car, coded as 0, and next state will be state 4. This process continues until the end of iterations.

In order to acquire an adaptive strategy, a genetic algorithm (GA) is applied to the FSM of each agent. A chromosome in GA encodes the transition function and the output function of an FSM with bit strings. A chromosome with length 60 bit strings encodes an FSM, which consists of 5x4 pairs of state and output. Figure 3 illustrates the process.

A state requires 2-bit strings. The value of 2-bit strings ranges from 0 (for binary code 00, the value is $0x2^1+0x2^0$) to 3 (for binary code 11, the value is $1x2^1+1x2^0$). A value of 0 represents State 1, a value of 1 represents State 2, a value of 2 represents State 3, and a value of 3 represents State 4. A choice of mode is represented by a single bit string, since the choices of mode are only two, car and bus. A value of 0 represents car and a value of 1 represents bus.

Genetic operators, such as selection and two-point crossover, are used. Mutation is not implemented in order to avoid capricious changes of output value (o) for x=1 and x=5. We can still maintain variation of chromosomes by crossover between travelers, since travelers are interrelated with each other on torus plane. The variation of chromosomes that can be obtained only from crossover is big enough to ensure optimality.

Agents require adaptive process in order to evolve their decision rules. There are two kinds of learning process that can be used by agents to acquire adaptive rules; individual learning and social learning. In individual learning, agents learn based solely on their own experience. Sometimes it requires longer time to acquire adaptive behaviors, and also it limits agents' knowledge about other kinds of rule instead of their own rules. Compared to individual learning, social learning has advantages since it can short-cut individual learning and acquire adaptive behaviors by learning from others. Considering the advantages of social learning and the nature of the social dilemma situation as a problem that is related to interactions between individuals, we use only social learning.

Agents are arranged on a kind of 3D plane, known as a torus plane, which are used in Yamashita et al. [11], so that it ensures that each individual agent has 8 surrounding neighbors. Figure 4 shows the rules-updating process, for example, of an agent (chromosome) No. 66, which is surrounded by 8 Neighbors from 1 to 8. All agents, including No. 66, compute their fitness (sum of payoffs) of their own rules, and Chromosome No. 66 updates his rule (FSM) based on the fitness of his own and 8 neighbors by implementing genetic algorithm. Each agent knows rules owned only by his 8 surrounding neighbors and payoffs gained by those rules, without having other knowledge than those, so that agents are assumed to operate with incomplete information regarding with other agents' behavior.

