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Table of Contents

Preface

Multi-Agent simulation is primary technology in AI. MASim methodologies/technologies have not been sufficiently mature though, its scientific significance is getting quite high to understand and analyze complex mega-scale systems, such as human societies. Data mining is another primary AI technology to retrieve hidden information or knowledge from big data. However, real data for the mining does not always include essential elements of a target complex system. Thus, a simulation is promising way to generate meaningful data which is hard to obtain in the real world.

In order to understand diverse mega-scale complex systems such as a human brain, social systems, Internet, and WWW, it is not enough to simply dig out knowledges from the vein of data. It is required to establish new "constructive data mining process" consisting of iterative processes of the generation of data veins and exploration of new knowledge from them. Therefore, we try to harness multi-agent simulation and data mining technologies and find the best mix of MASim and DM technologies.

It is inevitable to think about the scale of multi-agent simulations for the constructive mining. When we try to discover practical knowledge to understand complex phenomena in human society, it is required to achieve sufficient scale of simulations to reproduce target society. MMAS technologies can provide suitable infrastructures for mega-scale social simulations which can offer practical big data and insights.

To understand mega-scale complex phenomena, technologies/methodologies for simulation, knowledge discovery, and computational modeling are required. Although MASim and MMAS researchers are good at working on the implementation of tools for multi-agent simulations and the design of computational model, they are not necessarily experts of knowledge discovery who can extract essentials of complex systems. On the other hand, DM researchers are technicians for knowledge discovery though, it is usually hard for them to actively analyze obtained knowledge through simulations. Thus, we believe the workshop should be of interest to researchers addressing complex systems from different viewpoints, such as modeling, implementation, and data analysis.

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Modeling Human Behavior Selection under Environmental Subsidy Policy by Multi-Agent Simulation

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Abstract. In recent years, the importance of environment is widely recognized and various kinds of environmental policies have been implemented. However, when one establishes a policy, there are few cases that the contents and the period of the policy are evaluated by using prediction method for its effect. In this study, we aim to predict the effects of a policy in micro-level by using agent simulations and estimate the optimal period of the policy implementation by totally evaluating its effect. For sugarcane farmer of an area in Japan, we performed 200 thousand patterns of simulations in order to optimize the subsidy of green manure and its implementation period. In particular, when the values of the parameters in the simulation model are not clearly defined, we are able to show various futures caused by the policy implementation of interest based on large-scale simulations with a huge variety of the parameter values.

Keywords: Environmental Policy, Agent Simulation, Merge Action, Parameter Variety

1   Introduction

Recently, in the research of environmental economics, making suitable policy is very important for controlling the balance between economy development and conservation of environment. Although a lot of policies for conservation of environment have been considered, mathematical evaluation for their effectiveness has not been well studied.

In existing literature, human behavior was usually predicted by observed data [1] or results of questionnaire [2]. The data of questionnaire are usually obtained as non time-series, but as a snapshot when survey was done. The answers of questionnaire may be affected by the economic conditions of answerers; the conditions change, the results of questionnaire should be changed. Recently, a new approach on improvement of questionnaire was investigated and the changes of human behaviors were analyzed by considering answerers' conditions as a random variable [3]. Although extending this approach may be effective to model time series human behavior, long-term questionnaire survey like panel data is required.

In this study, for modeling human behavior under situations that the conditions vary due to the implemented policy directly, we use an agent simulation model. We

investigate farmers' behaviors in Ishigaki island, which is a part of Okinawa prefecture. Ishigaki island is located in the south sea and its main industries are agriculture and tourism based on natural environmental resources. In this region, cultivated crops are limited to sugarcane by its weather characteristics. However, in recent years, marine pollution by red clay flowed from agricultural field becomes a serious issue. To prevent the outflow, there are several ways that can be done by farmers who grow sugarcane. For example, construction of green belt or green manure can be considered. These methods, however, require additional cost to the farmers, but house budgets in that island are not so strong [4]; advance of environmental measures dose not have reality. On the other hand, by the problems related with the age of the farmers and with heirs, it is difficult to continue and expand their farming. Therefore, merging several small farmers to a big community has been discussed in order to obtain strong economy base. We investigate the choice of these two behaviors of farmers, i.e., "environmental operation by green manure" and "merging small farmers to a big one" by a given subsidy policy that supports the farmers' cost for using green manure.

A subsidy policy we considered is that farmers whose costs for green manure are in the specific range defined by the policy can be fully supported. For example, if the range is defined from 20,000 yen to 200,000 yen, a farmer whose cost is 30,000 yen can be supported and he does not need to pay anything. On the other hand, a farmer whose cost is 10,000 does not receive any support and he needs to pay all cost by himself. Therefore, such a subsidy policy becomes an incentive for small farmers to merge into a big farmer that can get the support for green manure. In this paper, we model this farmers' behavior selection by an agent simulation model and analyze the effect of the patterns of subsidy policy. Our agent simulation model consists of 301 farmers that are about 20% of the farmers in Ishigaki island. We also investigate the robustness of the results for the setting of the parameters included in the agent simulation model.

2   Agent Simulation for Modeling Farmers' Behavior and Policy Evaluation

2.1   Policies and Farmer's Behaviors

Suppose that S_i is the total area of the i-th famer's field (unit: a), T_i is the amount of the harvest per 10a (kg/10a) in the field of the i-th farmer, and C_i is the cost for the working of the i-th farmer per 1a. We set the price of the sugarcane 20,110 (yen/t) and the income B_i of the i-th farmer is represented by

$$B_i = \frac{20110}{1000} \cdot \frac{T_i}{10} \cdot S_i + \frac{360}{1000} \cdot \frac{T_i}{10} \cdot S_i - \frac{C_i}{10} \cdot S_i. \tag{1}$$

Here, C_i's were determined by the data of Japanese Ministry of Agriculture depending of their total area of the fields S_i.

As briefly mentioned in the previous section, we consider a subsidy policy for the cost of green manure. However, considering subsidy policy does not support all

farmers, but cover the all costs for some farmers who meet with a certain criterion. Actually, we can consider various criteria, but in this paper we consider implementing following rule. The subsidy policy has minimum and maximum values for the cost of green manure; if the cost, denoted by G, of green manure of a farmer satisfies $\alpha \leq G \leq \beta$, where α and β are the minimum and maximum of the range of the subsidy, respectively. On the other hand, farmers with $G < \alpha$ or $\beta < G$ do not obtain any subsidy. For such types of subsidy policy, we set 12 patterns of virtual environmental subsidy policies for farmers shown in Table 1.

Table 1. Virtually considered 12 patterns of subsidy policies in the simulation.

Policy	Min Cost (yen)	Max Cost (yen)
1	30,000	200,000
2	10,000	500,000
3	20,000	100,000
4	100,000	200,000
5	200,000	500,000
6	20,000	300,000
7	20,000	400,000
8	50,000	100,000
9	50,000	300,000
10	200,000	600,000
11	10,000	400,000
12	0	600,000

If a farmer wants to have a subsidy from government, his cost of green manure should be in the range of subsidy. Under this virtual policy, farmers can select whether they merge into bigger management communities or not; if small farmers who do not meet with the criterion of the subsidy form a community and can receive the subsidy, it may become an incentive of forming a community. This mergence action may depend on the preset subsidy range and the economic conditions of the farmers. In this situation, we define an agent simulation model for a farmer's behavior. We first define a probability of mergence willing for a farmer as:

$$P_i = \frac{2}{3}I(G_i < \alpha \cap B_i < 0) + \frac{2}{3} \times n \times \frac{1}{10}I(G_i < \alpha \cap B_i \geq 0) + \frac{1}{20}I(\alpha \leq G_i < \beta)$$

$$+ \frac{1}{20}I(B_i < 0) + \frac{1}{10}I(T_i > \tau_{80\%}),$$
(2)

where P_i is a farmer's mergence probability, G_i is the cost of green manure, α and β are the minimum and maximum of subsidy policy (yen), respectively and $\tau_{80\%}$ is the 80th percentile point of T_i's, and $I(x)$ is indicated function if the conditional equation is true, it returns 1, otherwise, it returns 0. Here n is the period of the subsidy and this factor realizes a flexible subsidy; if n is set by 2 (years), a farmer whose B_i was positive in the last 2 years cannot have the subsidy. In the simulation, we first set $n = 10$, i.e., no restriction is considered for the period of subsidy, because we perform 10

years' simulation. We also notice that the term $n/10$ in Eq. (2) represents an incentive of farmers for mergence for the period of the subsidy; short-term subsidy gives lower probability. Note that, beyond the period, a farmer whose B_i is negative can obtain the subsidy continuously. Also, we set that if the case of $n = 2$, in the first and second year, a farmer whose B_i is positive and who meets the criterion can obtain the subsidy.

We assume that the mergence is only carried out for the farmers who live in the same area. Although there are some exceptions, mergences in the same area is more common [5]. After merging into a big community, the economic conditions of the merged farmers will be improved by some reasons. In this simulation, we assume that the amount of harvest per 10a is improved by merging; the amount of harvest per 10a , denoted by T_C, of the newly established community is set by the average of those of the merged farmers:

$$T_C = \sum_{i \in C} T_i.$$

(3)

Since there is a tendency that T_i is larger than T_j for $S_i < S_j$, T_C improves the total economy of the merged farmers, i.e., established community. If a farmer receives the subsidy, he must use green manure. A farmer who does not obtain the subsidy uses green manure depending on his income and expenditure. We also assume that the green manure makes the amount of harvest per 10a 1.01-fold. Figure 1 shows the flowchart of farmers' behavior decisions.
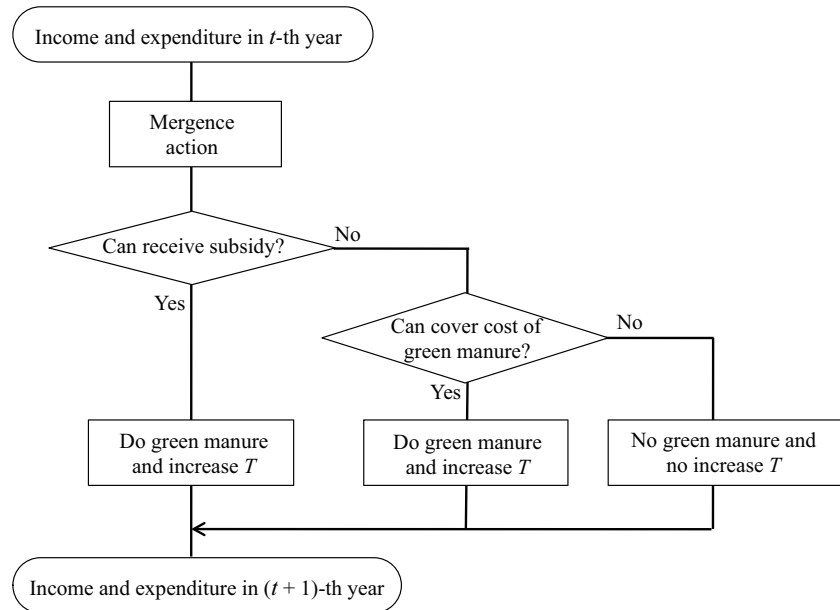

Fig. 1. The flowchart of a farmer's behavior in our agent simulation model.

We perform a simulation without subsidy policy for evaluating the effectiveness of the considered subsidy policy. In the simulation without subsidy policy, a farmer's probability is given by:

$$P_i = \frac{1}{20} I(B_i < 0). \tag{4}$$

A farmer wants to merge only when his income and expenditure is negative; he has a small probability, 1/20.

2.2   Simulation Results

First we perform simulations for fifth pattern of subsidy policy in Table 1. Figure 2 shows the results of simulation. The upper three figures indicate patterns of sum of Bi, total cost of the subsify and the executing rate (%) of green manure (from left to right) in the case on $n = 10$ and the lower three are in the case of $n = 2$. In this figure, the blue lines indicate the result with the subsidy policy and the red lines represent the results without the subsidy policy. By comparing with the results of two simulations, for the farmers' income and the executing rate of green manure, the period does not have strong effects. However, the total cost of the subsidy can be saved; from a cost performance point of view, the subsidy policy with $n = 2$ might be better than that with $n = 10$. Like this, it is possible that there exists an optimal period.
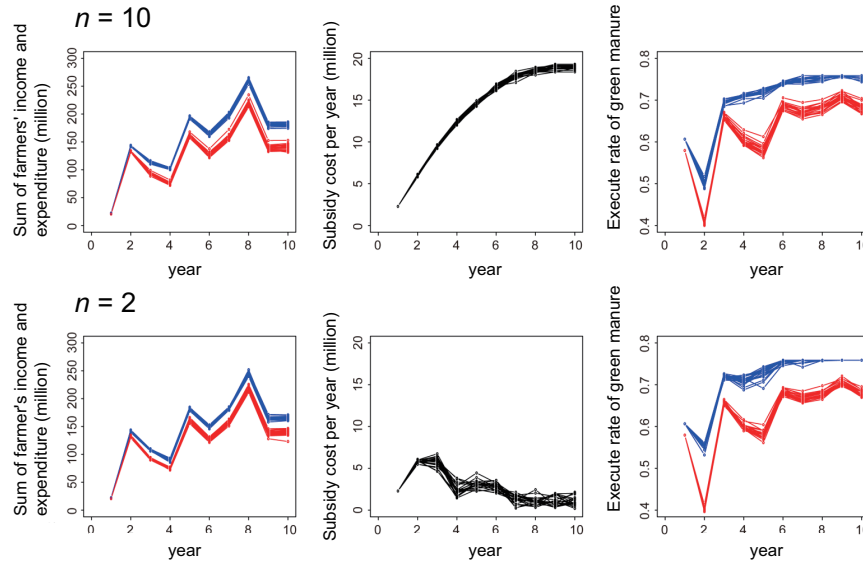

Fig. 2. Results of the simulation with the fifth subsidy policy.

