Modelling a Social Dilemma of Commuters' Mode Choice with Inductive Learning Machines

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Abstract – **This study attempts to apply an agent-based approach to modelling 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 conventional equilibrium analysis could 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 revealed 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.**

I. Introduction

In transportation modelling, equation-based approaches dominate most of models. But they have some disadvantages that may be covered by another approach named as 'agent-based approach'. An agent-based approach, of being validated at an individual level by comparing model output with real system behavior to study effects of a policy in transportation, gives the benefit of understanding individual's way of thinking, making decision, and learning

Shalizi [10] defines an agent-based model as a computational model, which represents 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] also stated the importance of agent-based modelling 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 introduced and illustrated 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 et al.[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 utilized a kind of inductive learning machine as a decision making rule.

Nakayama et al's [8] and Nakayama and Kitamura's [9] works on route choice behavior are the examples of agent-based approach in transportation modeling. Travelers were 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. One of the inspiring works by Kitamura et al. [5] is on travel mode choice by using a simple bi-modal transportation system and cellular automata. Agent-based approach made possible many things that could not be observed in conventional approach.

Our study focuses on travel mode choice behavior. Most modal-split models rest on the presence of equilibrium. Conventional analysis assumes rational choice and complete information. Many studies assumed that a traveler predicts costs of transport modes and chooses 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 [2] situation of travel mode choice by using a simple bi-modal transportation system, which consist of car and bus as choices of mode. Selfish behavior of people, who use cars based on personal interest of minimizing travel cost, creates traffic congestion, and furthermore increases travel cost for both users of car and public transport.

Utilizing a behavioural 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 influential. New findings are expected in order to gain an insight into the way of solving the social dilemma.

II. 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 has chosen. 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, counted as one generation. After that, an evolutionary process is utilized to update travelers' FSM by using genetic algorithm. The objective for each traveler is to acquire a FSM that gives high payoffs. The updated FSM is then being used for the next generation.

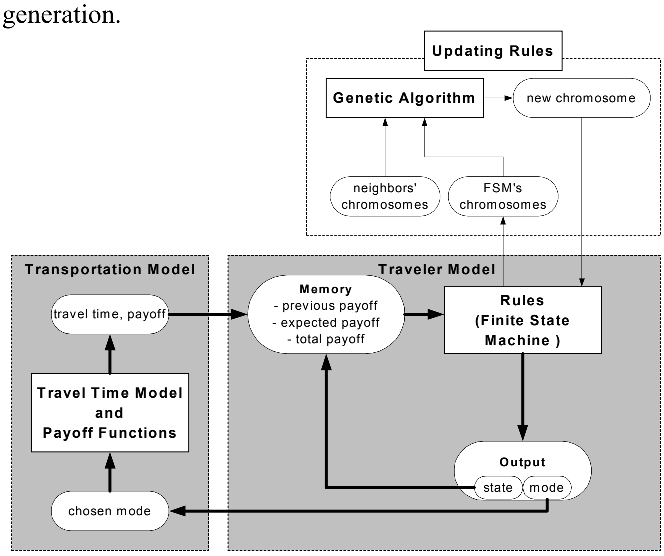


Figure 1: Multiagent simulation model

A. *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. The two 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. We derive equations and their parameters of generalized travel costs based on the work of Kitamura et al.[5] as follows, for car (A)and bus (B)respectively:

$$V_A = K_{A0} + K_{A1}T_A$$

$$V_B = K_{B0} + K_{B1}T_B + K_{B1}\left(FR_B / 2\right) + K_{B3}W_B$$

where V_A, V_B are the generalized cost of one-way travel, T_A, T_B are the one-way travel times, FR_B is the round-trip bus fare, and K_{mi} is the constant coefficient.

B. *Traveler Model*

We use a routine-based learning with a genetic algorithm to model a traveler's decision making and learning processes. The routine or rule is represented as a finite-state machine, which is evolved to change the mode choice strategy embedded on it. Evolving a FSM changes its structure into a more adaptive structure that gives better strategy on choosing mode.

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). 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, a FSM is a 5-tuple: M=(Q,τ,ρ,s,o) [4]. Where Q is a set of states, τ is a set of input symbols, ρ is a set of output symbols, s:Qxτ→Q is the next state function, and o:Qxτ→ρ 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 a finite-state machine with 4 finite states, 3 input symbols and 2 output symbols. A 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 a FSM which functions as a decision rule to choose mode of traveling. Each agent has a FSM with 4 states, 5 input symbols and 2 output symbols.