3. Simulation Results And Discussions

We run simulations with 4,096 travelers, who are arranged

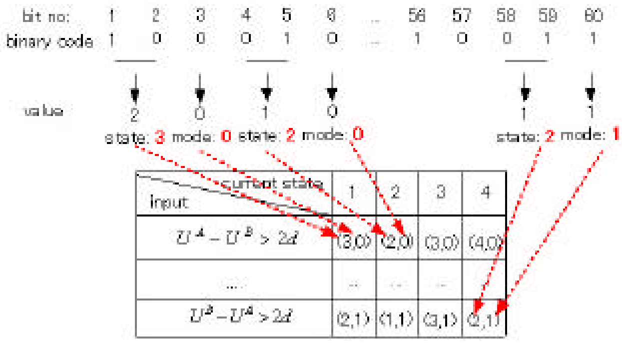

Figure 3: Decoding process of a chromosome into an FSM

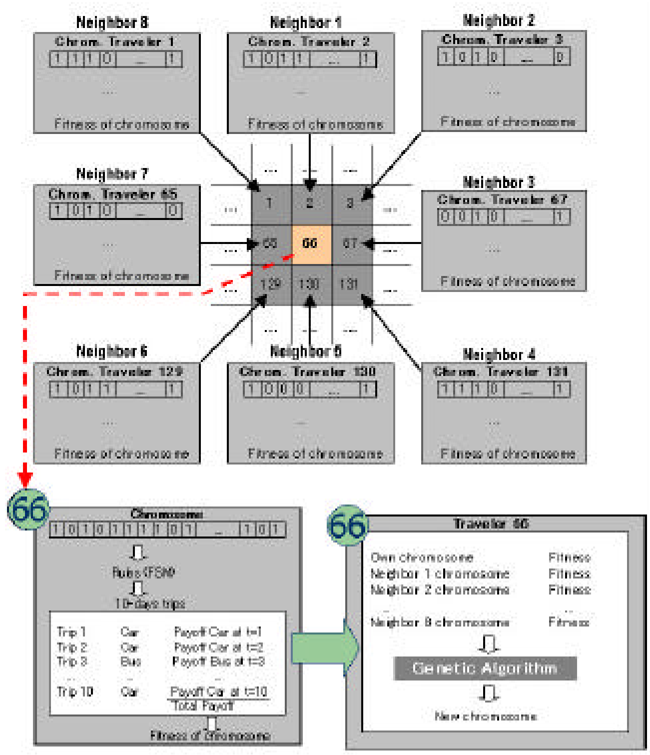

Figure 4: Rules-updating process of an agent

in a torus plane. Each traveler uses an FSM as a decision making rule. Due to simplification, memory weight for each traveler is assumed to be homogeneous. We choose w=0.9 for the experiments. If w is too small, travelers' expected payoff value would be easily changed by current payoff; this situation unlikely happens if travelers have already learnt from hundreds of iterations. We emphasize on studying the influence of the sensitivity parameter d, by varying the value from 0.05 to 0.15 with increment 0.025. Simulation is run up to 500 generations with 10 iterations in a generation.

Four simulation runs were made for each value of d. After observing the results, we decided to discuss the details for d=0.1 and d=0.05, since the former case resulted in a more stable situation than the cases of $d > 0.1$ and the latter case gave interesting results.

3.1. Dynamic Equilibrium Situation at d=0.1

We simulated four runs for this case. Statistics for the last 100 generation are summarized in Table 3. According to conventional analysis, a user equilibrium point is reached when the cost of car is equal to the cost of bus. For all the runs, the average cost of car is almost equal to the cost of bus. But, only for Run 1 and Run 4, the cost of car is significantly equal to the cost of bus by 95% confidence interval. The numbers of bus users in Run 1 and Run 4 are significantly the same, as well as are those in Run 2 and Run3. We will discuss Run 1 in more details from this section up to Section 3.4.

Figure 5 shows the day-to-day dynamics of number of bus users. The fluctuation is reduced to a small value after Iteration 2,000 (Generation 200) and maintains until the end of simulation, with only a few fluctuations around Iteration 4,000 (Generation 400). The system is stabilized at the user equilibrium point.

3.2. Travelers' Expectation

All agents start the simulation with a random value of expected payoffs for both car and bus. Day-by-day, they update the values of expected payoff based on payoff of the mode they choose. Since the weight factor (w) is 0.9, a current payoff contributes its 10 percent to the updated value of expected payoff.

Table 3: Averages and std. deviations (Gen.401-500)

Run	Bus users		Car cost		Bus cost	
	Avg	Std. Dev.	Avg	Std. Dev.	Avg	Std. Dev.
1	1161.85	55.17	2.1667	0.0976	2.1652	0.0536
2	1168.71	53.33	2.1543	0.0940	2.1584	0.0516
3	1169.90	52.81	2.1523	0.0931	2.1572	0.0511
4	1163.92	55.94	2.1630	0.0994	2.1632	0.0545