2.3 Evaluation of Simulated Policies

We tested 12 patterns of subsidy policies. Each simulation has three types of the results, i.e., income and expenditure of the farmers, total amount of subsidy paid by the government and the execution rate of green manure. Table 2 shows the results that 12 policies were ranked based on each of three characteristics. From the information presented in Table 2, we want to know which policy is the best. However, no policy is ranked as the top 3 in all three ranking tables, therefore it is difficult to determine the final ranking. There are several researches for the evaluation of multiple policies [6]. In this paper, we consider following points to define the policy evaluation method. From a government's viewpoint, lower cost of the subsidy is better. However, from a viewpoint of farmers' economy, more income is better. On the other hand, for environment, more execute rate of green manure is better. Therefore, there are various types of viewpoints depending on the subjects. Hence, for evaluating a policy, we need to consider such various values. We first define two types of scores, x_{j1} and x_{j2}:

$$x_{j1} = Income_j - Subsidy_j, \tag{5}$$

$$x_{j2} = Green_j - Subsidy_j. \tag{6}$$

The former score (5), x_{j1}, is the income and expenditure for jth subsidy. $Income_j$ indicates the sum of farmers' income and expenditure with jth policy minus without policy. $Subsidy_j$ indicates the total amount of subsidy. The next score x_{j2} is defined as the percentage of green manure multipliable one hundred million for money of subsidy (6). The percentage of green manure is too small figure to figure of subsidy, so we make up the number of digits to multipliable one hundred million. $Green_j$ is the sum of the percentages of green manure for ten years and multipliable one hundred million.

We want to define a new score by considering these two scores. However, x_{j1} and x_{j2} are different unit if we plus x_{j1} and x_{j2} directory, Income evaluates too high compared with Green. For this reason we normalize both two scores at the range of [0,1]:

$$y_{jk} = \frac{x_{jk} - \min_j \{x_{jk}\}}{\max_j \{x_{jk}\} - \min_j \{x_{jk}\}}. \tag{7}$$

We defined the final evaluation score by $Y_j = y_{j1} + y_{j2}$.

Table 2. Policy ranking based on separated evaluations.

Ranking	Farmer's Economy		Total Cost of Subsidy		Green Manure	
	Policy	Income*	Policy	Cost*	Policy	%(sum)
1	10	203.60	3	94.97	12	7.585
2	5	185.54	4	106.07	11	7.584
3	12	133.61	8	116.56	2	7.584

$* \times 10^6$

Table 3. Policy ranking based on the proposed scoring method.

Ranking	Policy	Min Cost	Max Cost	Score
1	5	200,000	500,000	1.376
2	10	200,000	600,000	1.300
3	4	100,000	200,000	1.201
4	8	50,000	100,000	1.076
5	3	20,000	100,000	0.646
6	9	50,000	300,000	0.416
7	12	0	600,000	0.349
8	2	10,000	500,000	0.300
9	6	20,000	300,000	0.295
10	1	30,000	200,000	0.282
11	11	10,000	400,000	0.272
12	7	20,000	400,000	0.266

Table 3 shows the ranking of 12 policies by the final evaluation score with $n = 10$. By this table, totally the most effective policy is the fifth policy. In this evaluation, we set the same value to both two scores, y_{j1} and y_{j2}, i.e., the final score is defined as the simple sum of two scores. However, if we want to put more value for environment, we can set more weight to y_{j2}. Therefore, we can set the final score depending on the main purpose of the policy and multiple policies can be evaluated in the same way.

2.4 Sensitivity of Simulations for Parameter Settings

In this section, we consider the sensitivity of the simulation results for parameter settings. In the mergence probability of a farmer defined by Eq. (2), there are four parameters, which need to be determined. In Eq. (7), although the values of four parameters were empirically determined, i.e., 2/3, 1/20, 1/20 and 1/10 in Eq. (2), it is possible to consider other values. A possible way is to do questionnaire surveys for these parameters like contingent variation method [7, 8]. However, it is worthwhile to test the sensitivity of the results for varying the parameter values before detailed surveys that need much cost. We consider six patterns of parameter settings shown in Table 4. Note that the original setting is mid1.

Table 4. Considered parameter settings.

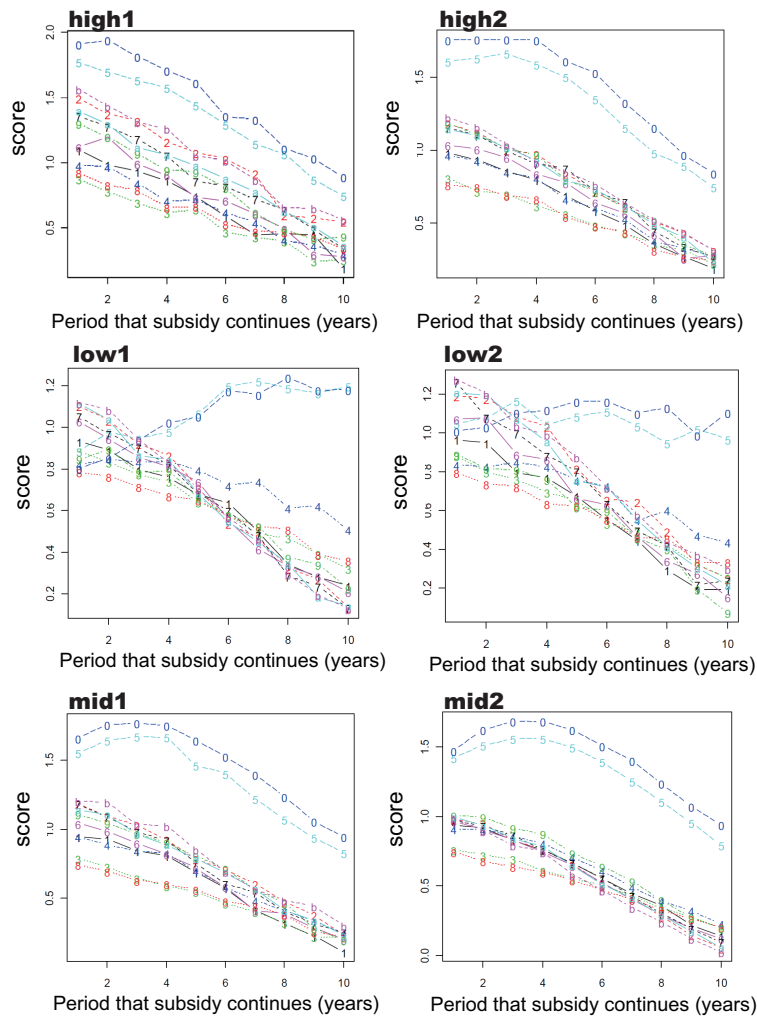|	High1	High2	Low1	Low2	Mid1	Mid2
A	0.8	0.8	0.1	0.1	0.67	0.67
B	0.1	0.05	0.01	0.01	0.05	0.01
C	0.1	0.1	0.01	0.01	0.05	0.05
D	0.5	0.1	0.01	0.1	0.1	0.01

Fig. 3. Variation of simulation results for policies with various parameter settings.

In Figure 3, x-axis shows that period that subsidy continues (years), i.e., n, y-axis shows the score for the evaluation of the policies. The numbers on the lines indicates 12 policies shown in Table1. From these results of simulation, when the mergence probability is high, i.e., high1 and high2, the effect of subsidy for large-sized farmers has strong impact on the speed of mergence; the farmers were rapidly merged in early timing of the simulation. When the mergence probability is set as middle, we observed that there is a peak of score at $n = 4$, and the optimal policy is the 10-th (subsidy range is from 200,000 (yen) to 600,000 (yen)). When the probability is set to be low, interestingly, the ranking of the policies is not stable and changes with respect to n. Especially, in low1, for two policies, the score increased; this means that long-

period subsidy is effective. This observation cannot be obtained without our agent simulations.

3   Discussion

In this paper, we construct an agent simulation model for modeling farmers' behavior under various subsidy policies. Under a subsidy policy for execution of green manure for environmental operation, farmers select their behavior, forming a big community and executing green manure. We defined a scoring method for comparing multiple policies by considering both farmers' economy and natural environment. Also, robustness of the results of the simulations for variability of the parameter settings was evaluated. As a result, basically our obtained results are stable, but in some extreme cases, i.e., mergence probability is low and subsidy targets larger farmers, different behaviors of the farmers were observed.

We consider the following points as our future researches: First, more parameter settings should be validated in order to evaluate the robustness of the simulations more accurately. Second, we should test other scores for evaluating policies. As we mentioned before, the score we used is to use farmers' income and environmental effect equally. However, we can change the balance of them. Third, although parameters in the simulation model were manually controlled in this paper, the value of the parameters can be automatically determined by some statistical methods like data assimilation. However, for this, we need to do questionnaire surveys for collecting observational data.

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TaxiSim: A Massive Multiagent Simulation Platform for Taxi Fleet Operations

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Abstract. Taxi service is an important mode of public transportation in most metropolitan areas since it provides door-to-door convenience in the public domain. Unfortunately, despite all the convenience taxis bring, taxi fleets are also extremely inefficient to the point that over 50% of its operation time could be spent in idling state. Improving taxi fleet operation is an extremely challenging problem, not just because of its scale, but also due to fact that taxi drivers are self-interested agents that cannot be controlled centrally. To facilitate the study of such complex and decentralized system, we propose to construct a massive multi-agent simulation platform that would allow researchers to investigate interactions among taxis and to evaluate the impact of implementing certain management policies. The major contribution of our work is the incorporation of our analysis on the real-world driver's behaviors. Despite the fact that taxi drivers are selfish and unpredictable, by analyzing a huge dataset collected from a major taxi fleet operator, we are able to demonstrate that driver movements are closely related to the relative attractiveness of neighboring regions. By applying this insight, we are able to design a background agent movement strategy that generates aggregate performance patterns that are very similar to the real-world ones. Finally, we demonstrate the value of such system with a real-world case study.

Keywords: multiagent simulation; transportation; driver behaviors; taxi fleet

1 Introduction

Taxi service is an important mode of public transportation in most metropolitan areas (e.g., in Singapore, taxi rides accounted for around 17% of public transports in 2007/08), since it provides door-to-door convenience in the public domain. Unfortunately, despite all the convenience taxis bring, taxi fleets are also extremely inefficient. In an ordinary city, a taxi can easily spend 50% of its operation time idling (waiting in queues or roaming around empty). For cities that are getting increasingly crowded, inefficient taxi fleet not only offers lower quality of service than its potential would grant, it also creates negative impacts on environment and road congestion. As such, improving the efficiency of the taxi fleet operation is an important issue for government agencies and taxi fleet operators alike.

Many past research efforts have been devoted to the modeling of the taxi fleet operations and also approaches that would improve the efficiency of taxi fleets. For example,

advances in technologies like Global Positioning System (GPS) and communication networks enable advanced dispatch system to be deployed [8, 7]. On the other hand, a series of work conducted by Yang et al. [13, 14] provides a good framework for understanding the equilibrium properties of taxis in a network at the macro level. However, by reviewing these past works (which are mostly published in the transportation literature), we notice that there are very few attention paid to the decentralized nature of the taxi system. One exception is the design of taxi dispatch systems, where we do see the application of multi-agent technologies [1, 12]; nonetheless, taxi dispatching is only one possible mode of operations and a comprehensive study that covers all modes of operations from a decentralized perspective is still not seen. Such decentralized perspective is critical in modeling taxi fleets because taxis can only be *incentivized* or *coordinated* and not centrally *controlled*. With proper models in place, not only can we improve the efficiency of current taxi fleets, a range of new services could be designed and evaluated as well.

In this paper, we propose to build an agent-based simulation platform, TaxiSim, to simulate the operation of taxi fleets. TaxiSim is designed to be capable of modeling individual taxi driver's strategies at micro level, and it's also designed to be scalable so that it can simulate thousands of taxis simultaneously. Real-world operational data, if available, can also be imported to TaxiSim, and this allows us to construct a highly realistic simulation environment. This would allow researchers and policy makers to study and evaluate potential mechanisms, policies, and new services for improving taxi services.

This paper is organized as follow. Section 2 provides a background on both taxi system analysis and the applications of multiagent technologies in the more general transportation domain. Section 3 outlines the design principle of our agent-based taxi operation simulation. Section 4 describes how we design the background strategy by analyzing a real-world dataset. In Section 5, we discuss how to calibrate the simulation so that it aligns with the collected real-world data. Finally, in Section 6 we provide an use case demonstrating how such framework can be useful in real-world analysis. The paper is then concluded in Section 7.

2 Background

Since the early days of digital computers, simulations have played an important role in transportation research. In all major areas of transportation studies, be it traffic signal control, traffic assignment (routing), or even regional planning, simulations are all involved deeply. With rapid development of computing technology, simulations have now become even more powerful and ubiquitous. Some of the well-known transportation simulation platforms include TRANSYT [11], CORSIM [5] and MITSim [9]. Each of them is designed with different granularity (could be macroscopic, mesoscopic, or microscopic), and each might be used for different applications as well (e.g., vehicle routing, demand forecast, or traffic signal control). More recently, the advances in multi-agent technology have also motivated researchers to construct simulations that are capable of treating individual actors inside a transportation system as agents. Some notable open-source multi-agent simulation projects include MATSim [10] and SUMO

[6]. This is a very incomplete listing and it's not our intention to conduct a comprehensive simulator reviews. Our purpose is to highlight the importance of simulation methods in conducting transportation studies, and also the growing trend of adopting multi-agent technology.

Despite all these efforts in building computer simulations for a wide range of studies, to the best of our knowledge, we cannot find any simulation platform that is capable of modeling realistic taxi fleet operations. Taxi fleet operation is special and cannot be modeled straightforwardly by using existing technologies for the following reasons:

– In most cities, taxi drivers pay a fixed rent and keep all remaining revenue. This revenue structure makes them naturally selfish, and to build a credible model, we need to understand how drivers make decisions empirically.
– Taxi drivers are subject to both voluntary and involuntary movements. Involuntary movements occur when customers board their vehicles. After a taxi reaches the destination specified by the boarded customer, it has to continue its voluntary movement from there. Such movement pattern is the most critical difference between taxis and ordinary passenger cars.

To address these unique requirements, we decided to develop our own multiagent simulation platform, TaxiSim.

3 System Architecture

TaxiSim is designed to be a decentralized discrete event simulation, focusing on modeling only taxi driver's behaviors. The traffic condition in the network is regarded as exogenous, and will not be modeled explicitly. This simplifies the design of TaxiSim, however, it should not have an adverse impact on the realism of the simulation, since taxis only constitute a small percentage of all vehicles. All taxi agents in TaxiSim are to be executed as individual threads in the simulation, and each agent maintains its own event queue. There are three major event types (the interactions among these events are illustrated in Figure 1):
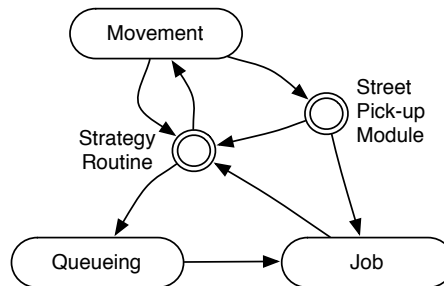

Fig. 1. Flow of events.

