Agent-based Approaches for A Social Dilemma of Travel Mode Choice

(交通手段選択の社会的ジレンマに対するエージェントベース・アプローチ)

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Abstract – **The research focused on modelling a social dilemma of travel mode choice for commuters. In order to understand behavioral process of individuals, two types of simulation model of multi-agent learning was built and applied to examining behavior of commuters. The first behavioral model is based on inductive-learning's capability of human beings and the second model is based on their beliefs and expectations. Evolutionary approach is introduced in order to simulate travelers' learning process.**

The first model showed that the same user equilibrium point as predicted by conventional equilibrium analysis could be reached and stabilized. At the equilibrium point, most of travelers specialize in a car-only user or a bus-only user, leaving a small number of mixed users. The stable situation is produced by interaction process among travelers and by behavioural change process of each traveler.

Furthermore, when travelers are very sensitive to payoff differences between car and bus, there is a situation that may produce other equilibrium points in addition to the user equilibrium point. In these new kinds of equilibrium, which are known as 'deluded' equilibrium and 'frozen' equilibrium, higher level of cooperation could be achieved and stabilized.

The second model revealed that some insightful results could be obtained, such as the conditions that make cooperation as a possible outcome. They are group-based interactions, limited information, and conformist transmission. Emergent phenomenon of the system may favor cooperation and resolve the dilemma of travel mode choice, if there exists a strong conformist transmission. This gives insight to the possibility of solving the social dilemma by incorporating an employer-based Travel Demand Management (TDM) measure.

Keywords: **travel mode choice, social dilemma, agent-based approach, microsimulation.**

1. Introduction

Most of models in transportation planning and analysis rely on the equation-based modeling. Agent-based approaches are still not as widely used as equation-based approaches. An agent-based model has the advantage of being validated at an individual level, since the behaviors encoded for each agent can be compared with local observations on the actual behavior of domain individuals. Understanding individual's behavior is important especially in studying effects of transportation policies.

Several works on route choice behavior by Nakayama et al [11][12] are the examples of agent-based approaches in transportation modeling. Travelers are modeled to have bounded rationality, limited information and also capability to do cognitive learning. Klugl and Bazzan [9] also studied route choice behavior by using a simple heuristic model. In travel mode choice, there are not so many works done by researchers. One of the inspiring works by Kitamura et al [8] is on travel mode choice by using a simple bi-modal transportation system and cellular automata.

Our study focuses on commuters' mode choice behavior. On the highway, all people have right of commuting by private car or public transport. As a common good, which is shared by people, a social dilemma [2] situation may happen on the highway. Selfish behavior of people, who use cars based on their personal interest to minimize travel cost, creates traffic congestion, and furthermore increases travel cost for users both of car and public transit.

By using a simple bi-modal transportation system, the social dilemma situation of travel mode choice is modeled. Travelers who use public transit, for example bus, are called as cooperative travelers, since they behave cooperatively for the sake of all people's benefit. Car users are defective travelers since they consider only their personal interests.

This study aims to provide an agent-based simulation model of travel mode choice in order to understand behavioral process of commuters on choosing travel mode. A user equilibrium point may also be reached, but more important is the process to reach the point and the behavioral change of travelers during the process. We attempt to observe complex dynamical processes of commuters' behavior by considering interactions and learning processes influential. New findings are expected in order to gain an insight into the way of solving the social dilemma.

2. Simulation Model: Modelling by Finite-State Machines

Two types of simulation model of multi-agent learning was built and applied to examining behavior of commuters. The first behavioral model is based on inductive-learning's capability of human beings and the second model is based on their beliefs and expectations. Evolutionary approach is introduced in order to simulate travelers' learning process. In this section, we will focus on the first 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. After that, an evolutionary process to update travelers' FSM by using genetic algorithm is utilized in order to acquire adaptive behavior.