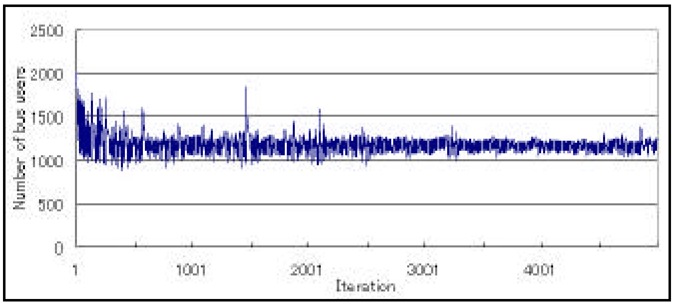

Figure 5: Dynamics of number of bus users

A traveler decides a mode of commuting based on rules in an FSM and differences of expected payoffs. If the difference between car payoff and bus payoff is observed to be very high for a traveler ($U^A - U^B > 2d$, or $U^B - U^A > 2d$), then the traveler make a decision to use either car or bus without considering using both modes. But, if he observes that the difference is small to medium, which depends on the value of d, then he has a wide range of probabilities of choosing car or bus based on the state and the output of his FSM.

Figure 6 shows the change of expected payoff of car and bus. One dot represents a pair of expected payoff of car and bus for a traveler, so that in a small column in the figure we plot 4,096 travelers' pair of expected payoffs. In the first 50 generations, the scatter plots spread in around a 3x3 column (column size: 0.1x0.1). At that time, there existed some travelers who experienced a high difference of expected payoffs, so that they used either input symbol 1 (always choose car) or input symbol 5 (always choose bus). Some travelers experienced medium differences, so that they used either input 2 (higher probability to car) or input symbol 4 (higher probability to bus). Generation by generation, the spread of scatter plots has become smaller, which means travelers experience only small differences of expected payoffs so that they decide solely based on the rule of FSM. At the end of generation (Generation 500), the average value of expected P_A is 0.8699 with variance 0.0014 and the average value of P_B is 0.8521 with variance 0.0005. This means that most of travelers experience only slight differences of expected payoff between car and bus.

3.3. Travelers' Specialization

Figure 7 shows the specialization of travelers based on their choices of mode in every 10-iterations. All-times car users always choose car in each 10-iterations and all-times bus users always choose bus. All-time users dominate the system, but there are also a small number of mixed users at the end of simulation (less than 10% of all travelers; not included in Figure 7) who choose both car and bus during each

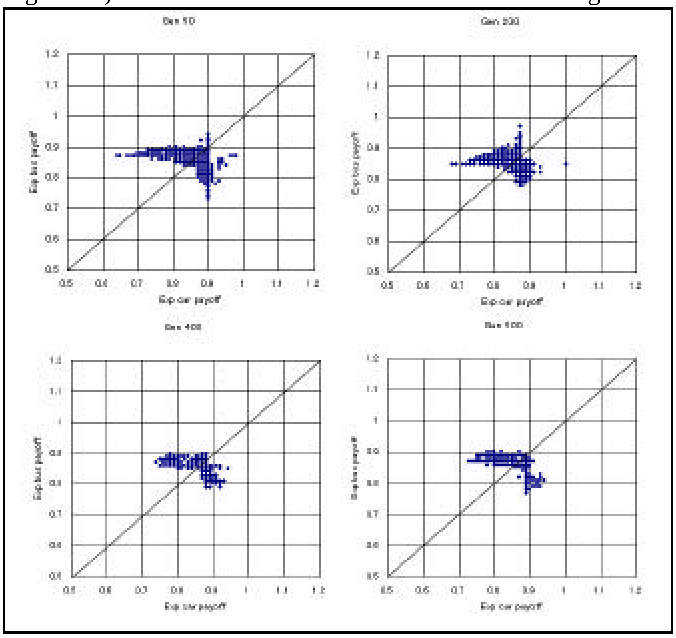

Figure 6: Scatter plots of travelers' expected payoffs at d=0.1

10-iterations. At the equilibrium point, the number of bus users is around 1,200, with 1,000 all-times bus users. The number of car users is about 2,900, with 2,750 all-times car users. It can be inferred that travelers are mostly specialized in either an all-times car user or bus user, leaving a small number of mixed users.

3.4. Emergence of Choice Stability

A traveler' specialization of mode changes usually from an all-times car user to a mixed user and then to an all-times bus user, or reversely from an all-times bus user to a mixed user and then to an all-times car user. Even though a traveler has a tendency to become an all-times car (or bus) user in every generation, sometimes an interaction with other travelers makes him change into a mixed user, following the change of his FSM due to crossover of chromosomes with neighbors. Figure 8 illustrates changes of travelers' choice of mode from generation to generation, which have finally resulted in an all-times bus user or all-times car user.