- Movement event: move to a particular location. This event is generated by the main strategy routine. The expiry time of the event is the expected travel time from the current location to the destination. When the movement event expires, the street pickup module (to be described in detail later) will be invoked (if the service mode is roaming) to determine whether a street job can be picked up. If a job can be picked up, a job event will be spawned.
- Queueing event: join a particular queue. This event can only be generated if the current location is at the queue and queueing is chosen as the service mode. The expiry time of the event is the expected waiting time in the queue before picking up a job. When this event expires, the job event will be spawned.
- Job event: serve a client who intends to move to a particular location. The expiry time is the expected travel time from the current location to the destination. At expiry, revenue will also be generated.

With these event definition, the progression of the simulation can be described by the following steps:

1. (Initialization) Invoke main strategy functions in all threads, and one of the three events will be generated.
2. (Iteration) The main thread queries for the earliest event expiry time from all threads; that thread will be asked to pop and execute the event. For all other threads, their local clocks will be progressed to this earliest expiry time.
3. Step 2 will be executed until the stopping criterion is met (e.g., when the simulation clock exceeds 12 hours).

We can see that the event structure of TaxiSim is relatively simple and the progression of the simulation depends heavily on the implementation of taxi agent's strategy. To simplify the design of agent strategy, we further decompose the agent strategy into components in Figure 2. The role of each component is briefly explained. A full-blown example on the strategy design is deferred to the next section.

- **Taxi Initialization Module**. This component is responsible for *warming up* the simulation with an initial taxi distribution. This module has to generate two pieces of information: 1) geographical location and 2) agent type (which includes both the strategy and the strategy-related parameters). For geographical location, the simplest generation scheme is an uniform acceptance-rejection scheme, i.e., generates initial geographical locations uniformly randomly, and each generated location is only accepted if it is geographically feasible. Alternatively, one can also generate the initial locations based on relative taxi densities, which can be obtained from the real-world data. Independent of the geographical location, the taxi type information is generated according to a predefined distribution of strategies. The initialization module is controlled by a list of user-supplied parameters, and if necessary, users can supply their own initialization routines as well.
- **Time Keeping Module**. This module repeatedly queries for the earliest event expiry time from all threads and also synchronizes the local clocks at all threads.
- **Mode Selection Module**. This module decides what mode of operation should be used. This is the first major function required to define an agent's strategy.
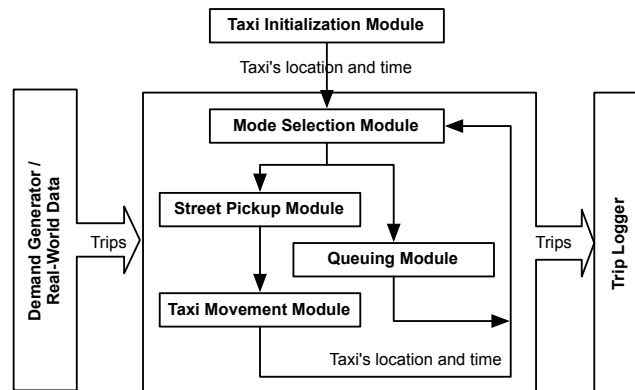
Fig. 2. An agent-centric view of the system.

– **Queueing Module**. Suppose an agent chooses to join a particular taxi queue, the taxi queue will be simulated specifically by the queueing module. The most important queueing features to simulate is the arrival of customers at the queue according to demand data provided by the demand generator and the maintenance of currently queued agents.

– **Street Pickup Module**. If an agent decides to roam the street, this module will determine which areas it should go towards. At each discrete epoch, it will also determine whether this agent can pick up a street job. The model we used in determining such pickups will be described in more detail in later section

– **Taxi Movement Module**. This module dictates how a taxi moves from one point to another on the road network. This is the second major function required to define an agent's strategy. A default background strategy is provided, however, it can be replaced if necessary.

– **Demand Generator**. Customer demands are generated by this module. The demand generated can be either based on real-world data or completely fictitious. No matter how a demand is generated, it must come with four parameters: a) origin, b) destination, c) time, and d) fare.

– **Logger**. This module logs completed trips. If any additional information needs to be logged, user-defined loggers can be implemented based upon a common logging interface.

The simulation framework in TaxiSim allows a wide variety of servicing strategies to be implemented. A background strategy that closely resembles aggregate driver behaviors is included as the default strategy in TaxiSim. If necessary, user-defined strategy can also be designed easily by using the provided API.

4   Designing the Background Strategy

In TaxiSim, taxi driver's behavior consists of two components: 1) service mode choice and 2) service strategy. For a taxi driver, the service mode choice refers to the choice of operation mode (roaming, queueing, or waiting for dispatch job). After the service mode is chosen, a taxi driver will then try to decide the best operational policy to use in that mode. For example, a taxi driver, on choosing the roaming mode, will have to decide which region to roam and what path to take. The implication of this design is that strategies can be built incrementally. For the background strategy, we initially include only street roaming (the dominant mode of operation), and if necessary, add additional modes later.

When designing the background strategy, our goal is to create a fleet of simulated taxis that is representative of real-world fleets. We do not intend to model taxi behaviors at micro level, instead, the macro-level regularity is what we are after. We made such modeling choice since micro-level real-world patterns are extremely noisy, and it's often difficult (if not impossible) to infer individual's intention from the observed data traces. Moreover, even when we have accurate behavioral models for certain individuals, it is still far from being representative of real-world fleet.

The macro-level regularity we are interested in is the pattern of revenue accumulation over time. The revenue accumulation pattern is chosen as the target since it aligns with agent's objective function and the day-to-day pattern observed from the empirical data is consistently recurrent.

The design idea for the background strategy comes from our analysis of the empirical data, which is described in the following subsection.

4.1   Quantifying Drivers' Behaviors

The source of data that supports our analysis comes from a taxi fleet operator in Singapore. Our analysis on the dataset reveals a surprising resemblance of the aggregate driver's behaviors to the greedy strategy. More precisely, the greedy strategy refers to choosing zones to move to according to the relative density of trip originations. The definition of zones is adopted from the official zoning defined by the Singapore Land Authority, which can be seen in Figure 3.

The available data for our analysis includes trip information and movement logs. For each captured trip, the dataset contains fare, origin coordinate, destination coordinate, and times at departure and arrival. For movement logs, each log entry captures time of the log, latitude, longitude, and taxi status (free, hired, or others). The time-dependent density of trip origination out of each zone can be easily measured by accumulating trip counts based on origin coordinates and trip starting time. The movement of free drivers can be derived from filtering the movement logs. After this filtering is done, we then aggregate all inbounding flows according to zones and hours.

If drivers indeed adopt greedy-like strategy in aggregate, we should see strong positive correlation between outgoing trips from a zone (which represent how attractive this zone is) and incoming flows to the same zone (which represent drivers' aggregate intentions to go to this zone). To ensure meaningful comparison, all counts per hour are converted to percentages of total counts over all zones per hour.
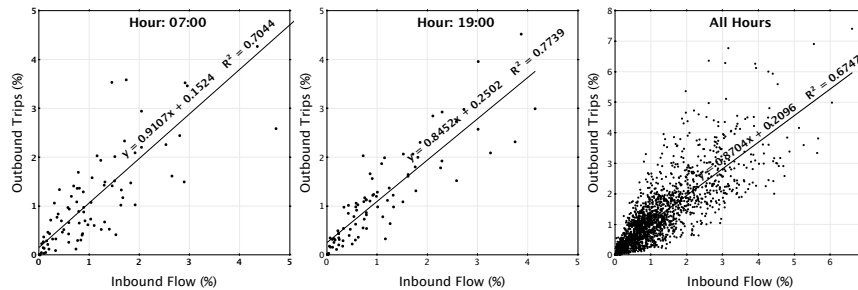
Fig. 3. Zones defined in Singapore.

Fig. 4. The correlations between outgoing trips and incoming flows at 7am, 7pm, and all hours.

The correlation between outgoing trips and incoming flows can be seen in Figure 4. The data used in our analysis is collected from the weekdays of July 2009, and we choose two most representative times to illustrate the results of our analysis. Two high-lighted time frames, 7–8am and 7–8pm, are the morning and evening rush hours and their R^2 values are 0.7044 and 0.7739 respectively. For all time frames, the R^2 value is slightly lower at 0.6747. This is expected since travel patterns during morning and evening rush hours are usually more predictable. However, even 0.6747 demonstrates sufficiently strong positive correlation.

4.2 The Background Strategy

Based on our empirical findings, we design a roaming strategy that makes probabilistic moves toward different zones according to their relative attractivenesses (pre-computed based on historical demands).

Formally speaking, zones are predefined polygons that are mutually exclusive and collectively cover the whole area of interest (the main Singapore island in our case).

The relative attractiveness of zone j, denoted as a_j, can be quantified by

$$a_j \propto \frac{d_j}{r_j(p)^2},\qquad(1)$$

where d_j is the number of trips departing from zone j and $r_j(p)$ is the distance between the centroid of zone j and the location p. This definition is quite intuitive: a zone will be more attractive if it has more trips and is closer to the current location. a_j is inversely correlated to the square of $r_j(p)$ since we want to account for the fact that longer distance incurs both higher movement cost and also longer traveler time. The background strategy is designed to follow the attractivenesses computed in (1): the probability that the agent moves toward a particular zone is proportional to its attractiveness, i.e., $p_j = a_j / \sum_j a_j$, where p_j is the probability that zone j will be chosen.

5 Calibrating TaxiSim

The introduction of the background strategy allows us to put together a working simulation. However, to have a realistically useful simulation, we still need to calibrate it with the real-world dataset that we have. Of the three operational modes (roaming, queueing, and job dispatching), queueing and job dispatching are very easy to calibrate, as these modes both follow very specific rules, and in most cases the operations of these two modes are quite predictable. The most difficult mode to deal with is the roaming mode, since a lot of external factors (most of them uncertain) are involved. Therefore, when calibrating TaxiSim, most of our focus is placed on the roaming mode (or street pickup mode). In this section we will first provide a detail description on the street pickup module, mentioning all the important parameters that we can tune, and then proceed with the discussion on how these parameters can be calibrated.

5.1 The Street Pickup Module

To ensure that the roaming strategy performs realistically in a simulated environment, the street pick-up module needs to be designed carefully. The street pick-up module determines whether an agent can pick up a job at its current location based on the following factors:

1. Spatial constraint: The agent must be within certain radius to the prospective job in order to pick it up.
2. Temporal constraint: The agent can only pick up jobs that are already revealed.
3. Competition: Even when the agent meets both the spatial and temporal constraints, it still has to compete with other agents (which may or may not be included in the simulation) for the revealed job.

Formally speaking, we define a job j to be the tuple $(p_s^j, p_e^j, t_s^j, t_e^j)$, where p_s^j, p_e^j, t_s^j, and t_e^j are respectively the job's origin coordinate, destination coordinate, departing time, and arrival time. With these notations, the set of feasible jobs at time t_c and location p_c can then be defined as:

$$J_p(t_c, p_c) \equiv \{j \mid t_s > t_c + T(p_c, p_s), T(p_c, p_s) \le \epsilon\},\qquad(2)$$

where $T(p_c, p_s)$ refers to the travel time from p_c to p_s and ϵ refers to the duration of one time unit in our simulation.

For jobs in $J_p(t_c, p_c)$, the probability for a job to be picked up should depend on the relative distance between a job's originating location and the taxi's current location. This comes from the intuition that taxis closer to a customer should have greater chances of getting the job. Similarly, the temporal difference between a job's reveal time and the time when the taxi spot that job should also follow similar intuition, i.e., a taxi closer to a job's reveal time should be more likely to pick up that job than taxis that come later. In addition, the chance to pick up jobs also depends on how competitive an area is. All things being equal, it should be more difficult to pick up a job in a more competitive area.

To summarize the influences of both the spatial and temporal distances, we define the normalized composite (NC) distance from a taxi to a job as:

$$\delta = \frac{1}{2} \cdot \left[\frac{\delta_d}{D_\epsilon} + (1 - \frac{\delta_t}{\epsilon}) \right], \tag{3}$$

where δ_d and δ_t refer to the spatial and temporal distances between the job and the taxi respectively and D_ϵ refers to the maximum distance the taxi can travel during one time unit. By construction δ should be in the range of $[0, 1]$.

When $\delta = 1$, the chance of picking up a trip is 0.1. When $\delta = 0$, the chance of picking up a trip is 0.8. For $0 < \delta < 1$, the pickup probability follows an exponential function, and can be parametrized as $p(\delta) = \alpha e^{\beta \delta}$. α and β can be solved by using the above boundary conditions.

The level of competition in a zone is summarized by the *chance of retrying* and it represents how likely a taxi can keep looking for jobs in a time period. If a particular zone is very competitive, then there should be fewer such retrying opportunities, and the chance of retrying should have a smaller value.

To determine whether an agent can pick up a job at the current location and in the current time period, the following steps will be utilized (for the ease of presentation, assume that $J_p(t_c, p_c)$ is an ordered set with elements $j_1, j_2, \ldots$ and $\delta_{j_i} \leq \delta_{j_{i+1}}$ for all i):

1. Set the counter $i \leftarrow 1$.
2. For j_i, the probability that it will be picked up is $p(\delta_{j_i})$. Sample from $p(\delta_{j_i})$, if the result is positive, stop and return j_i (and j_i will be removed globally from all agents' considerations). Otherwise, move to the next step.
3. With probability $(1 - q_{z,t})$, the street pickup module will terminate the search, return to the main strategy module, and notify the agent to take next action. If the search is not terminated yet and $i+1 \leq |J_p(t_c, p_c)|$ (implying that there is available job in set $J_p(t_c, p_c)$), increase the counter, $i \leftarrow i + 1$, and repeat step 2.

When the above procedures terminate, the agent will either be awarded a job (which will trigger the creation of a job event) or it will be ordered to move. The parameter $q_{z,t}$ introduced in step 3 is the retrying probability mentioned earlier, and it reflects the likelihood that the taxi will be granted an additional chance in trying to search for another job. In a more competitive area, such retrying will be less likely and it is

reflected in having a lower $q_{z,t}$. As we should see in the next section, this parameter is our main focus in calibrating the simulation.