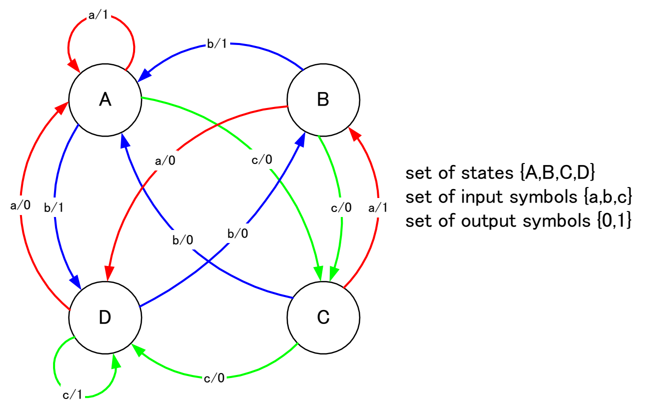


Figure 2: An illustration of a finite-state machine

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

input \ 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)

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 received payoff P_t^j of using mode j at time t. This payoff is then recorded and used to update its expected payoff. The expected payoff U_t^j is updated according to Equation (1).

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

where A means automobile or car and B means bus. Only expected payoff of the chosen mode is updated. When a traveler choose car, his expected payoff of car is then updated. But expected payoff of bus will not be updated until the traveler chooses bus.

Weight factor w ranges from 0 to 1. It depends on a 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.

There are 5 input symbols that are used in the agent's FSM (see Table 2). They represent choices of strategy for a traveler to decide which mode they will use for next trip. Each choice of strategy has a range of value to differentiate it to other choices of strategy. How much is the difference can be categorized into several levels, depending on the value of d. Parameter d represents the sensitivity of a traveler the difference between payoff of car and bus. A larger value of d implies that a traveler does not consider so much about payoff differences when choosing mode. For example, for a traveler who has a low value of d, if he observes that the expected payoff of car is much higher than bus, then the input symbol will be 1. But for a traveler with high value of d, he might behave differently.

Initially, for input symbol 1, choices of mode in its set of strategy are only car, and for input symbol 5 are only bus. Input symbol 2 has 75% choices of car and input symbol 4 has 75% choices of bus. Input 3 has 50-50 proportions of car and bus. In the beginning, all commuters received a random initial value of expected payoff of car and bus ranged from 1 to 2. The first choice would determine all the following choices without any variation, if an initial value were not assigned.

Decision making processes of a commuter starts with input symbol 3 and state 1. For example, a commuter, say commuter C, has a FSM as in Table 2. 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 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 had chosen a mode based on their FSM, they received a payoff of their decision. P^A is given to commuters who chose car and P^B is given to commuters who chose bus. Commuter C received P^A and then he updated his expected payoff of car using Equation (1) ($U^A = 0.9 \cdot 1.1 + (1-0.9)P^A = 0.99 + 0.1P^A$). He observed that $d < (0.99 + 0.1P^A) - 1.2 \le 2d$, so that for next iteration, the input symbol is 2. Based on input symbol 2, and next state 3, Commuter C got new pair of state and output from his FSM. The pair is (4,0), so that the decision is to choose car, coded as 0, and next state will be state 4. These processes continue until the end of iterations (10 trips).

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

input \ 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)

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 FSM in each agent with bit strings. A chromosome with length 60 bit strings encodes a FSM, which consists of 5x4 pairs of state and output. Figure 3 illustrates the process.

For a state, it requires 2-bit strings. The value of 2-bit strings ranges from 0 (for binary code 00, the value is $0.2^1+0.2^0$) to 3 (for binary code 11, the value is $1.2^1+1.2^0$). 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 for input symbol 1 and 5. We still maintain variation of chromosomes by crossover among travelers, since travelers are interrelated with each other.

Travelers learn socially through interaction among them, so that we arrange agents in a kind of plane without border, known as a torus plane, which were used in Yamashita et al [11], so that each agent has 8 surrounding neighbors. It makes possible for them to interact each other. Each agent updates his rules (FSM) based on the fitness (sum of payoffs) of his own rules and also his neighbors' rules. Each agent only knows rules owned by his neighbors only and also payoffs gained by those rules, so that agents are assumed to operate with incomplete information regarding with other agents' behavior. The learning process of users is in the process of evolution of rules. Figure 4 illustrates the rules-updating process of each agent.