3.5. Effect of Travelers' Sensitivity at d=0.05

We find an interesting phenomenon when the value of parameter *d* is at 0.05, which means travelers are 2 times more sensitive to payoff difference than *d*=0.1. In all four runs, the systems converge to other equilibrium points (see Figure 9), where the number of bus users in all runs is higher than the user equilibrium point (dashed line in the figure).

Further discussions now focus on Run 2. An emergent process starts from an outbreak of number of bus users at iteration 8 in generation 31 (see Figure 10).

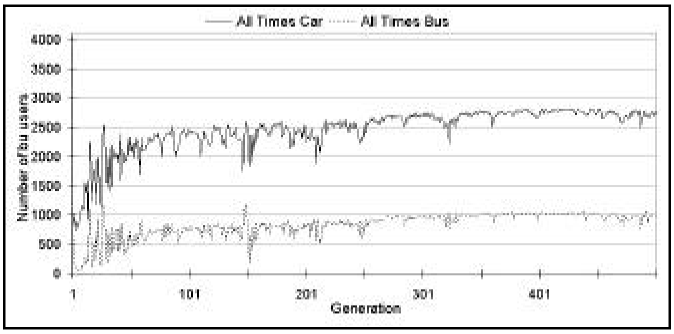

Figure 7: Number of travelers in each level of chosen mode

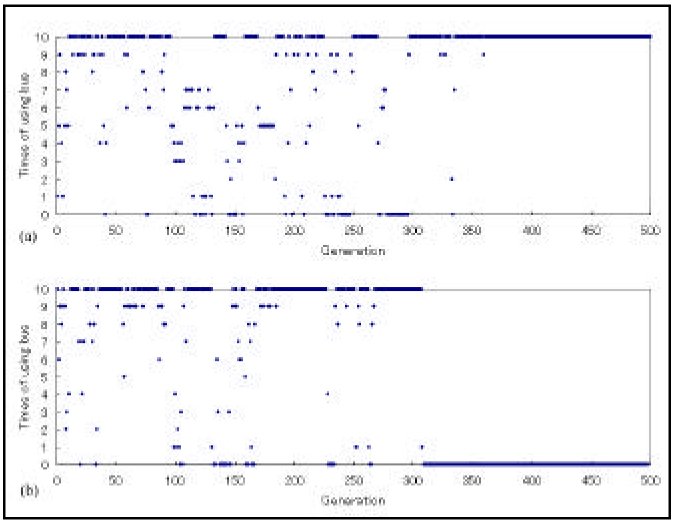

Figure 8: Travelers' changes of choice: (a) finally an all-times bus user and (b) finally an all-times car user