5.2 Simulation Calibration

In this section, we propose a simple calibration process that is shown to be very effective in modeling unobservable competitions. As mentioned in the previous section, we have summarized the level of competition using the retrying probability. Therefore, the calibration of TaxiSim can be abstractly viewed as an optimization problem, with decision variables being the retrying probabilities and the objective function aiming to minimize the absolute difference in average revenues between the simulation and the real-world data. Expressed formally, for zone z and time t, the optimization problem is:

$$\min |r_{z,t}(\{q_{z,t}\}) - R_{z,t}| \tag{4}$$
$$\text{s.t.}$$
$$q_{z,t} \in [0,1], \forall z, t,$$

where $r_{z,t}$ and $R_{z,t}$ are average revenues obtained from the simulation and real-world data respectively. Although Problem (4) looks simple, it's in fact very difficult to be solved exactly because $r_{z,t}(\{q_{z,t}\})$ can only be evaluated by executing several simulation runs.

Due to the intractable nature of Problem (4), we have proposed a simple hill-climbing heuristic for the simulation calibration. This heuristic is described by the following steps:

1. Initialize retrying probability $q_{z,t}$ to 0.4 and step size $\epsilon_{z,t}$ to 0.1 for all (z,t) tuples.
2. Execute the simulation by using the current vector of $\{q_{z,t}\}$. Compute the average revenues $r_{z,t}$ for all tuples.
3. For each (z,t) tuple, if $r_{z,t} > R_{z,t}$, let $q_{z,t} \leftarrow q_{z,t} - \epsilon_{z,t}$, otherwise let $q_{z,t} \leftarrow q_{z,t} + \epsilon_{z,t}$. If the gap (i.e., $|r_{z,t}(\{q_{z,t}\}) - R_{z,t}|$) narrows over previous iteration, let $\epsilon_{z,t} \leftarrow 0.5\,\epsilon_{z,t}$.
4. Check if the stopping criterion is met; if not, go to step 2, otherwise, stop.

The stopping criterion can be either time-based, in which the process will execute a fixed number of iterations, or performance-based, in which the overall performance is monitored, and the process will terminate if it is not making sufficient improvement.

To summarize the overall calibration performance over all tuples, we compute a weighted sum of all gaps: $\sum_{z,t} w_{z,t} |r_{z,t}(\{q_{z,t}\}) - R_{z,t}|$, where $w_{z,t}$ is the percentage of trips originating from zone z in time period t. This weighting definition straightforwardly incorporates the relative importance of different tuples.

To calibrate TaxiSim, we load the simulation with 1,000 agents, each running the background strategy, and the calibration result is plotted in Figure 5. The result shows that after calibration, the average difference of revenue between our simulation and the real-world data is around $0.46. Considering that the average revenue per hour is around $12, this translates into a mere 3.8% error rate.
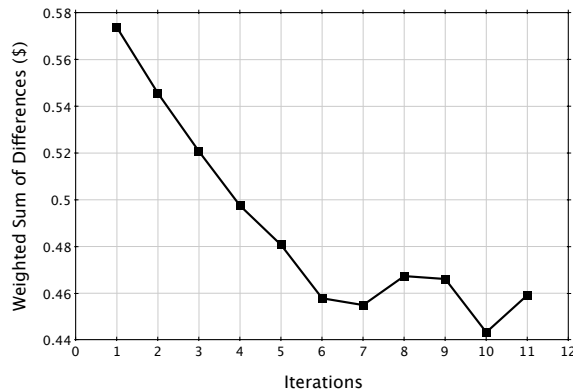
Fig. 5. The evolution of weighted sum of differences over iterations. Note that the value stabilizes after iteration 5.

6 Use Case: Evaluating a Strategy Profile

In this section, we evaluate the performance of a new strategy for taxi drivers and a potential information service from the fleet operator. We first describe the basis of the strategy, then our simulation setup and finally our analysis of the simulation result.

6.1 Optimal Service Choice Strategy

For individual agents, one of the difficulties in choosing service mode (and also service strategy) is that agents usually have very limited information regarding remote locations. Without such information agents will have to make their own predictions and this potentially can incur significant errors (and resulting in sub-optimal decisions). The inefficiency of such decision making process in real-world operations is quantified in an earlier study by [3], and one potential solution is for the taxi fleet operator to provide agents with necessary real-time information so that they can compute their "optimal service choices".

However, if we evaluate such proposal at the system level, it is not clear if executing such strategy at a global level would be a good idea. We suspect that due to the lack of strategic reasoning (recognizing the fact that other drivers also possess similar information), agents might end up clogging the queue when the expected revenue at the queue is high, and unnecessarily avoiding the queue when the expected revenue at the queue is low. This not only might cause drivers to suffer, it might also create adverse effects at the queue (the queue will constantly be either too crowded or too underserved). A formal analysis and studying of such phenomenon is beyond the scope of this paper, but we would like to present some initial simulation results from this study to demonstrate how TaxiSim can be used in assisting research agendas on quantifying driver's intentions as well as on designing incentive mechanism to better coordinate a fleet of selfish drivers.

6.2   Simulation Setup and Result

We set up a simulation with 2,000 taxis, and we try to experiment with different market penetration ratios of the "intelligent service choice technology". We start our experiment with only one agent equipped with such technology, and then gradually increase the ratio to 20%, 40%, 60%, 80%, and then finally $\sim$100% (all but one taxi adopt intelligent technology). For simplicity, we assume that there is only one major queue that agents can choose to go to. From the dataset, we recognize that the airport is the single largest queue (can hold several hundreds of taxis during the peak hours), thus it will be chosen as the designated queue. We also assume that agents by default will follow the background strategy, and it will only join the designated queue at random (a small probability derived from the real-world dataset). For agents holding the intelligent technology, they will query this technology for advices whenever they are choosing their service mode, and if the suggestion returned is to go to the airport queue, they will make a shortest-path travel there and join the queue.

The result of the simulation is illustrated in Figure 6, and it confirms our earlier conjecture: increasing market penetration ratios in our simulation study indeed causes the average performance of intelligent technology holders to deteriorate steadily. However, from the result we can also see that the drop in the performance is most significant when the ratio moves from $\sim$0% to 20% (a drop of around 12%), after which the decline is much gradual (all around 1% to 3%). Another interesting finding is that even in the case where intelligent technology floods the market and causes its holder's performance to drop, its average performance is still better than that of the background strategy (who only makes ad hoc visits to the queue).
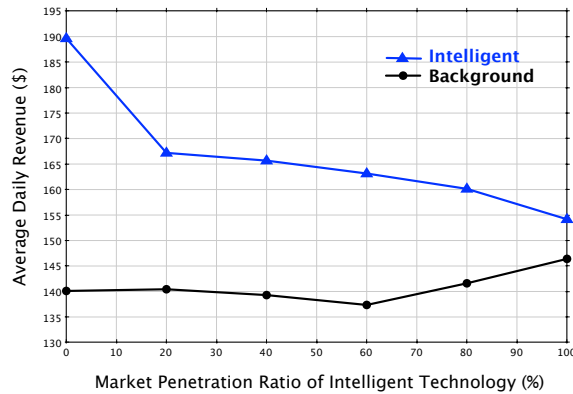

Fig. 6. Background drivers v.s. intelligent drivers under different market penetration ratios.

7 Conclusions

In recent years, more and more AI research efforts are being introduced to transportation, a traditionally OR-dominated domain. For example, an agent-based approach is recently demonstrated to be a more effective alternative to the traditional intersection control technology [4]. Also, traditional transportation researchers are increasingly more acceptable to the idea of multiagent technology; for example, the potentials of agent-based technologies and machine learning techniques in traffic control are highlighted in a recent review by [2].

This paper contributes to this increasingly promising line of research, and in particular, we contribute to the study of taxi fleet operations, an important yet overlooked area in the urban mobility research. Our primary contribution is the methodology used in creating TaxiSim, a highly realistic agent-based simulation platform dedicated to taxi fleets. In developing TaxiSim, we have successfully extracted a representative agent strategy from our analysis of the real-world dataset. We have also proposed a simple yet effective process for calibrating TaxiSim. Finally, we present an use case on how TaxiSim can be practically used to study complex strategic interactions in taxi fleet operations.

We show that TaxiSim is a good platform for evaluating and experimenting advanced strategies for taxi drivers, as well as new policies and mechanisms which affect the dynamics of the whole taxis eco-system. Taxi fleets in urban environments are agile and flexible. With proper coordinations and incentives, they can be utilized to improve the urban mobility eco-system. Realizing the full potential of these taxi fleets with AI techniques will remain one of our major research directions in the future.

8 Acknowledgment

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Parallel Agent-based Simulator
for Influenza Pandemic

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Abstract. We have developed a parallelized agent-based influenza pandemic simulator, which is applicable to cities which consist of the down town and suburbs are connected by railway lines. We carried out a simulation of an epidemic for a half year in a model city which consists of towns connected by a railway line. The population of the city is one million and this simulation is completed around one hour.

Key words: agent-based simulation, influenza pandemic

1   Introduction

Highly pathogenic avian influenza A(H5N1) viruses may cause a serious pandemic, if the viruses acquire the capability of human-to-human transmission. Our interest is to develop simulators that support planning of interventions against influenza epidemics, when such a novel influenza virus is introduced into a certain metropolitan area. For example, simulation results for different effectiveness of vaccine and different targets of vaccination are useful information, since the effectiveness of vaccine against a novel virus is uncertain (a general estimation is discussed in the report [1]) and the amount of vaccine that can be prepared is limited.

In this paper, we develop an agent-based parallel simulator. The difference in probability of secondary infection among public spaces and interventions for specific targets (e.g. school closures and vaccination for individuals) can be naturally described in agent-based simulations. In a metropolitan area, such Tokyo city, trains play an important role in spread of epidemic. Not only trains transport persons between suburbs and the down town, but also trains themselves are a public space with a high contact rate. To this end, we design our simulator so that a simulated city is a set of towns connected by railway lines, and each town contains several kinds of public spaces. The reason why we make simulations in parallel is to complete those with a large population within a reasonable time. Although simulations could be sped up by reducing the number of agents, the

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uncertainty in predictions estimated by a small scaled simulation is larger than the case of a simulation with a realistic number of agents.

This paper is organised as follows. In Section 2, the design of our simulator is summarised and a model city used in experiments is introduced. In Section 3, we examine the effect of parallelization and compare the results of a simulation with a large population to that with a small population. In Section 4, this paper is summarised.

2   Simulation model

2.1   Design of simulator and its mathematics

Our simulator aims particularly at epidemic spread in Metropolitan cites. In cities, the concentration of population in particular places related to human activities (e.g. corporations, trains) affects on the infectious transmission, rather than the concentration in some geometrical regions. Hence, we abstract way the geometrical information, and model the cities as a set of *cells* that contain persons in the city. This approach and target are contrastive to the case of the entire nation or the region including several nations being targeted. For example, in a pandemic simulation in Southeast Asia [3], the effective radius of circles, inside which persons are contactable and infectious disease is transmissible, is one of the most important parameter.

Hierarchical structure of entities in the simulated city is described below. A city consisting of several local towns which are tightly connected by trains is dealt in our simulator. Each town consists of different kind of places and persons living in the town. We consider parks, supermarkets, homes, corporations, and, schools. These places hold current numbers of persons for respective health states and the degree of infectious efficiency. Possible roles of persons are classified into *employee*, *student*, and *housekeeper*. Simulator prepares a behavioural template for each role. For example, these templates describe that an employee should go to a corporation and return to home in every weekday, or a housekeeper should visit a supermarket at least once every day. In addition to own role, each person has health state and set of places that the person can visit.

Following to the concept of the SEIR model [4], we consider four health states: *susceptible*, *exposed*, *infected*, and *recovered*. Hereinafter, we denote each state by its initial letter. These states correspond to persons who have never infected by the virus concerned, who have been infected but never acquired infectiousness, who has acquired infectiousness, and who has recovered to acquire immunity against the virus, respectively. The health state of a person follows a stochastic process such that transition probability $\pi(x \to x')$ from state x to state x' per unit time is

$$\pi(S \to E) = \beta N_I / N_0$$
$$\pi(E \to I) = \alpha$$
$$\pi(I \to R) = \gamma,$$

where the other transition probabilities to a different state are zero, N_I is the number of infected persons in the place where the person currently visits, N_0 is the total number of persons in the place, $1/\alpha$ and $1/\gamma$ are the mean latent and infectious periods, and β describes the infectious efficiency of the place. We assign typical values [5] for these periods $1/\alpha = 3.5$ days and $1/\gamma = 3$ days. In the early stage of an epidemic, we can assume that the number of susceptible $N_S \approx N_0$ in any places. Under this assumption, let us estimate how many persons become infected due to a single infected person. A susceptible person who contact with a infected person for time Δt transit to the exposed state in probability $\pi(S \to E)|_{N_I=1}\Delta t$, and the infectiousness sustains for time $\pi(I \to R)^{-1}$. Therefore, the number of infected persons owing to a single infected one is given by

$$N_S \cdot \pi(S \to E) \cdot \left.\frac{1}{\pi(I \to R)}\right|_{N_I=1} = \frac{N_S}{N_0}\frac{\beta}{\gamma} \approx \frac{\beta}{\gamma} \equiv \mathcal{R}_0.$$

The parameter $\mathcal{R}_0$ is called the *basic reproduction number*. Any infected person finally tends to the recovered state. However, since they *produce* $\mathcal{R}_0$ infected persons, the number of infected person increases if $\mathcal{R}_0 > 1$, and otherwise a sequence of transmission will eventually die out. This is confirmed by checking the sign of

$$\frac{d(N_I + N_E)}{dt} = N_S \cdot \pi(S \to E) - N_I \cdot \pi(I \to R) \approx (\beta - \gamma)N_I.$$

The value of $\mathcal{R}_0$ ranges typically 1 to 2, and not more than 3 in cases of influenza epidemic [6, 7]. This should be considered a constraint on the value of reproduction number averaged over all places in the city, and there may be a large variety among individual places. We give the mean reproduction number for each kind of places as 0.5 in parks, 1.5 in homes, 0.3 in supermarkets, 1.8 in schools, 3.0 in corporations, and 3.0 in trains, and let places of each kind follow a (truncated) Gaussian distribution with standard deviation being 10% of the mean. This contrast among kinds reflects the following belief: (i) persons are sparsely distributed in parks, (ii) persons are densely distributed in their home, but infected members may be properly isolated, and (iii) persons have much opportunity to contact each others in schools and corporations.