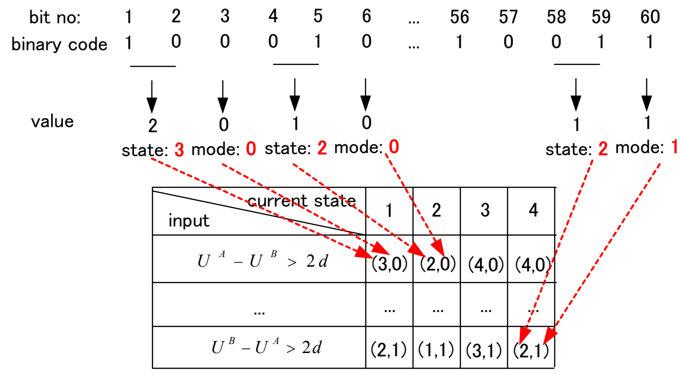


Figure 3: Decoding process of a chromosome into a FSM

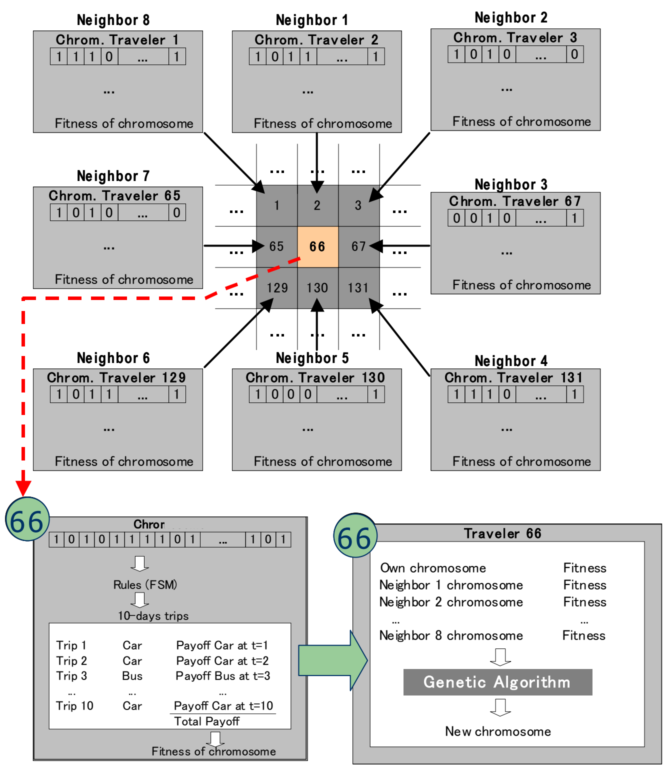


Figure 4: Rules-updating process of an agent

III. Simulation Results And Discussions

We run simulations with 4,096 travelers, who are arranged in a torus plane. Each traveler has a finite-state machine as a decision making rule. Memory weights w of travelers are assumed to be 0.9. To study the influence of the sensitivity parameter d, we vary 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.

A. *Dynamic Equilibrium Situation at d=0.1*

We run four runs for this case. Statistics for last 100 generation is summarized in Table 3. Similar to conventional analysis, a user equilibrium point is reached when the cost of car equals to the cost of bus. For all these runs, the average cost of car is almost equal to the cost of bus. But statistically with 95% confidence interval, only for Run 1 and Run 4, the cost of car is significantly equal to cost of bus. The number of bus users in Run 1 and Run 4 are significantly the same, as well as the equality between Run 2 and Run3. We will discuss in more details for Run 1 in this section up to Section D.