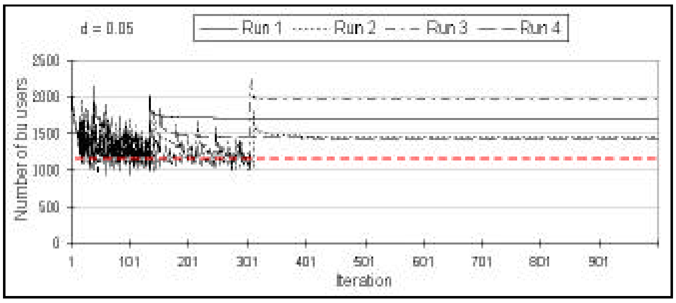

Figure 9: Dynamic of number of bus users at d=0.05

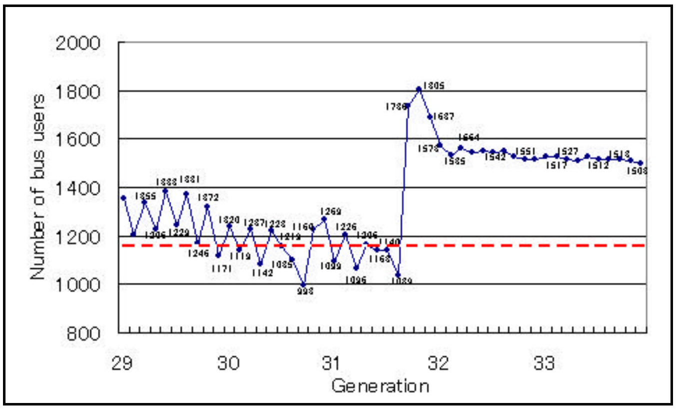

Figure 10: Dynamics of number of bus users at gen. 29-33

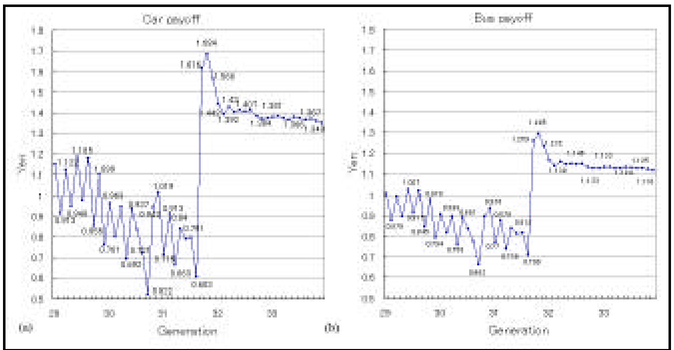

Figure 11: (a) Car payoff P^A and (b) bus payoff P^B at gen. 29-33

The outbreak starts with the decrease of bus users to a lower level than the user equilibrium point, so that travel time increases and payoff for all users decreases, but payoff of bus is slightly higher than car. Some travelers observe this situation and at the same time they choose bus, resulting in a sudden increase of bus users.

The huge increase of bus users increases the payoff of car and bus (see Figure 11). However, higher level of increase is for car payoff than bus payoff, since car cost has a stiffer curve than bus cost. At this time, travelers who have car as their choice receive high increase of expected payoff as well as travelers with bus as their choice. They observe that the payoff of the chosen mode is much higher than the other one, so that they use input symbol 1 or 5 in their FSMs and continue to use car or bus. If majority of travelers experience those processes, then the system converges to another equilibrium point.

Figure 12 shows changes of expected payoffs of a traveler before and after the outbreak of cooperation. From the beginning of generation 29 until the beginning of generation 31, the traveler mostly choose car, so that the changes of expected payoffs are mostly on car. But during three iterations before the outbreak, he chooses bus and the outbreak pushes his choice into bus only.

The changes of expected payoffs of all travelers can be seen in Figure 13. Fundamental changes happened during generation 30-40's as the results of the cooperation outbreak. Starting from generation 31, travelers split off into two groups, a group of car users and a group of bus users.