2.2   Modelling of cities

We introduce a model city that is commonly used in experiments in Section 3. This city consists of five towns connected by one railway line (Fig. 1). Each town has 200,000 persons, 10 schools, 20 corporations, and 10 supermarkets. Trains from town A to E run every twenty minutes, and vice versa. As persons who has already been infected at the start of simulations, we introduce 30 persons in town C. The structure and the scale of the model city is designed under the assumption that our simulator will be applied to cities such as Tokyo, which has a structure such that a central area is surrounded by suburbs and several

rail way lines emanate from the central area to the suburbs. The population of each town in this model city is comparable to the daily number of boarding passengers of main five stations in the rail way line.
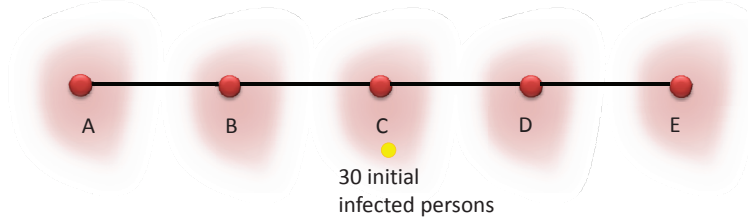

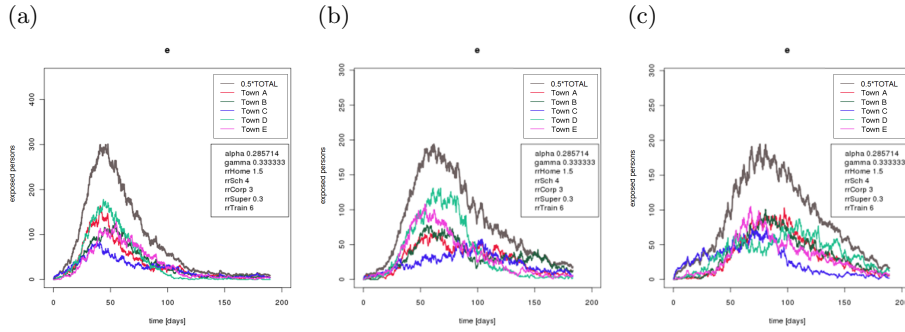**Fig. 1.** The structure of model city used in experiments.

Fig. 2. Three typical profiles in the evolution of exposed populations.

3   Experiments and Results

3.1   Parallelization

If the computation of our simulator is sufficiently fast, the effectiveness of intervention can be measured by performing this simulation. The simulation speed can be increased if the population of the model city are reduced. However, the difference in epidemic spread among Monte Carlo runs is expected to be larger than the reality. We have carried out 20,000 different Monte Carlo runs in the model city which is the same as the city of Section 2.2 but there are only 3,000 person in each town. Three classes are detected in the profile of the evolution of the infected population as is shown in Fig. 2. The peak of infected population spans from 50 to 75 days among classes. Profiles in this figure indicate that

time of the peak reflects the initial increasing rate, whose variety is particularly enhanced in small scaled simulations.

In order to realise a fast simulator which can deal with massive population, we have developed a parallel simulator for shared memory machines using OpenMP. In the rest of this subsection, we study how the speedup increase depends on the number of thread does, and discuss the relation between this dependence on the implementation of the simulation single step. Experiments to obtain the elapsed time of simulations were carried out on the PC workstation NEC Express5800/T120a-E, which has two CPUs Intel Xeon X5550 2.67GHz, containing 16 logical cores, and 48GiB memory.

(a) Write and read operations are done in different iteration loops:

1. For `area ∈ city.areas`,   For `person ∈ area.persons`,
   - Following to `person.schedule`, update `person.visit`.
   - Following to transition probability `area.places{key=person.visit}.pr`, update `person.health`.
2. For `area ∈ city.areas`,
   - For `place ∈ area.places`, `place.nVisitors = 0`.
3. For `person ∈ area.persons`,
   - increment `area.places{key=person.visit}.nVisitors{key=person.health}`.
4. For `area ∈ city.areas`,
   - For `place ∈ area.places`, calculate `place.pr` from `place.nVisitors`

(b) Write and read operations are unified in the same iteration loop:

1. For `area ∈ city.areas`,   For `person ∈ area.persons`,
   - Following to `person.schedule`, update `person.visit`. If `person.visit` changes from u to v (u ≠ v), then
     - decrement `area.places{key=u}.nVisitors{key=person.health}`.
     - recalculate `area.places{key=u}.pr`.
     - increment `area.places{key=v}.nVisitors{key=person.health}`.
     - recalculate `area.places{key=v}.pr`.

Fig. 3. Two approaches of implementation to advance simulation time.

We consider two implementation approaches to advance the simulation time. Procedures are summarised in Fig. 3 as pseudo codes. Iteration loops in the procedures are automatically parallelized by compiler, if OpenMP directives are specified. In the approach of Fig. 3 (a), variables for places, which has a field of $\pi(S \rightarrow E)$ (`area.places{}.pr` in pseudo codes), are updated only in Steps 2, 3, and 4, whereas variables for persons (`area.person`) are updated only in step 1. This approach aims to separate the reading phase and the writing phase for variables containing places and persons, respectively. If these steps were mixed, frequent occurrence of cache invalidations might degrade the performance. Figure 4 (a) shows the number of threads versus speedup to the single thread case,
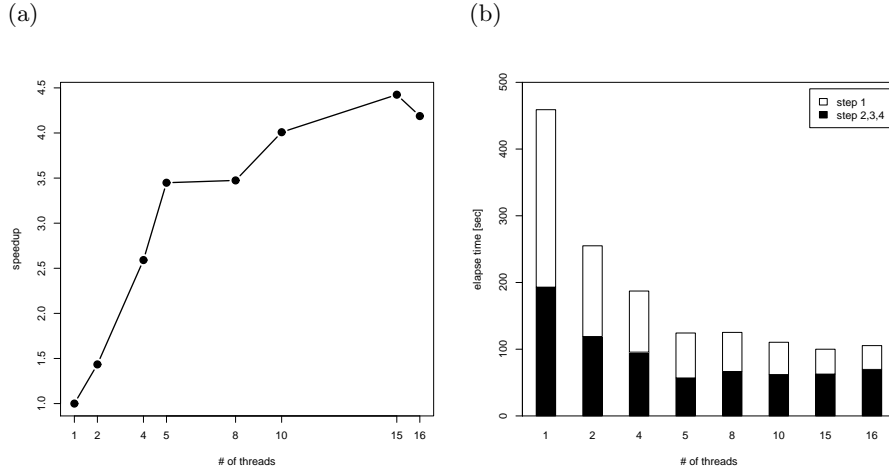
(a)   (b)

Fig. 4. The number of threads versus (a) speedup against the single thread case, (b) occupations of Step 1 and Steps 2–4 of the procedure of Fig. 3 (a) in the elapse time. The referred elapsed times are measured for simulations of 2880 time steps (2 days in simulation).

when simulation runs are carried out in the above-mentioned model city for two days. The saturation of speedup is observed at five threads. This saturation is considered to be due to the part Steps 2–4 being not sped up by parallelization. The ratio of elapsed time, shown in Fig. 4 (b), indicates that the portion of Step 1 becomes smaller as the number of threads increases, whereas the portion of Steps 2–4 is almost constant when the number is greater than five. The reason is not clear, although the necessity of atomic operations in Steps 3, in which the `nVisitors` field of the same place may be updated by two or more threads, could affect the computation speed.

In another approach, in Fig. 3 (b), the number of visitors and $\pi(S \rightarrow E)$ are updated immediately after respective persons change their visiting place. Contrary to our expectation that this approach would degrade the performance, this approach prevents the saturation in execution time. Figure 5 shows that the speedup continuously increase to reach 7.2 at 15 threads. As a reason why the expected inefficiency does not realise, there is a possibility that the number of persons who move at each time step is much smaller than the population of the city.

3.2   Simulation test

We carried out simulation tests for a half year, which is enough to follow an entire epidemic. First, we observe a typical evolution of an epidemic. A time series of the number of exposed persons has a peak between 40 and 50 days, in the case of Fig. 6. The timescale in which the number of infected persons
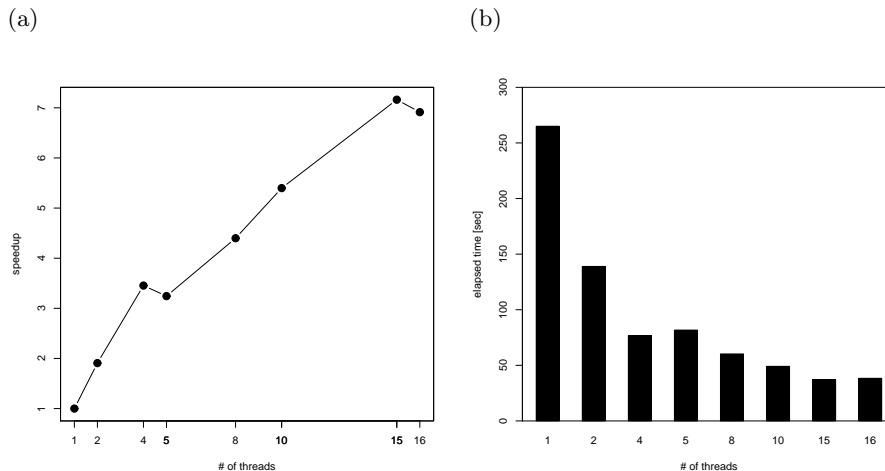
(a)   (b)

Fig. 5. The number of threads versus (a) speedup against the single thread case and (b) the elapsed time. The configuration of the simulation is the same as that of Fig. 4 but the numbers of visitors are calculated in a different way.

increases or tend to decrease depends on the number of places, as well as on latent and infectious periods. These numbers are chosen so that the timescale agrees with that of an earlier work [2], which dealt with a similar model city to ours. Daily and weekly periodic variations are clearly observed in this time series, whereas these periodic variations do not appear and random one rather appears in time series yielded by small scaled simulations, for example, in Fig. 2. For this contrast, we consider that the number of persons is not enough to represent real evolution of epidemics at least the scale of several thousand per town.

Next, we study how the scale of the numbers of places affects evolution of epidemics. This is important because these numbers are not clearly determined. For some kind of places, a reliable statistic data for the number of the places in the target city does not exists, and we have to estimate the number that the simulation yields an allowable epidemic spread. Moreover, the number obtained from statistics should be adjust to a value, according to the dynamics of the model. For example, a large corporation should be regarded as several small corporations. The way of scaling is also unclear when a real city is scaled down to a model one. To this end, we try to give a constraint based on the timescale of infected persons diffusing. To measure of the spatial spread of the infected population, we use a percentage of places where at least one infected person has come until the present time. This measure of diffusion, for example in a seasonal influenza, could be obtained if some of corporations and/or schools cooperated with the investigation. Figure 7 shows how the diffusion of infected persons is delayed as the scale of the number of places increases. In original scale, all corporations encounter infected one employee within 20 days in original scale,
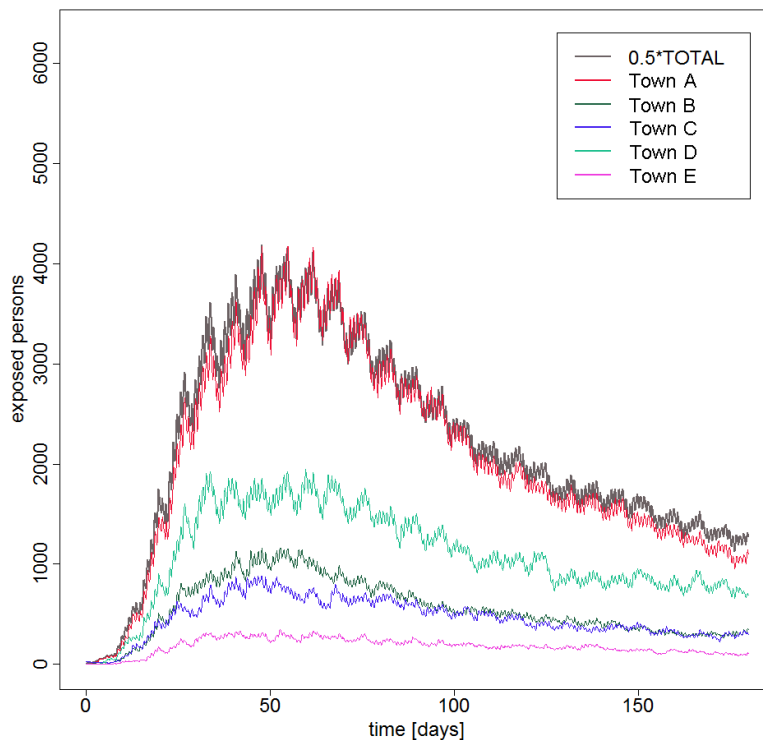
Fig. 6. Evolution of the numbers of exposed persons in five towns. The gray line shows the sum of all towns in half scale.

whereas more than 80 days are needed to cover all corporations in the city having 100 times larger number of places.