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

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

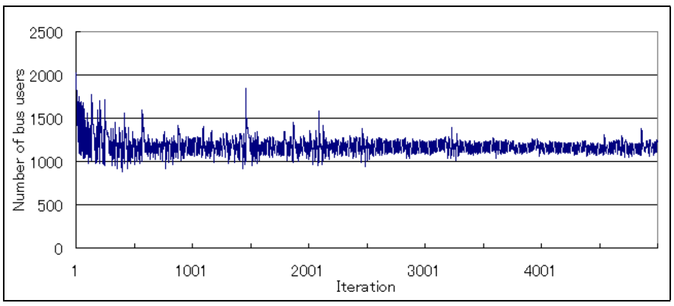


Figure 5: Dynamics of number of bus users

B. *Travelers' Expectation*

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

A traveler decides a mode of commuting based on rules in a FSM and differences of expected payoffs. If the difference of 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 will 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 plot spreads in around a 3x3 column. The column size is 0.1x0.1. At that time, there exist some travelers who experience the high difference of expected payoffs, so that they use either input symbol 1 (always choose car) or input symbol 5 (always choose bus). Some travelers experience medium differences, so that they use either input 2 (higher probability to car) or input symbol 4 (higher probability to bus). Generation-by-generation, the spread of scatter plot became smaller, which means travelers experienced only small differences of expected payoffs so that they decided 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 experienced only slight differences between expected payoff of car and bus.

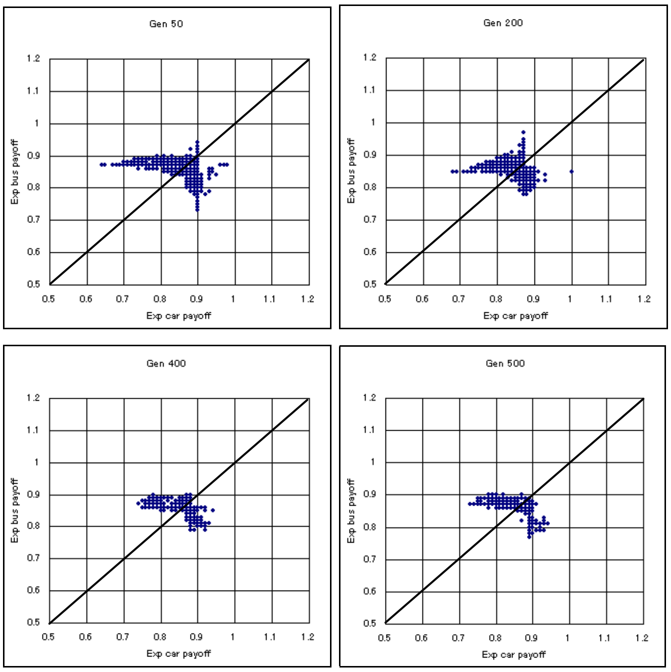


Figure 6: Scatter plots of travelers' expected payoffs at d=0.1

C. *Travelers' Specialization*

Figure 7 shows the specialization of travelers based on their choices of mode in every 10-iterations. All-times car users always chose car in 10 iterations and all-times bus users always chose bus. There are also many mixed users who chose both car and bus during 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 a car user or a bus user, leaving a small number of mixed users.

D. Emergence of Choice Stability

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

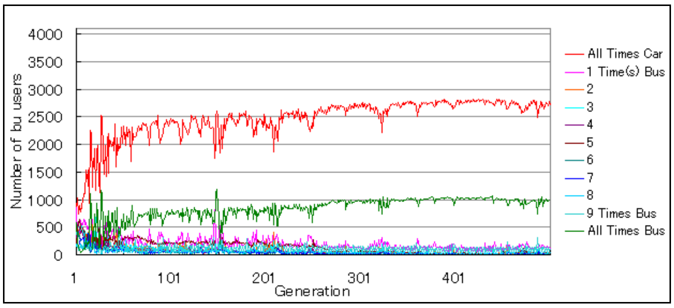
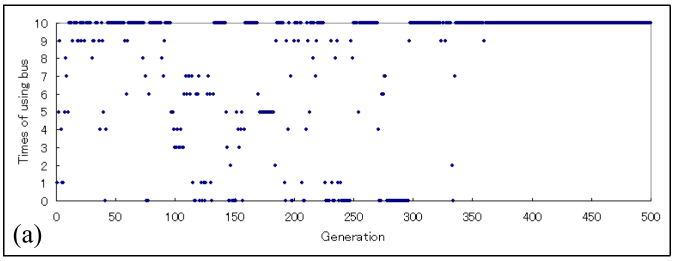