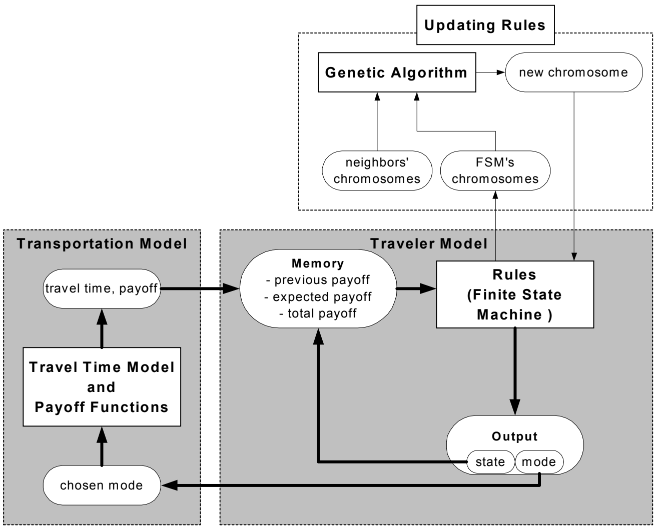

Figure 1: Multiagent simulation model by FSMs

2.1 *Transportation Model*

A simple bi-modal transportation system, which comprises private car and bus as choices of commuting, is used as a transportation model. The two modes are assumed to be operated in the same lane so that there will be more interactions than if they are operated in exclusive lanes. This simple model is used in order to understand basic travel mode choice that represents social dilemma situation.

All travelers own cars so that they can easily change modes and they only know the cost of mode they choose. Private car users are assumed to be solo drivers. For public transport, bus operating frequencies and fare are adjusted so that bus passengers can pay the full cost of operating buses. Equations and their parameters of generalized travel costs for car and bus are derived from the work of Kitamura et al [8].

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). 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) [3]. Where Q is a set of states, τ is a set of input symbols, ρ is a set of output symbols, $s{:}Q \times \tau \rightarrow Q$ is the next state function, and $o{:}Q \times \tau \rightarrow \rho$ 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.

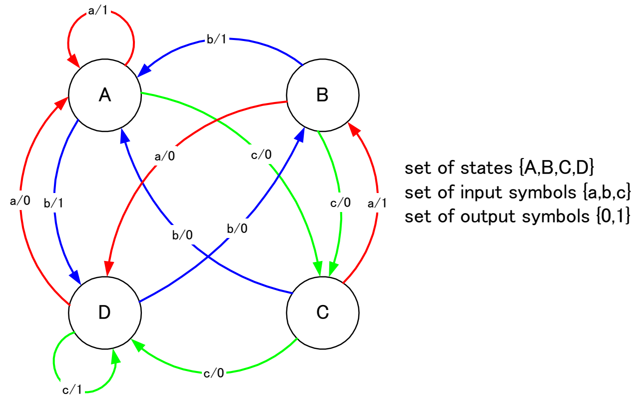

Figure 2: An illustration of a finite-state machine

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

current state / input	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 [10]. 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).

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

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 $d < (0.99 + 0.1P^A) - 1.2 \leq 2d$, 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) $d < U^A - U^B \leq 2d$	(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) $d < U^B - U^A \leq 2d$	(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.

Agents must have adaptive process in order to evolve decision rules they have. 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, travelers learn based solely on their own experience. Sometimes it requires longer time to acquire adaptive behaviors, and also it limits travelers' 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. In this paper, we utilize social learning only.

Social learning requires interaction among agents, so that we arrange agents in a kind of plane without border, known as a torus plane, which were used in Yamashita et al [13], 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. Genetic algorithm is implemented to evolve agents' 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.