4   Summary

We have demonstrated our simulator dedicated to influenza epidemics in a city connected by a railway line. Parallelization succeeded to speedup 7.1 times and to complete a simulation involving one million persons for a half year in one hour or more. We also study how epidemic spread depends on the number of places in each town and each kind. A significant delay is observed for the increase of the number of places. For example, the time needed for infected persons to cover all corporations is delayed from 20 to 80 days if the number of places increases 100-fold.
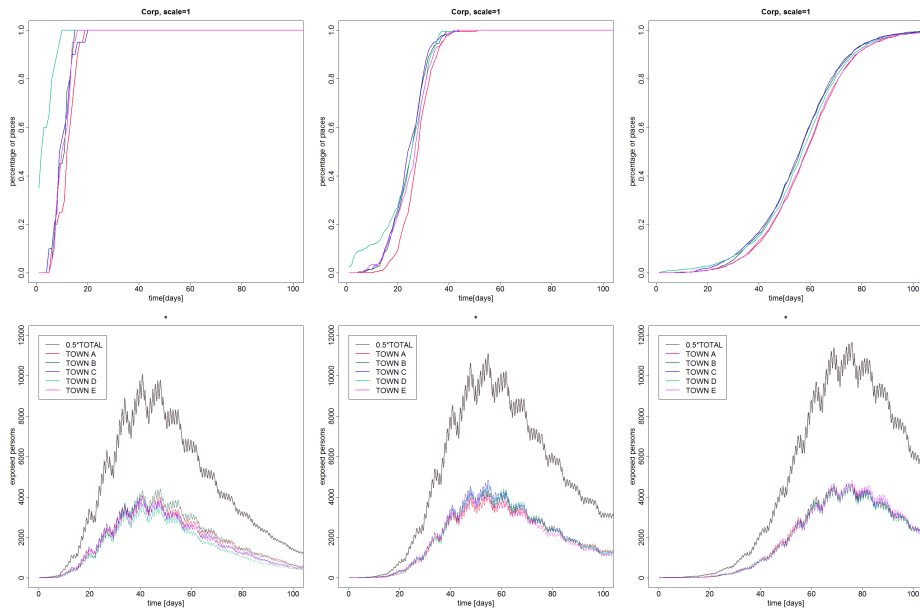
Fig. 7. The portion of corporations where one or more infected persons visited (the upper panels) and the number of persons in exposed state for different scales of the number places (the lower panels). From the left to the right, the number of places are increased 1-fold (original), 10-fold, and 100-fold. In the original case, each town has 20 corporations, 10 schools, 10 supermarkets, 2 parks, respectively.

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A Hybrid macro-micro pedestrians evacuation model to speed up simulation in road networks

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Abstract. The major methodologies of crowd simulation in dynamic
environment are either based on micro and macro models. Each of the two
types of model represent choices in the trade-off between level of details
and efficiency. The domain of pedestrian flow simulation in road networks
is no exception and theories rely either on equation based model (LWR)
or agent based models. There is a growing interest for hybrid modeling
that combines both models together. This paper addresses the problem
of combining both micro and macro models of pedestrians to speedup
identification of optimal evacuation plan. The goal is therefor to use
efficient macro modeling in part of the road networks that do not require
fine grained model and less efficient but more detailed micro modeling
elsewhere. The key issue raised by such an approach is to demonstrate the
consistency of the resulting hybrid model. Preliminary results presented
in this article are a proof of concept of how important speed up may
be obtained using hybrid model to simulate evacuation plan in road
networks.

Keywords: Crowd computing technology for MASim, Hybrid model-
ing, Scalability, road networks Applications of massively multi agent
systems.

1 Introduction

Nowadays, panic situation (fire, bomb attack, tsunami, earthquake, etc) in urban
areas threaten more and more human lives. Evacuation plan in panic situation is
becoming an important application of simulation in many projects [11],[2]. Real
environments for such simulation often include road networks. The movement
of pedestrians in road networks is a complex system to study. Evacuation simu-
lation can be used to predict the performance of evacuations and thus become
importance method for evacuation analysis. Evacuation in Geographic Informa-
tion Systems (GIS) representing road networks in reality needs to carry out.

Optimizing evacuation plan in Nhatrang city is the issue that we desire to
address in the long term. Nhatrang is a famous beach for tourism but it is

near earthquake sources from Philippine that may cause tsunami disasters. The problem studied in this paper is building the model of the evacuation in a road networks with the assumptions of J junctions, B different safe places that pedestrians ought to reach, one direction to escape from endangered places.

Macro model of the evacuation problem is often described using fluid dynamic model. Environment of this model is often considered as homogeneous and the the fluid system dynamics is represented by density of evacuees. The road networks of macro environment is considered a finite directed graph. The macro model can calculate the parameters of the model is fast and simple. Nevertheless, to find a solution for the macro model usually requires many assumptions that do not match at all human behaviors. On the contrary, agent bases models consider each pedestrian supporting very realistic models. Each agent has a specific set of behaviors, actions and relationship with other agents. This model shows us the interaction of the agent with other agents and the internal changes of the agent. In addition, heterogeneous environment GIS is considered in this model. The evacuation issue can also be looked at as macro point of view if we estimate the parameter of all agents. The weak point of such models is its data and huge computation time. The problem using simulations to optimize rescue plan becomes intractable. The focus of the paper is therefore to explore *hybrid modeling* to benefit from the efficiency of macro model and the advantage of agent based model.

2 The approaches applied in pedestrian flow

When we consider the environment being very large, all areas of the environment are not equally important in the evacuation issue. There are importance areas that should be observed in detail under the micro model but the others areas could be reviewed under the macro model.

Hybrid model integrate micro macro models of pedestrians to speed up identification of optimal evacuation plan.

The road networks that use in maco model is represented as a finite directed graph $\mathcal{G} = (\mathbf{E}, \mathbf{V})$ that edges and vertices are roads and junctions of the road networks respectively where $\mathbf{E}$ is the set of roads and $\mathbf{V}$ is the set of junctions. At the junction $V_\alpha \in \mathbf{V}$, let $\delta_\alpha^-(resp.\delta_\alpha^+)$ the set of indices of all the incoming roads to $V\alpha$ (resp. outgoing roads from $V\alpha$). The safe places are called destinations. The dangerous places that pedestrians want to escape are sources. Every edge $(u, v) \in \mathbf{E}$ has a non-negative, real-valued capacity $c(u, v)$. If $(u, v) \notin \mathbf{E}$, we assume that $c(u, v) = 0$. We distinguish two special set of vertices: set of a sources $\mathcal{S} = \{S_1, S_2, \cdots, S_n\}$ and a set of destinations $\mathcal{D} = \{D_1, D_2, \cdots, D_m\}$.

2.1 Macro model

This subsection deals with a macro model of pedestrian flow on a road network. The pedestrians are homogeneous with the spatial and the time is continuous. More precisely, we consider the conservation law formulation proposed
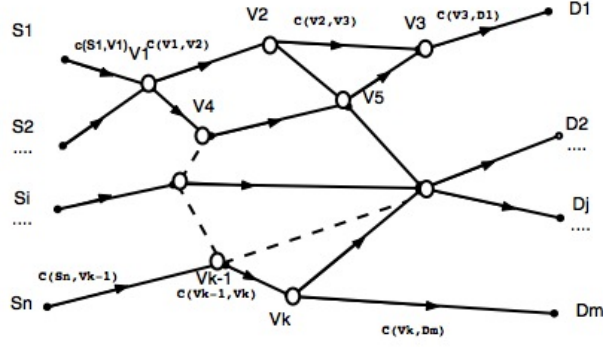
Fig. 1. road networks are modeled as directed graph have sources and destinations .

by Lighthill, Whitham and Richards (LWR) [9] represented the fluid dynamic by partial difference equations. This nonlinear framework is based simply on the conservation of density pedestrians in one road and is described by the equation:

$$\frac{\partial p}{\partial t} + \frac{\partial}{\partial x} f(p) = 0, \tag{1}$$

where

$$f(p) = pv(p), v(p) = v_{max} \left(1 - \frac{p}{p_{max}} \right). \tag{2}$$

and $(t, x) \in \mathbf{R} \times \mathbf{R}_+$ are time variable and spatial variable. $p = p(x, t) \in [0, p_{max}]$ is density of pedestrians, $v = v(t, x)$ is the average velocity pedestrians and $f(p) = pv(p)$ is the pedestrian flow. if there is an initial value, the equation (1) is called Riemann. The initial values is chosen as following

$$p(x, 0) = \begin{cases} p_l & \text{if } x \leq 0, \\ p_r & \text{if } x > 0. \end{cases} \tag{3}$$

where p_l, p_r are two parameters being constant values.

Because the function $f(p)$ is concave, the weak solution of the Riemann problem that published in [6], [9] is.

(i) if $p_l < p_r$ the solution including a shock wave is given by

$$p(x, t) = \begin{cases} p_l & \text{if } x \leq v_{max} \left(1 - \frac{p_r + p_l}{p_{max}} \right) t, \\ p_r & \text{if } x > v_{max} \left(1 - \frac{p_r + p_l}{p_{max}} \right) t. \end{cases} \tag{4}$$

(ii) if $p_l < p_r$ the solution of the equation is

$$p(x,t) = \begin{cases} p_l & \text{if } x \leq v_{max}\left(1 - \frac{2p_l}{p_{max}}\right)t, \\ \frac{p_{max}v_{max}}{2v_{max}+p_{max}} & \text{if } v_{max}\left(1 - \frac{2p_l}{p_{max}}\right)t \leq x \leq v_{max}\left(1 - \frac{2p_r}{p_{max}}\right)t, \\ p_r & \text{if } x > v_{max}\left(1 - \frac{2p_r}{p_{max}}\right)t. \end{cases} \quad (5)$$

(iii) if $p_l = p_r$ the solution is constant and given by: $p(x,t) = p_l$.

We investigate with a network of roads, as in [9]. This means that we have a finite number of roads (with one of the two endpoints possibly infinite) that meet at some junctions. Each road i is modeled by an interval $I_i = [a_i, b_i]$, possibly with either $a_i = -\infty, b_i = +\infty$.

In the case of the LWR model the conserved quantity is the variable $p_i = p_i(x,t) : I_i \times \mathbf{R}_+ \rightarrow \mathbf{R}$, so that on each edge i of the network, the pedestrian is governed by the following scalar conservation law:

$$\frac{\partial p_i}{\partial t} + \frac{\partial}{\partial x}f(p_i) = 0, \forall i \in \mathbf{I} \quad (6)$$

where

$$f(p_i) = pv(p_i), v(p_i) = v_{i,max}\left(1 - \frac{p_i}{p_{i,max}}\right), \forall i \in V. \quad (7)$$

In addition, the initial values of road i are two constant values, i.e

$$p_i(x,0) = \begin{cases} p_{i,l} & \text{if } x \leq 0, \\ p_{i,r} & \text{if } x > 0. \end{cases} \quad (8)$$

The solution in each road has the same formulas with the case of one road that we has just represented above. This model is appropriate to reveal shock formation as it is natural for conservation laws, whose solutions may develop discontinuities in finite time even for smooth initial data. However, the behaviors of pedestrians are distinguish but they can not represent in the LWR model. The importance behaviors in evacuation are investigated by agent based model. In addition, at an junction of road networks dynamic of flow changes complex so micro model will be used and be investigated in the next subsection.

2.2 Micro model

In micro model, we use agent based model for the issue. We choose method to build the model by the Overview Design concepts Detail (ODD) protocol. The ODD protocol is famous and use widely in represent agent-based model that we can read detail in [3], [4].

Overview

– Purpose

This model represents the issue in detail that pedestrians are agents and we find the emergence when pedestrians moving in the road networks environment to the safe places. Moreover, pedestrians behaviors decides time spending in evacuation.

– Entities, state variables and scales

In our model, we introduce two kinds of entities. First, the pedestrians are entities. The pedestrian who knows to help other pedestrians and was trained evacuation in the past or knows all information about environment to get the safe place effectively is called fox agent. The pedestrian evacuating randomly or following one fox agent is called sheep agent. Second, each road in the road networks is component of GIS environment as entity. The heterogeneity GIS environment plays an important role in decision-making of agents. We choose GIS 2D plane to present the environment in this model.

The pedestrians has state variables that are the positions (in road or safe place, perception in moving of the pedestrians). The agent pedestrian is an agent with his own behavior, his own purpose and his own environment knowledge. The knowledge environment of the agent depend on the spatial that the agent can see. The decisions of the agent are generated based on its perception environment and the information shared by the other agents. Before the agent moves, he needs to know the other agents surround, road infrastructure. The constraints in the dynamic traffic, the agent interact other agents. The agent collects all information that he observes his neighbors about the positions, velocities. During agent moves, he adapts his speed to reach his desired speed. Indeed, if his speed is less than the desired speed, and if there is enough space, he may decide accelerate.

Spatial scale in this model is meter and the unit time is minute. We consider the time that all the pedestrians move to the safe places and the specific area.

– Process overview and scheduling

First, agent pedestrian moves one direction to escape the dangerous place. In this model, we assume that from the left hand side to the right hand side.

If he is sheep agent, at junction he choose randomly road. If he is fox agent, he moves to the shortest path. During he moves, he helps the others neighbors.

In the panic situation, the pedestrians want to escape the dangerous place as quickly as possible. If they have not any information to evacuate, they often move randomly or follow the crowd pedestrians.Because of complexity of the road networks, sheep agent is difficult in finding the safe place or reaches the safe place is too late.

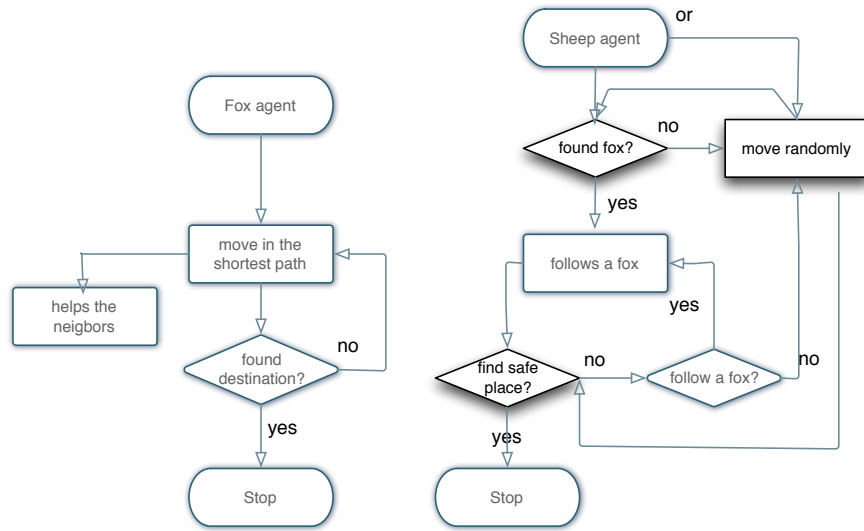The finding roads of the agents follow diagram (2.2)

Fig. 2. Process of sheep agent and fox agent in moving

Design concepts

– Basic principles

The agents follow one direction moves on the road to safe place. Fox agent chooses the shortest path and
   sheep agent moves randomly path or follows one fox agent.

– Emergence

The result shows that more the number of foxes in population lesser time spending of the population.