Figure 7: Number of travelers in each level of chosen mode



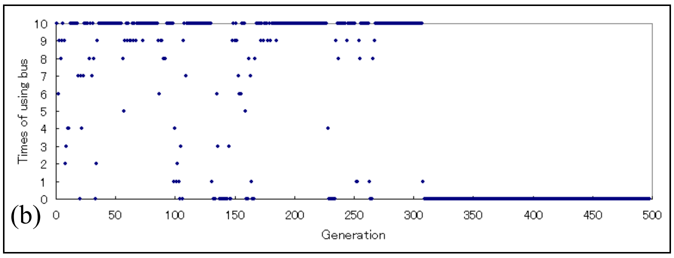


Figure 8: A traveler's changes of choice: (a) finally became a bus user and (b) finally became a car user

E. Effect of Travelers' Sensitivity at d=0.05

We found 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 system converged 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 will be focused on Run 2. An emergent process started from an outbreak of number of bus users at iteration 8 in generation 31 (see Figure 10). The outbreak started with decreasing bus users to a lower level than the user equilibrium point, so that travel time increased and payoff for all users decreased, but payoff of bus was slightly higher than car. Some travelers observed this situation and at the same time they chose bus, resulting in a sudden increase of bus users.

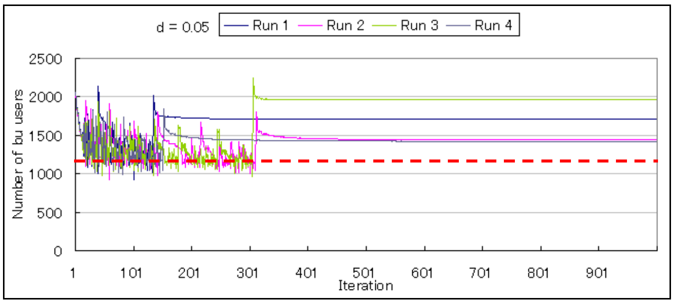


Figure 9: Dynamic of number of bus users at d=0.05

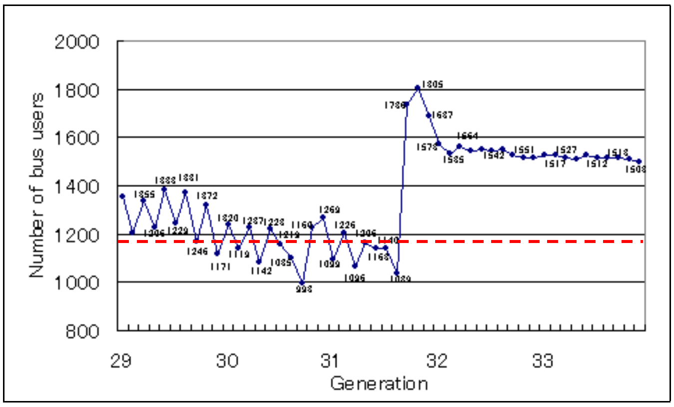


Figure 10: Dynamics of number of bus users at gen. 29-33

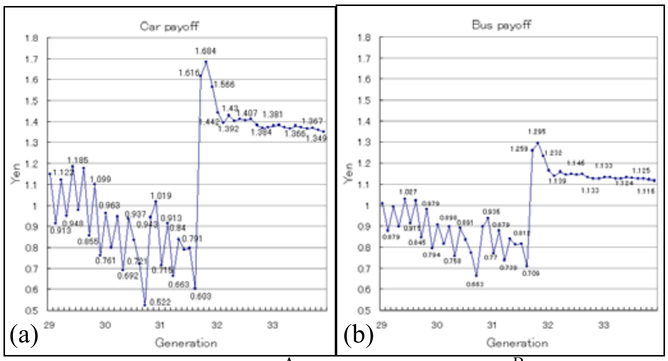


Figure 11: (a) Car payoff P^A and (b) bus payoff P^B at gen. 29-33

The huge increase of bus users increased the payoff of car and bus (see Figure 11), with higher level of increase for car payoff than bus payoff, since car cost has stiffer curve than bus cost. At that time, travelers who had car as their choice received high increase of expected payoff as well as travelers with bus as their choice. They observed that the payoff of the chosen mode was much higher than the other one, so that they used input symbol 1 or 5 in their FSMs and continued to use car or bus. If majority of travelers experienced those processes, then the system converged 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 beginning of generation 31, the traveler mostly chose car, so that the changes of expected payoffs are mostly on car. But during three iterations before the outbreak, he chose bus and the outbreak pushed 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 a result 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.