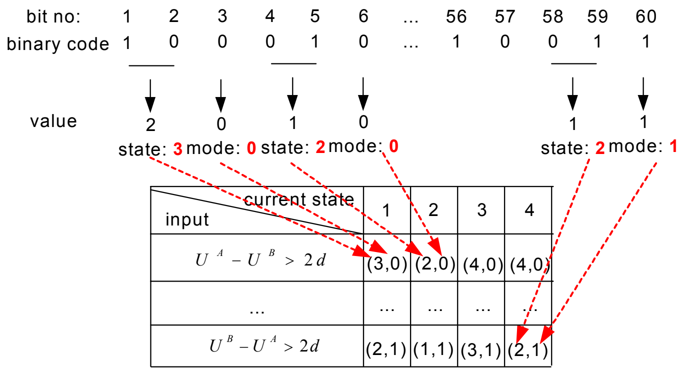

Figure 3: Decoding process of a chromosome into a FSM

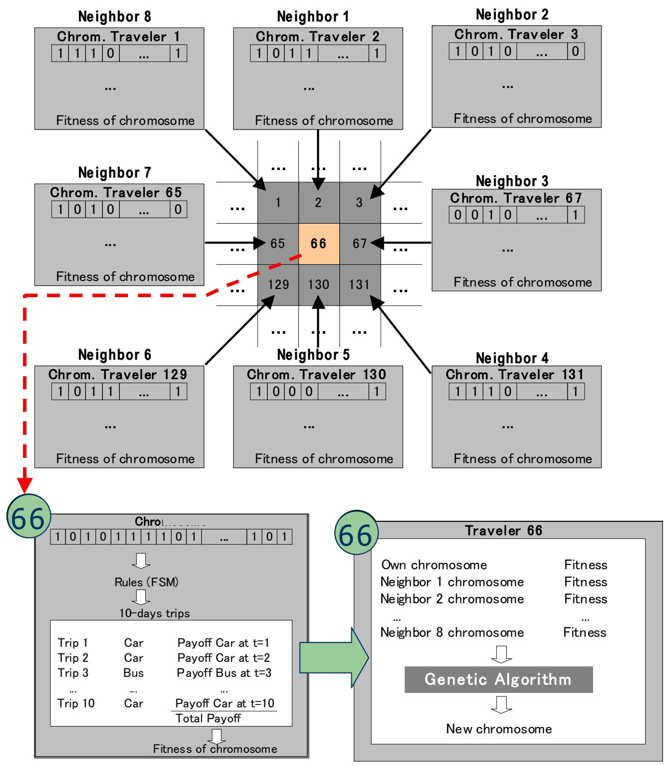

Figure 4: Rules-updating process of an agent

2.3 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 C.

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

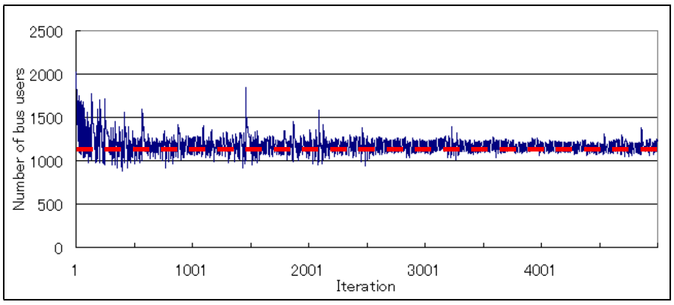

Figure 5: Dynamics of number of bus users

B. Travelers' Specialization

Figure 6 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.

C. 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 7 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.

D. 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 8), 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 9). 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.

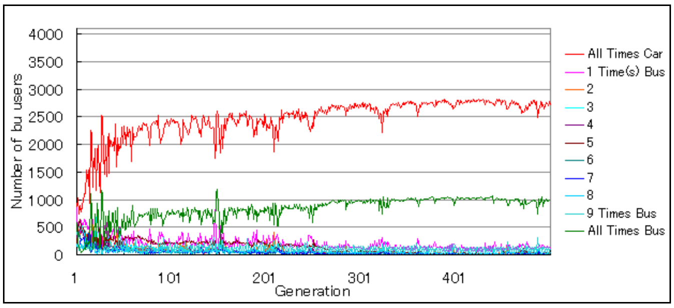

Figure 6: Number of travelers in each level of chosen mode

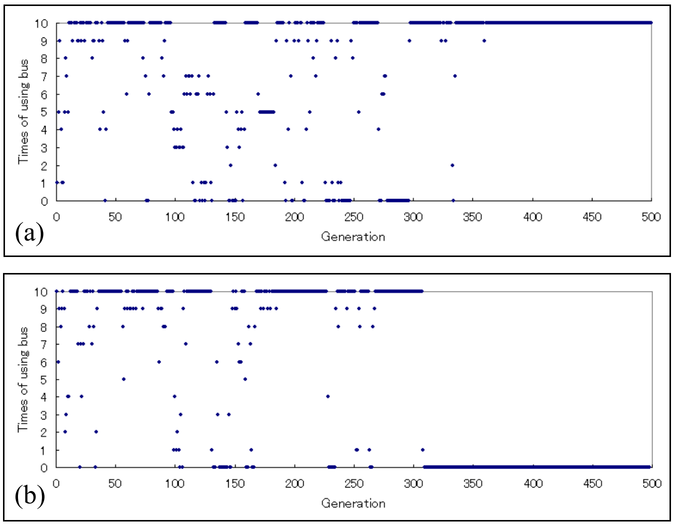

Figure 7: A traveler's changes of choice: (a) finally became a bus user and (b) finally became a car user