– Adaptation

Fox agent choose the effective information that helps him goes to the safe place as quick as possible. We consider an agent i arbitrary. His velocity depends on the neighbors forward his position and the capacity of the road. If a number of neighbors are greater than a critical then he can not move forward so the velocity is equal 0. if the neighbors are crowd then it moves slowly, contrary if the neighbors are few then he moves fast follow himself velocity. His velocity is represented:

$$v(i) = v_{average} \left(1 - \frac{neighbors(i)}{critical} \right) \tag{9}$$

where *critical* depends on the capacity of the road and the local density of the agent i. Each agent will have an argument about the position, velocity, different

goals, the circle observation, his decision choose direction when he stands at the junctions.

– Objectives

Fox agent's objectives are finding the shortest path from current position to one of safe places and helping the sheep agents. The objectives of sheep agent are finding an fox agent and exploring a safe place when he can not find any fox agent.

– Prediction

Fox agent can predict the block of the traffic when he senses the crowd. The prediction of the fox agent helps himself and the followers evacuate more effectively.

– Sensing

A fox agent has two level in sensing environment. The high level of sensing that fox agent finds the sequence of roads that is shortest path form his position to one of destinations. The low level of sensing is local environment that help him to avoid the obstacles, the crowd and moves on the road.

A sheep agents has only low level in sensing and try to find an fox agent.

– Interaction

The sheep agent tries to find a fox agent and he always follows him. The fox agent considers information form the panels that help he get information from environment and temporary situation.

– Collectives

The sheep agents follow on fox is called group. The fox agent of each group is the leader that help all members of the group to escape dangerous to the safe place.

Detail

– Initialization

The initial data are the number of agents evacuating, the number of safe places, the road networks is represented GIS environment.

– Input data

Data are the densities and velocities of sources. The proportion of fox agent in the pedestrians.

3 Hybrid evacuation flow model on road networks

3.1 Environment of the hybrid models

The environment in hybrid is Gis road networks.

Each road in the simulation is huge so we separate by three small patches. The role of each part of each road in the simulation is not equal. There are some areas are very importance in evacuation but some areas can be ignored. Unimportance areas are represented macro model and the importance areas are represented micro model. Simplify the representation model in this paper, each road is divided in three patches. The patch 1 and 3 are micro model, the patch 2 is macro model.
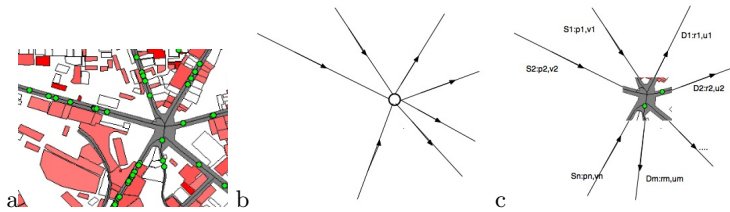
Fig. 3. a, The Gis environment in the micro model; b, the abstract environment representing direct graph in macro model; c, hybrid environment in hybrid model.

– Micro patch 1

Pedestrians are simulated by agent based model that each agent is fox or sheep. The simulation in this patch is represented in the micro model. The environment is represented by GIS.

– Macro patch 2

This patch is stretch of the road, hybrid simulation of this patch has two triggers that aggregation trigger changes pedestrians from micro patch to density of pedestrians in macro patch and disaggregation trigger does vice versa. The length L_i and capacity c_i of the road i are parameter of patch 2. The pach 2 is two special positon, the position changing from patch 1 to patch 2 is called source and the end position changing from patch 2 to patch 3 is called destination.

– Micro patch 3

This patch is simulated the same patch 1.

The environment is represented in direct graph in marco model, GIS road networks in micro model and combined graph and GIS in hybrid model. The figure a) shows the micro environment, the figure b) represents the macro environment and the hybrid environment is showed in the figure c) that width roads dedicate for the micro environment and others represent macro environment.

3.2 Interfacing the two models

Transition from micro to macro models Micro pedestrians moving towards the macro patch. The micro pedestrians transfer to the parameter in macro. Each road has three patches. We choose one arbitrary road i and consider detail

- The number of pedestrians at source the from the time t to $t + 1$. The aggregation trigger changes number of pedestrians of micro model to the flow of pedestrian as the parameters $p_i(t, source)$ of macro that is investigated in patch 2.
- The average velocity of the number pedestrians at source gives the velocity of flow pedestrian in the macro patch 2 $v_i(t, source)$.
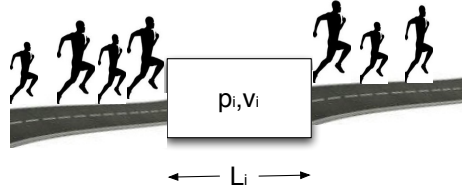
Fig. 4. The macro transform to micro.

Transition from macro to micro models The figure (3.2) illustrates the transition from the macro patch that is called tube to the micro patch.

The length of the macro patch of road i is denoted L_i.

- The macro values $p_i(t)$, $v_i(t)$ of source is used for the the initial of macro model. The average time flow of pedestrian to pass the tube of the road i is

$$T(t) = \frac{L_i}{v_i(t, source)}.$$

Applied formula solution of the macro model, at the time $t + T(t)$ we have results about density and velocity of pedestrians flow at the destination $p_i(t + T(t), destination), v_i(t + T(t), destination)$. The flow of pedestrian at $t + T(t)$ is

$$q_i(t + T(t), destination) = p_i(t + T(t), destination).v_i(t + T(t), destination).$$
(10)

These results are the parameters of micro model for the patch 3. Firstly, We assume the flow of pedestrians is Poisson process that was used in [10], [8]. Using the Poisson distribution with parameter $\lambda = mean = q_i(t + T(t), destination)$ at destination generates the number of pedestrian agents.

– Velocity of each pedestrian is generated by the normal truncated distribution with the $\mu = mean = v_i(t + T(t), destination)$, at destination.
– The time for one agent order k at the time t comes into the tube is released out of the tube to the patch 3:

$$t + T(t) + g[k, q_i(t + T(t), destination)].\qquad(11)$$

where $g[k, q_i(t + T(t), destination)]$ is value of Gamma distribution

$$\text{Gamma}\,[k, q_i(t + T(t), destination)]$$

This formula is based the theory of Poisson process that we can read in [13][14]. The arrival time of agent order k follows Gamma distribution with parameter $q_i(t + T(t), destination)$.

4   Implementing the model

This section present a hybrid macro-micro evacuation of pedestrians in road networks. Each road is divided three patches, patch 1 and patch 3 are micro patch and the patch 2 is the macro patch. To simplify the program, we consider a road networks having 9 roads as figure (4)
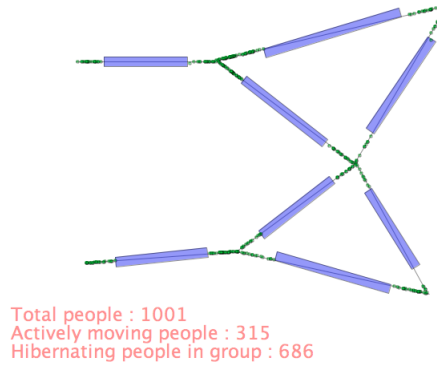

Total people : 1001
Actively moving people : 315
Hibernating people in group : 686

Fig. 5. Micro model of the road networks and Hybrid model of road networks are implementation. The number of people hibernating (not simulated in the ABM) are proportional to the speedup provided by the hybrid modeling. Indeed, only the fraction of the total pedestrians are effectively consuming simulation CPU.

Hybrid model in road networks is represent GIS of road network in the figure (4) . Each road has three patches, the micro model is simulated in GIS and the stretch as a tube like a edge of directed graph is considered macro model. Therefore, all junctions respectively the begin and the end of the roads are investigated detail in micro model.

5 Discussion and conclusion

The problem of speeding up very large ABM such as the ones used in crowd simulation is key to support the definition of Decision Support Systems. In this paper we have given an approach to Hybrid modeling for evacuation simulation. The key idea is to exploit advantages from both macro and micro modeling. The problem we have solved in this paper is the central question of having entities that are shared by both models. In other words, the two models of interactions are defined so as to exchange agents at their boundary. A case study of the hybrid modeling shows that it not only offers more efficient execution than micro, but also improves the simulation quality in comparison with macro model. The results presented are yet to be extended to very large simulations including hundred of thousands of pedestrians. Nevertheless, the preliminary results are a proof of concept in the sense that they demonstrate where the source of speed-up of such simulation may be found. Future work includes large scale simulation and exploring various emergent behavior resulting from various types of behaviors.

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A Unified Agent-Based Model to Analyze Organizational Deviation and Kaizen Activities

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Abstract. This paper presents a new agent based model for unifying organizational deviation and Kaizen activities. Deviation and Kaizen are both activities in business firms to break standards in operations. However, it is assumed that the former and the latter are different in terms of external utilities. Under the assumptions, we have developed a unified model and conducted simulations. The results show deviation, Kaizen, and stagnation phenomenon that are caused by the change of utility landscapes, diversity of agents, and reward distribution system. We have suggested the harnessing mechanism of deviation and Kaizen based on the experiment results.

1 Introduction

Companies tend to control organizational deviation strictly because they would get serious damage when it has been revealed. Direct control of deviation may, however, reduce the power of Kaizen, which means continuous productivity improvement efforts in companies, because both organizational deviation and Kaizen have similar mechanisms of breaking standards.

This paper presents a new model for unifying the activities of organizational deviation and Kaizen, and for distinguishing the results of them. It also presents an indirect mechanism for harnessing agents' behaviors in order to inhibit deviation, which would provide the disutility for a society.

1.1 Similarity of Organizational deviation and Kaizen

In sociology, deviation is classified into three categories [5]. First is criminality, second is violating conduct norms, and third is labeling. This paper is based on the concept of the second category, because it contains similar notions to Kaizen. Kaizen is continuous activities for organizational improvement by breaking standards [6].

Our model is built from the belief that organizational deviation and Kaizen have similar mechanisms, but that they are different in the external utility or disutility.

Organizational deviation does not always occur according to immoral agents' wrongdoing [3]. It may emerge from unintentional behaviors of the agents with the bounded rationality, because they tend to act shortsightedly and to converge to local optima [2]. It means that if agents have behaved aiming at Kaizen, they would commit deviation unintentionally by producing disutility for society. The shortsighted behavior is enhanced by the difficulty with recognizing the utility landscape. Therefore, we incorporate a hierarchical utility landscape into our model by expanding the landscape theory [2] [9] in order to increase complexity.

1.2 Cases of Japanese Companies: Toyota and a Pastry Company

To convince the idea of the unified framework, we will show cases of Japanese companies. First case is about Toyota, it conducted huge amount of recalls with break system failure. It is said that increasingly sophisticated break systems sometimes have problems with unpredictable handling by users. In other words, excessive Kaizen may be a cause of this trouble.

In another case, a Japanese pastry company was accused on suspicion of falsifying the expiration dates of its products. By the analysis, it was revealed that the excessive effort to avoid disposing products was one of the causes of this case. The pastry company possibly did not falsify the expiration dates intentionally. They attempted Kaizen activities excessively in order to extend product expiration, and that leads them to the violation of law as a result. This case explains that the border between Kaizen and deviation is subtle in some cases, and both phenomena can emerge by slight changes in circumstances.

The rest of the paper is organized as follows: Section 2 explains our unified model of deviation and Kaizen; Section 3 shows the simulation experiment settings and results; and Section 4 presents our findings and remarks as a conclusion.

2 A Unified Model of Deviation and Kaizen

This section describes our unified model of deviation and Kaizen, which simplifies a real structure of a organization and the relation between a organization and a society. In this model, hierarchical utility landscape is implemented that consists of three classes: individual, organizational and social utility.

Figure 1 shows outline of hierarchical utility landscape in our model. Utility function of individuals means experience and values of each agent. Utility function of organization means strategy and business model of a company. Utility function of society means social norms.
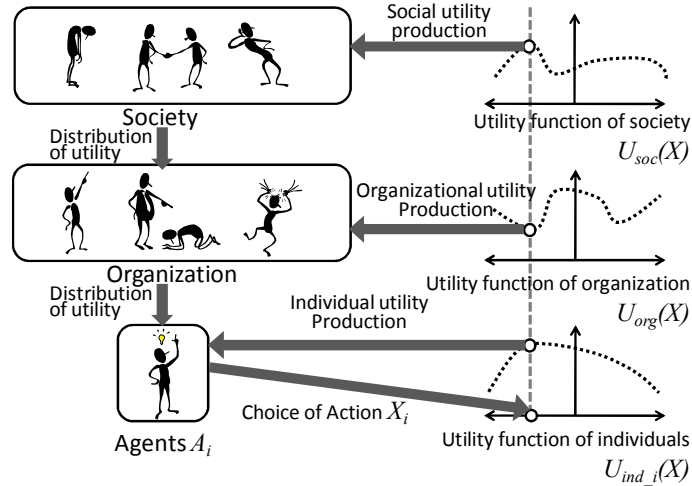
Fig. 1. Hierarchical utility landscape is implemented in this model. When agents choose their action, their own utility and their contributions to external utilities are determined. Society's utility is distributed to organization, and organizational utility is distributed to agents through reward system.

In this model, agents choose their actions according to the rewards from organization and information from neighbors. As a result, their utility production amount for an organization and a society is determined based on utility landscape. Agents can recognize their own utilities, however, they cannot recognize organizational and social utility landscape completely. Therefore, both deviation and Kaizen may emerge depending on experiment conditions in this model.

For example, in the previous pastry company case, employees could recognize their individual utility: the reduction of product disposals is consistent with their beliefs. On the other hand, they could neither recognize the social regulations, nor company's damages due to consideration of violating law. In other words, they could neither recognize social utility nor organizational utility landscape thoroughly. As a result, they conducted organizational deviation despite they aimed at Kaizen.

Based on the above understanding, we difine three types of phenomena as shown in table 1 according to our model: a) Kaizen is the increasing of both organizational and social utility production, b) Organizational deviation is the decreasing social utility production, and c) Stagnation is the decreasing of organizational utility production.

We focus on organizational utility and social utility in this paper.

Table 1. The Definition of phenomena in our model

	Definition	Organizational utility production	Social utility production
a)	Kaizen	increase	increase
b)	Deviation	increase/decrease	decrease
c)	Stagnation	decrease	increase/decrease

2.1 Utility Function based on NK fitness landscape model

The Utility functions which are described in the previous section, are based on the NK fitness landscape model by Kauffman [7] [8]. NK model determines the values of N integers sequences, and utility landscape is defined by the combinations of K integers.