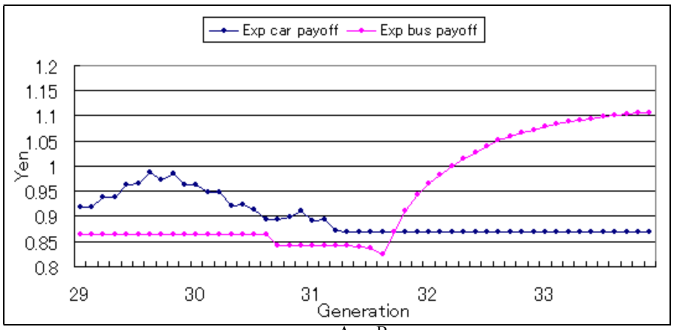


Figure 12: Expected payoffs (U^A,U^B) of a traveler at gen. 29-33

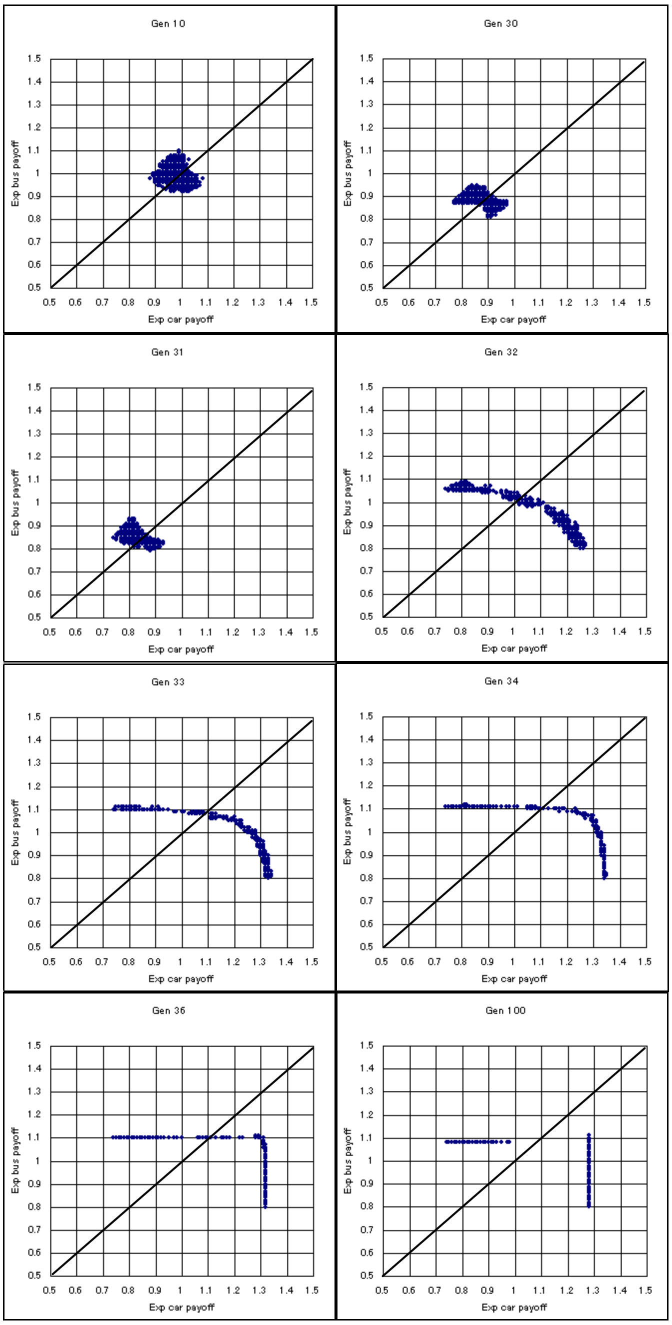


Figure 13: Scatter plots of travelers' expected payoffs at d=0.05

The kind of equilibrium found at d=0.05 is called as 'deluded equilibrium' [8][9]. If travelers expect that the payoff of a mode is much higher than another one, then they will continue to choose the 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].

IV. Conclusion

A simulation model of commuters' learning on choosing mode was built by using a finite-state machine as behavioral rules. A user equilibrium point as predicted by 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 equilibrium point, there exist car users, bus users and mixed users. Most of travelers are specialized in either a car user or bus user, leaving a small number of mixed users.

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

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