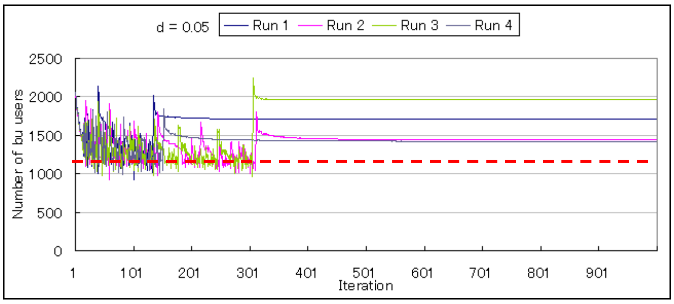

Figure 8: Dynamic of number of bus users at d=0.05

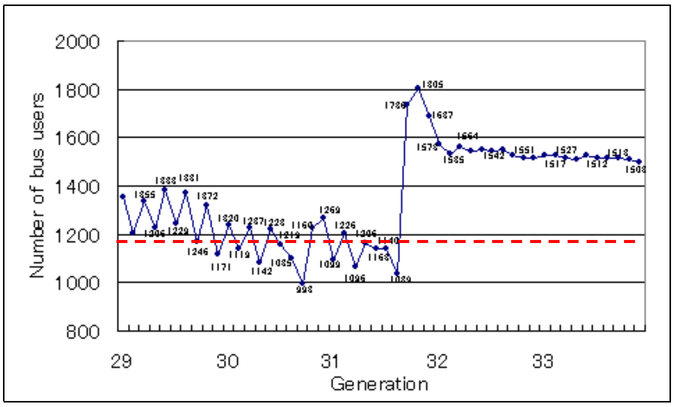

Figure 9: Dynamics of number of bus users at gen. 29-33

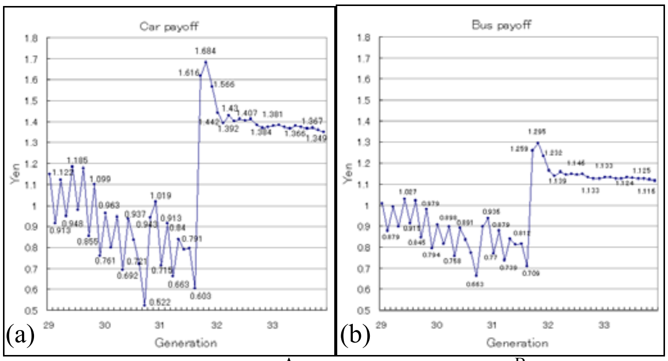

Figure 10: (a) Car payoff P^A and (b) bus payoff P^B at gen. 29-33

The huge increase of bus users increased the payoff of car and bus (see Figure 10), 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 11 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 12. 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.