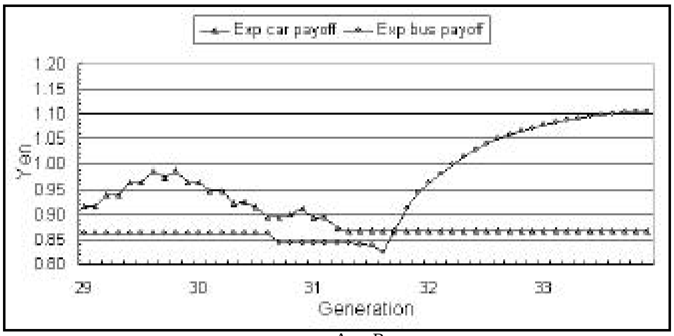

Figure 12: Expected payoffs (U^A,U^B) of a traveler at gen. 29-33

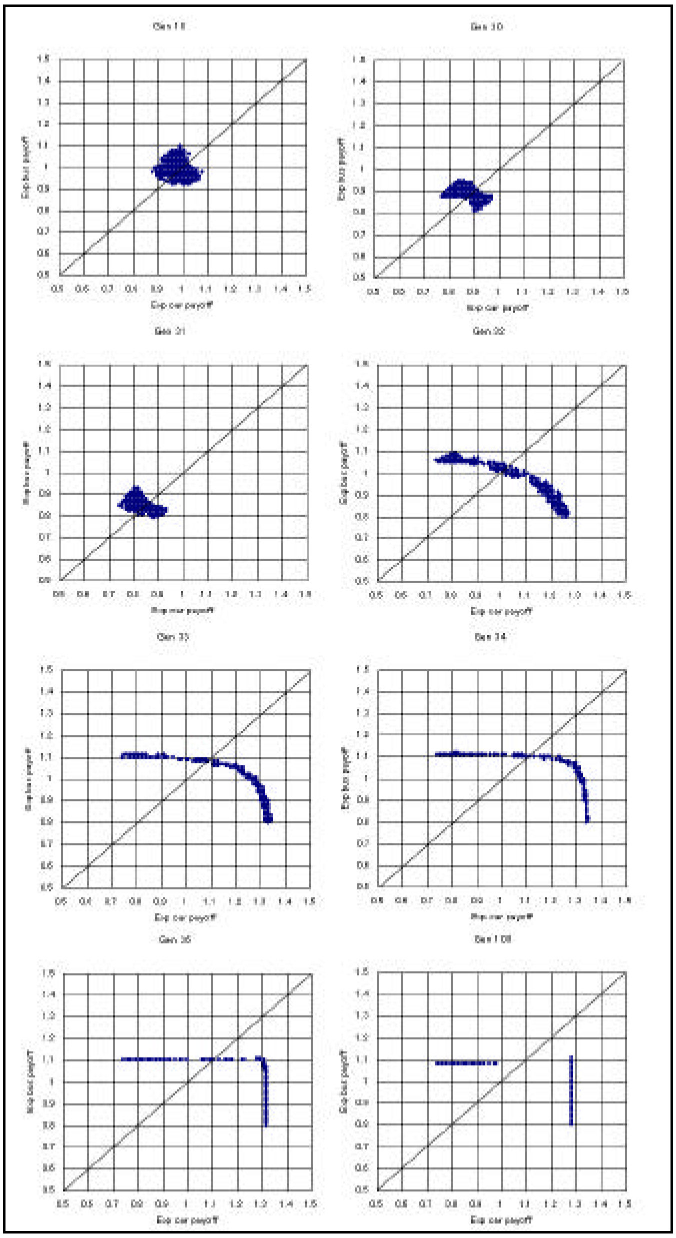

Figure 13: Scatter plots of travelers' expected payoffs at d=0.05

The kind of equilibrium found at d=0.05 can be called as a 'deluded equilibrium' [8], [9]. If travelers expect that the payoff of a mode is much higher than the other one, then they will continue to choose the same mode again. A deluded traveler cannot acquire information about the choice of another mode anymore, so that the delusion cannot be dissolved. Even though the actual payoff of car is higher than payoff of bus, travelers continue to use car, because in their perception the expected payoff of bus is much higher than car.

If delusion continues, travelers form a habitual behavior and they totally exclude other choice of mode from consideration. When all of them are frozen to their choices, the equilibrium becomes a 'frozen equilibrium' [9].

4. CONCLUSION

A simulation model of commuters' learning on choosing mode is built by using an FSM as behavioral rules. A user equilibrium point predicted by the conventional analysis can be reached and stabilized by interaction process among travelers and by behavioral change process of each traveler, without any central or external rule that organizes the objective function of the system. The equilibrium is a result of self-organization and complex process among travelers. At the user equilibrium point, most of travelers are specialized in either an all-times car or all-times bus user, leaving a small number of mixed users.

When travelers are very sensitive to payoff differences, an outbreak situation produces another equilibrium point, instead of the user equilibrium. The outbreak, as an emergent process of the system, makes travelers perceive an excessive increase of payoffs and forms a habit of choosing only either car or bus until the end of the simulation.

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