Figure 2 describes a sample of integer combinations and their values, in case of N=6 and K=1. The variation of utility functions is described by number sequences and their evaluation values. Evaluation value is given between 0 to 1 depending on combinations of integers. The complexity of utility landscape depends on the number of integers and their combinations. We have set N=5 and K=2 in the experiment.
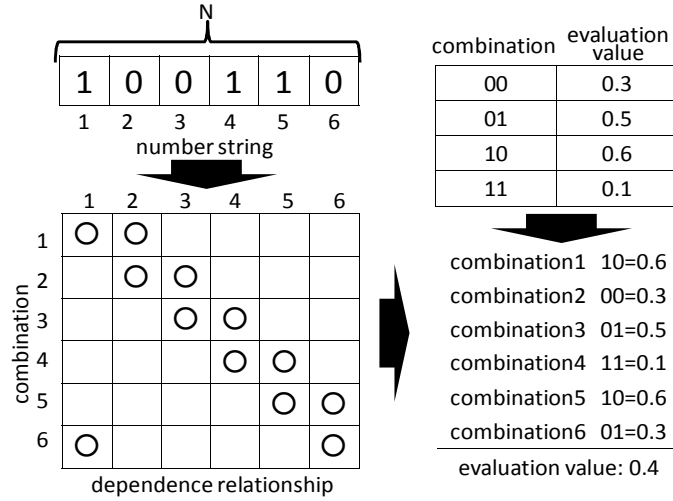
Fig. 2. NK fitness landscape model.

2.2 Choosing Actions of Agents

Each agent changes their action in order to increase their satisfaction according to the following formula. The degree of satisfaction of agents increases along with the rising of their individual utilities: $U_{ind\_i}(X)$, rewards from organization: R_e, and contributions for social utility: $U_{soc}(X)$.

$$S(U_{ind_i}(X), Re_i) = U_{ind_i}(X) + Re_i + U_{soc}(X) \tag{1}$$

Agents imitate the actions of other agents whose actions are similar to them and receiving more rewards from organization, according to the following formula. L_{ij} means the similarity of action between agents. Agents evaluate their satisfaction after

imitation, and then return to original action when their degrees of satisfaction have been declined by the imitation.

$$P_j = \frac{Re_j \times L_{ij}}{\sum_{k \neq i} Re_k \times L_{ik}} \tag{2}$$

The agents produce their own utility, and contribute to organizational and social utility as the result of their actions. The contributions of agents are accumulated in a organization and a society.

2.2 The Variation of Reward Distribution

The accumulated external utility is distributed to agents based on their amount of contribution through the system of rewards. The degree of result-based reward is strengthened progressively as shown in figure 3.
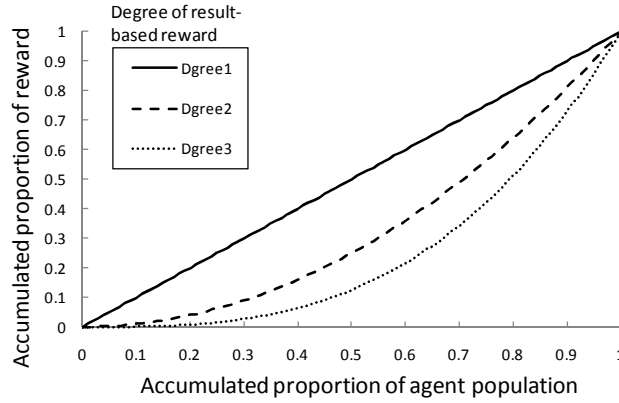
Fig. 3. Variation of reward distribution

In order to alter degree of result-based reward progressively, cumulative distribution of reward is set according to following formulas.

$$IR_e = IP^D \tag{3}$$

$$Re_i^k = D\left(\frac{n - Ra_i^k + 1}{n}\right)^{D-1} \frac{\sum_{i=1}^{n} U_{org}(X_i^k)}{n} \tag{4}$$

$$Z_D = \left(1 - \frac{2}{D+1}\right) \tag{5}$$

Each character in these formulas means as follows: IRe is cumulative distribution of reward, IP is cumulative population ratio of agents, D is degree of reward

distribution, Ra_i is ranking of organizational utility production amount of agent A_i, Z_D is Gini's coefficient of reward distribution. The result-based reward is strengthened by value of D.

3.3 Organizational Structure

Hierarchical organizational structure which consists of three layers is brought into our model, because hierarchical structure is seen in many companies. Figure 4 shows the structure of organization and the number of agents in each layer. There are 39 agents in total.
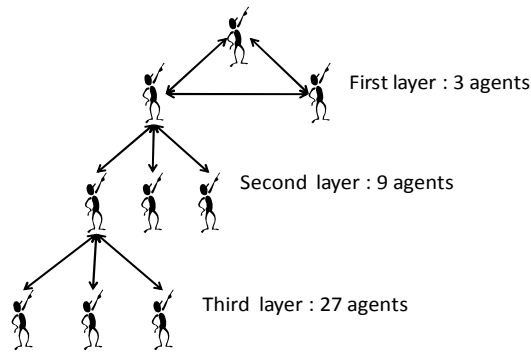

Fig. 4. Organizational structure.

3 Simulation Experiment

Based on the descriptions of the previous section, we have developed the simulator according to agent based computational architecture [1] in Java language. This section describes settings and results of the agent based simulation experiment.

3.1 Experiment Settings

In this experiment, we set the three types of parameters. Those are 1) conflict of utility function, 2) diversity of agents, and 3) degree of result-based reward as shown in table 1. We set each experimental condition, and investigate the changes in utility production amount of an organization and a society by altering the combinations of those parameters. In the next subsections, simulation experiments are organized according to those parameters.

Table 2. Experiment Parameter Settings

Parameters	Conditions		
1 Conflict between social utility function and organizational utility function	0 synchronized	⇔	1 contrary
2 Diversity of agents	0% uniform	⇔	100% diversified
3 Degree of result based reward	1 even	⇔	36 highly result based

3.2 Experimental Results of Conflicts among Different Utility Functions

At the beginning, figure 5 represents the result of changing conflict degree between social utility and organizational utility functions. The other conditions are fixed; diversity of agents is 100% and result-based reward is second degree.

In figure 5, both social utility and organizational utility production are declining with strengthening of contradiction in social and organizational utility function.

This result means that conflict in the utility landscape prompts organizational deviation and also causes stagnation phenomenon according to the deffinitions in Table1.
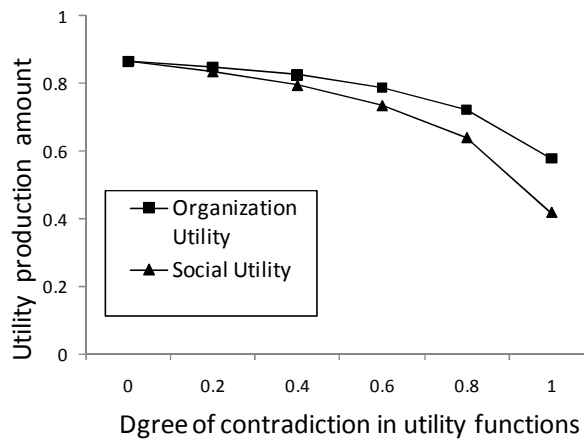

Fig. 5. Utility production change that occurs with strengthening of contradiction in utility functions.

3.3 Experimental Results of Heterogeneity of Agent Characteristics

Figure 6 shows the result that is occured when improving diversification in agents. We control the diversity by increasing and decreasing the number of agents who have same individual utility function. All agents have unique utility functions in the organization with 100% diversity, while they have common utility functions in the organization with 0% diversity. The other conditions are fixed; conflict degree between utility functions is 0.4 and result-based reward is second degree.

In figure 6, both social utility and organizational utility puroductions are increasing with improving diversification. This result suggests that the diversification in agents prompts Kaizen type activities according to the deffinitions in Table1, and the result is crresponding to previous study [10].
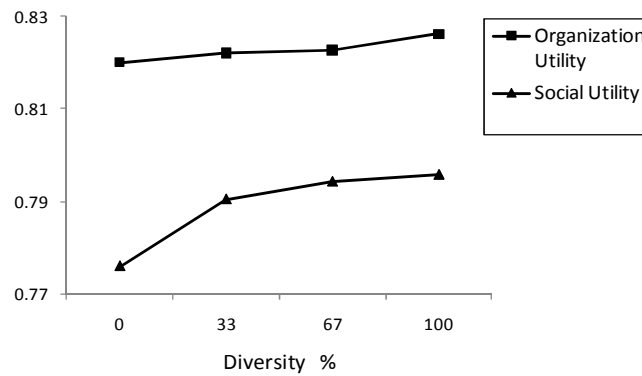

Fig. 6. Utility production change that occurs with diversification.

Next, figure 7 and 8 represent the distribution of social and organizational utility production in the same condition as figure 6. The number of dots is 1000 because we have conducted simulation 1000 times. Figure 7 shows the result of uniform organization and figure 8 shows that of diversified organization. The distribution trend in diversified organization is more convergent compared to uniform organization.

Those results suggest that uniform organization's behavior is more unpredictable than diversified organization, because it swings over from Kaizen to deviation. Each dot can be recognized as a company's status; for example, Toyota and a pastry company, that are previously mentioned, could be the upper left dot in figure 7. It means that they may neglect social utility while pursuing organizational utility because they may have strong common values of emphasizing organizational utility; increasing sophistication of break system in Toyota and avoiding product disposals in the pastry company. The uniform organizations which have strong common values may cause organizational deviation according to the result in figure 7.
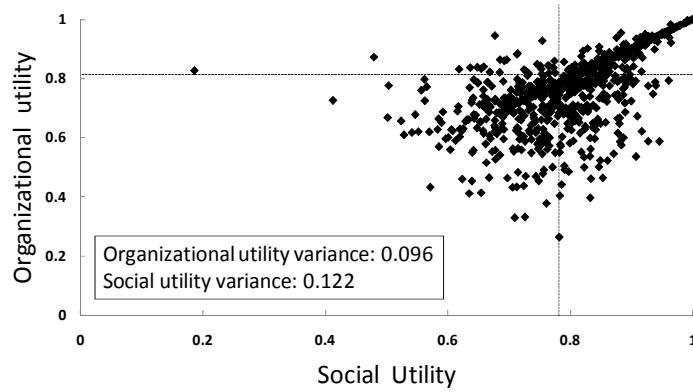
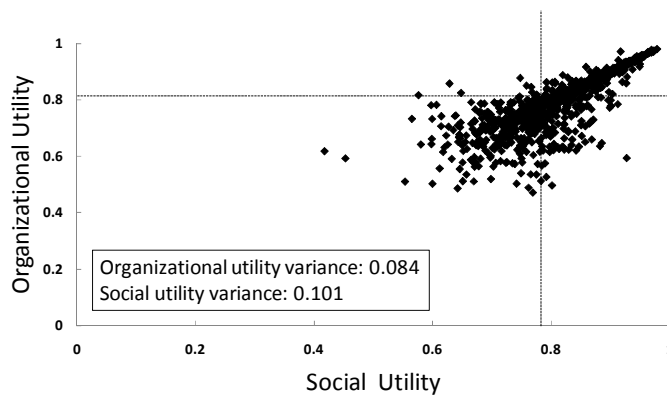**Fig. 7.** Utility production distribution (diversity 0%).

Fig. 8. Utility production distribution (diversity 100%).

3.4 Experimental Results of Changes of Levels on Result-Based Rewards for Agents

The last result is about reward system. Figure 9 shows the utility production change by strengthening the degree of result-based reward. The other conditions are fixed; conflict degree between utility functions is 0.4 and diversity of agents is 100%.

At the beginning, both social and organizational utility production amounts are increasing, then they are decreasing gradually with strengthening degree of result-based reward.

This result suggests that the excessive result-based reward system could prompt organizational deviation and also stagnation according to the definitions in Table 1. We assume that this phenomenon is emerged because agents could pursue short-term

gain of reward and converge on local optimum of utility production. We also assume that agents could decline their intention to contribute to social utility because they could improve satisfaction by gaining reward from organization.
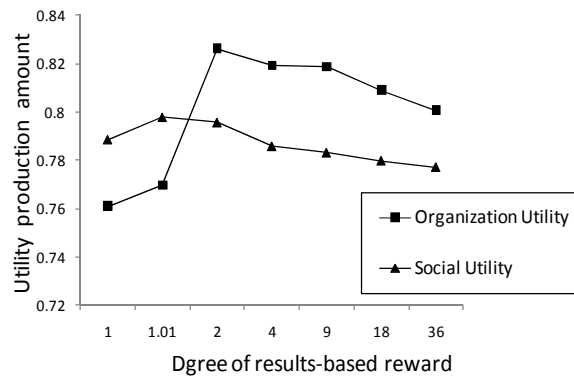

Fig. 9. Utility production transition that occurs with strengthening of result-based reward.

4 Conclusion

This paper has presented a unified model of organizational deviation and Kaizen activities based on Organizational Deviation theory and Landscape theory. In this paper, we have intended to contribute to Organizational Deviation theory by providing clearer definition through comparison with Kaizen by utilizing hierarchical utility landscape.

Both Toyota and the pastry company intended to conduct Kaizen in order to increase their organizational utilities, however they fell into deviation by unintentional decreasing of social utility. For example, Toyota conducted huge amount of recalls with break system failure and the pastry company falsified the expiration dates of products. Based on our model and experiments, those deviation cases may be caused by bounded rationality and lack of diversity in employees.

The advantage of this model is the representation of both deviation and Kaizen by a set of observable variables. Through the proposed model, we have demonstrated that either organizational deviation or Kaizen emerges from the behavior of agents with bounded rationality on complex utility landscape.

According to the results of experiments, the emergence of deviation or Kaizen depends on those conditions; utility landscape, diversity of agents, and the reward system. It is clear that Kaizen activity emerges on the consistent utility landscape and diversified organization. On the other hand, Kaizen activities could occur also in uniform organization, however uniform organization's behavior is unpredictable compared to diversified organization and it may swing over to deviation easily.

The unified model also suggests that the excessive result-based reward could be a cause of prompting organizational deviation. It also implies that improvement of consistency between organizational utility and social utility landscape is more effective than control of reward system.

In the further work, we would implement utility landscape changes over time, because social norms and strategies of organization tend to change in different time line. In addition, we would conduct additional experiments and analysis by appending various factors because the simulation was executed under limited condition. We would like to detect more factors for harnessing agents' behaviors in order to pursue the mechanism of prompting Kaizen activities while preventing organizational deviation.

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