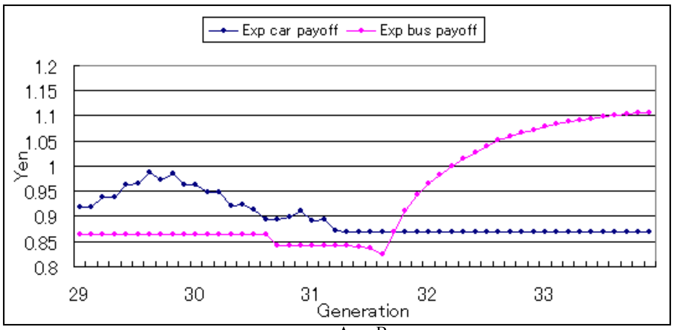

Figure 11: Expected payoffs (U^A,U^B) of a traveler at gen. 29-33

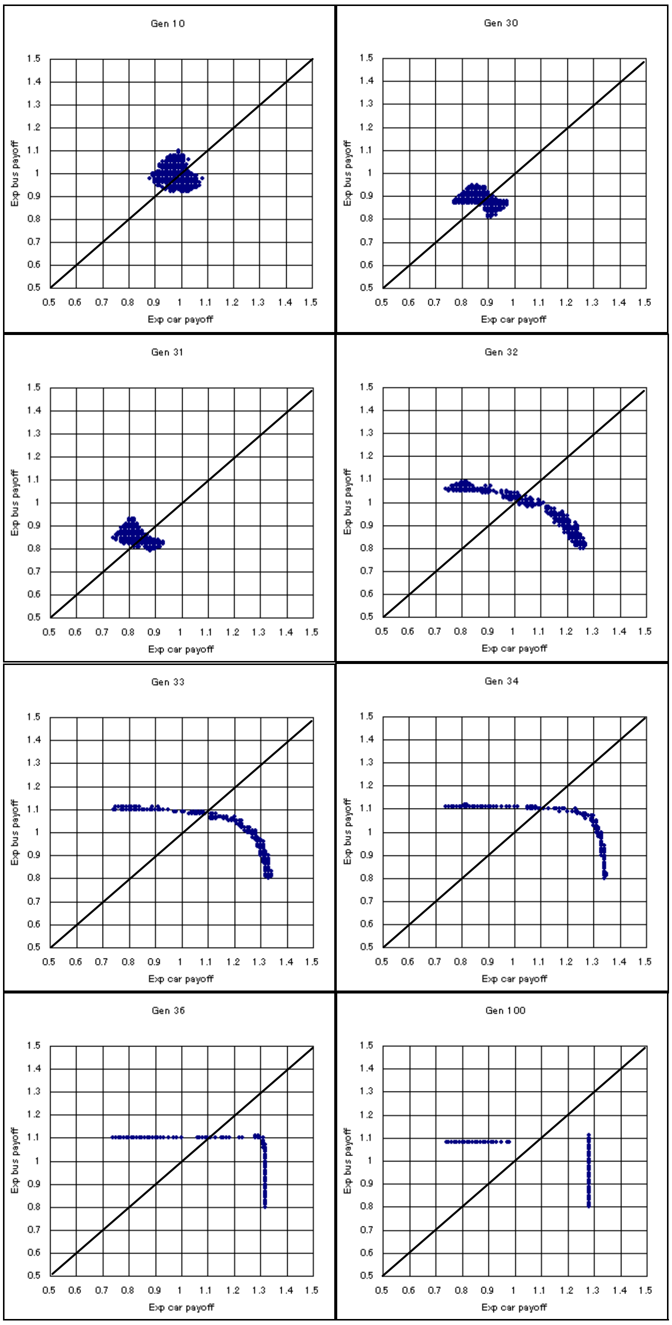

Figure 12: Scatter plots of travelers' expected payoffs at d=0.05

The kind of equilibrium found at d=0.05 is called as 'deluded equilibrium' [11][12]. 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' [11].

3. Simulation Model: Modelling by Beliefs and Expectations

The second model also consists of traveler and transportation model (see Figure 13).. The transportation model is the same as the first model, but in the traveler model, travelers decide a mode based on the rules of expectations, which shows traveler's belief about the influence of his action on other members of the group

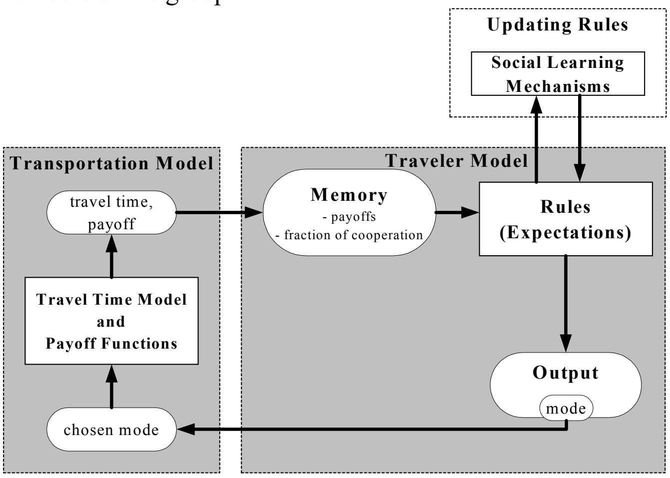

Figure 13: Multi-agent simulation model by beliefs and expectations

3.1 Transportation model

Please see Section 2.1.

3.2 Traveler model

A. Decision making rules: expectations' curve

Behavior of a traveler is represented by an expectations curve, which shows traveler's belief about the influence of his action on others [4]. Two classes of beliefs were considered in the model: bandwagon expectations and opportunistic expectations [7]. For each type, there are three types of curve that represent agents' level of expectations: pessimistic, normal and optimistic. In this paper, we deal with only the bandwagon expectations (see Figure 14). A probability of cooperating represents a degree of an individual's beliefs about the influences of his action on others; and a criteria, which lies on 45 degree of straight line and the value is equal to the fraction of cooperation, represents a base of beliefs.

Figure 15 shows decision making processes of a traveler. Initially, travelers are given a type of curve and a randomly chosen mode. Travelers make decision at an asynchronous time so that only 10% of them observe current level of cooperation and make a choice at the same time. Another 90% continue to use their current mode of commuting. Based on travel mode they chose, travelers receive payoffs and accumulate them. After 10 iterations, the accumulation of payoffs is used as the fitness of agents' type of curve.

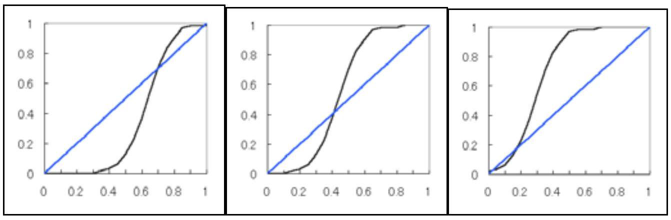

Figure 14: Types of bandwagon expectations curve (from left to right; pessimistic, normal and optimistic. x axis: fraction of cooperation, y axis: probability of cooperation)

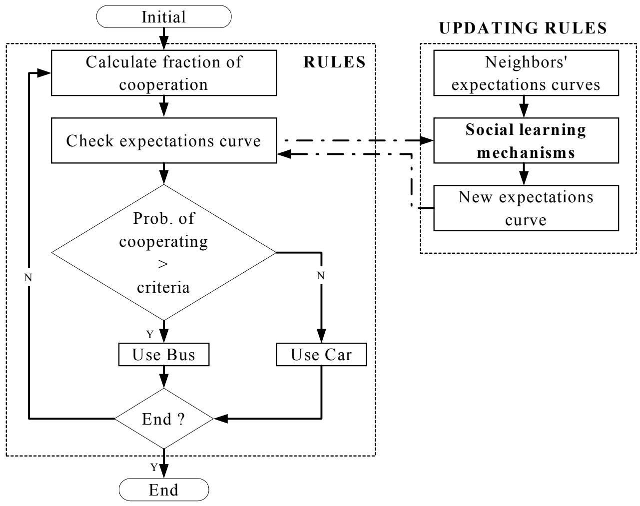

Figure 15: Decision making of a traveler

B. Interaction among agents: group-based interaction

A possibility of incorporating employer-based TDM measures to solve a social dilemma of travel mode choice is studied by introducing a group-based interaction, where a group represents employees of a company. We also need this grouping to make travelers interact each other in order to acquire adaptive behavior by local interactions. A traveler interacts with travelers of the same company he works in a torus plane so that eight neighbors around him influence his choice of behavior. Each group is independent from others so that there is no interaction among members of different companies. Assuming limited information, a traveler knows only his own payoff information and types of expectations curve of eight surrounding neighbors.

C. Evolution of expectations by imitation

We apply an imitation game based on social learning mechanism in order to evolve expectations' curve of each traveler. Two kinds of mechanism are used: payoff-biased transmission and conformist transmission [5]. The relative strength of each transmission depends on the strength of conformist (α) in a traveler's psychology [6]. For each traveler, there are α probability to use conformist transmission and $(1-\alpha)$ probability to use payoff-biased transmission.

3.3 Simulation Results and Discussions

A number of agents, exactly 4096, are assigned into 16 homogeneous groups with size 256. Each agent has a type of bandwagon expectations curve (pessimistic, normal or optimistic), which is assigned randomly giving the same proportion of agents for every type of expectations' curve. We run a simulation with various initial levels of cooperation, ranging from 0.2 to 0.8 with increment 0.1. The strength of conformist transmission (α) ranges from 0.0 to 0.4. Simulations are run up to 100 generations with 10 iterations per generation.

A. *Social learning mechanism by payoff-biased transmission (α = 0.0)*

The simulation resulted in an equilibrium point for initial level of cooperation from 0.2 to 0.7 (see Figure 16). According to the cost functions defined before, the number of bus users at the equilibrium point should be around 1200 or equal to 30% of travelers. High initial level of cooperation (0.8) resulted in full level of cooperation (all travelers chose bus) because for all types of curve, the probability of cooperating at a fraction of 0.8 was higher than the criteria (see Figure 14), so that all travelers suddenly cooperated.

Observing which kinds of type exist at the end of simulation, all three types of curve still exist as seen in Figure 17. Pessimistic type was chosen by the highest number of members, around 2500 travelers. Followed by normal type with around 1000 members and the rest is optimistic type.

B. *Dynamics within a group at α = 0.0*

Dynamics of behavioral change within a group can be seen in Figure 18, which is taken from a simulation run with initial level of cooperation 0.5. The number of bus users is taken from the average value of 10 iterations in one generation. Within Group 1, all members finally chose car. Pessimistic behavior dominates the group with around 200 agents. Small numbers of normal and optimistic agents could not increase the level of cooperation and furthermore they chose defection.

The situation in Group 7 is quite different. Group 7 shows the role of optimistic agents to elicit cooperation, since they acted alone as altruist agents following the fall of normal agents. They could maintain the level of cooperation and increased to the maximum level, after some pessimistic agents changed type to optimistic one.

C. *Combining payoff-biased transmission and conformist transmission (α=0.1 - 0.4)*

The strength of conformist is represented by a value of α. High value means high probability of using conformist transmission for an agent. For α=0.1 and 0.2, the dynamics are only slightly different from α=0.0, so that we will focus on α=0.4 (see Figure 19). The dashed line is the user-equilibrium line. At α=0.4, a higher level of cooperation than the user equilibrium point could be reached for all initial levels of cooperation.

Low initial level of cooperation (0.2) gave a quite different behavior, because in the beginning the cost of bus was lower than car, so that most of users preferred bus to car. The level of cooperation suddenly increased and the conformist transmission spread cooperative behavior to other travelers. If the strength of conformist were strong enough then cooperative behaviors could spread fast to make all group members cooperate and stabilize cooperation within the group, without giving payoff-biased transmission a chance to push the global cooperation to the equilibrium point. It can be seen that low initial level of cooperation 0.2 gave higher convergence value than initial level 0.3, 0.4, 0.5, and 0.6.

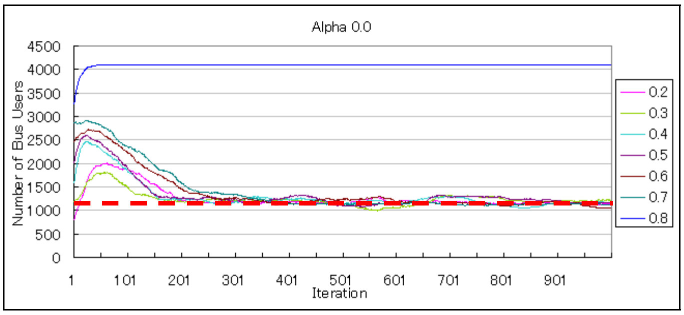

Figure 16: Dynamics of cooperation level (α=0.0)

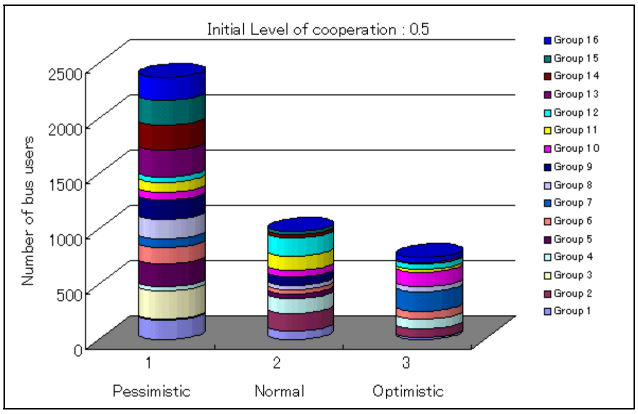

Figure 17: Type of curves at end of simulation (α=0.0)

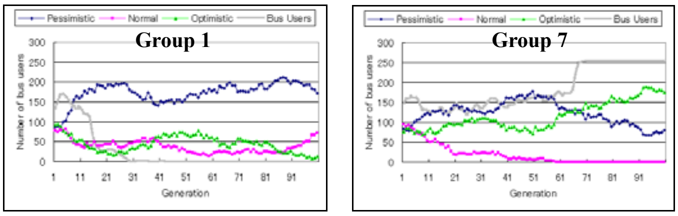

Figure 18: Dynamics of behaviors within a group (α=0.0)

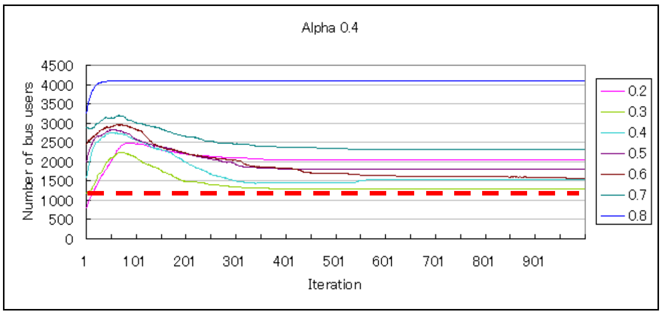

Figure 19: Dynamics of behaviors within a group (α=0.4)

Middle to high initial value of cooperation (0.4-0.7) had different processes. In that range, the higher the initial level, the higher is the convergence point. Let us focus on the case of α=0.4. In the beginning, cooperation increased suddenly because of the existence of optimistic agents who chose cooperation, since the initial fraction of cooperation was higher than the criteria of cooperation. They were followed by some normal agents who later also cooperated, after observing a certain level of cooperation which was higher than their criteria. Finally, payoff-biased transmission that has probability 0.6

(1-α), had pushed the cooperation level to lower state before the system converged. High initial level of cooperation (0.8) favored cooperation for all types of expectations so that full level of bus users was achieved.

D. Dynamics within a group at α = 0.4

Early dynamical processes within a group are complex and important to determine the succeeding processes and ending results of simulation (see Figure 20). Conformist transmission helped the spread of a type of expectations' curve and later the group would become homogeneous with an only type of curve. In some groups, optimistic expectations may dominate (eq. Group1). But in some other groups, pessimistic or normal expectations may also dominate (eq. Group 2).

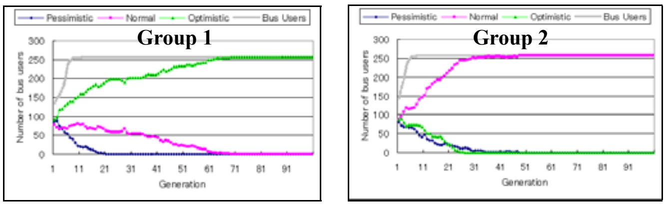

Figure 20: Dynamics of behaviors within a group (α=0.4)

These results prove that the conformist transmission might be able to stabilize cooperation when it is strong enough compared with payoff-biased transmission. By using a complex process of interactions among agents, a combination of payoff-biased and conformist transmissions, and also other emergent components, a high level of cooperation can be achieved.

4. Conclusion

Simulation models of commuters' learning on choosing mode were built and applied to examining behavior of commuters. Both models showed that 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.

The first model revealed that an outbreak situation might produce other equilibrium points, in addition to the user equilibrium point**,** when travelers were very sensitive to payoff differences. In these new kinds of equilibrium, which are known as 'deluded' equilibrium and 'frozen' equilibrium, higher level of cooperation could be achieved and stabilized. The outbreak itself, as an emergent process of the system, made travelers perceive an excessive increase of payoffs and form a habit of choosing only either car or bus until the end of the simulation.

The second model shows that cooperation level within a group is highly related to the existence of type of expectations. Domination of pessimistic agents would make a group converges to all defection and the appearance of optimistic agents is very important to pioneer cooperation within a group.

The model revealed that some insightful results could be obtained, such as the conditions that make cooperation as a possible outcome. They are group-based interactions, limited information, and conformist transmission. If there exists only payoff-biased transmission (α=0.0), then a user equilibrium point is reached. But, if there are a strong conformist transmission (α=0.4) and an emergent phenomenon in the system, they may favor cooperation and resolve the dilemma of travel mode choice. This gives insight to the possibility of solving the social dilemma by incorporating an employer-based Travel Demand Management (TDM) measure.

In general, this research demonstrated the capability of agent-based approaches to simulate dynamics of travel mode choice under a social dilemma situation and to reveal some findings, which are undisclosed by conventional analyses.

The results of both models showed that travel behaviour has a dynamic nature as the results of learning process of each individual commuter. They also gave a new perspective on changing the paradigm of modelling travel behaviour of commuters, from a conventional and static analysis into a more dynamic analysis by using agent-based approaches

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