Discussion paper issued without formal editing

FOR PARTICIPANTS ONLY
23 April 2013
ENGLISH ONLY

UNITED NATIONS
CENTRE FOR REGIONAL DEVELOPMENT

In collaboration with

Ministry of Transportation, Government of Indonesia
Ministry of the Environment, Government of Japan

SEVENTH REGIONAL EST FORUM IN ASIA
&
GLOBAL CONSULTATION ON SUSTAINABLE TRANSPORT IN THE POST 2015 DEVELOPMENT AGENDA,
23-25 APRIL 2013, BALI, INDONESIA

INTELLIGENT TRANSPORT SYSTEM: A VISION FOR 21ST CENTURY CITIES

(Background Paper for Plenary Session 10 of the Provisional Programme)

Final Draft

This background paper has been prepared by Prof. Takayuki Ito and Mr. Shantanu Chakraborty, for the Seventh Regional EST Forum in Asia. The views expressed herein are those of the authors only and do not necessarily reflect the views of the United Nations.

Intelligent Transport System: A vision for 21st Century Cities

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1. Why we need intelligent and smart transport system

The current transport infrastructure and management approaches are unable handle traffic. The urbanized nations are battling traffic congestion, with growing populations and the proliferation of cars making the situation worse. Moreover, for developing nations the situation is more severe. Congestion is a source of costly delays and frustration, pollution and wasted fuel – not to mention crashes. Beyond the cities, poor transport infrastructure is holding back the economy, with ships waiting to unload in into ports and half-empty containers travelling across the country. To date, usual governments policies have been largely focused on short-term fixes to eliminate these problems: building a new motorway, widening a road, putting up signs and establishing commuter lanes. While providing temporary relief, these short-term solutions only add to the long-term problems by increasing the number of vehicles on the road and exacerbating the related environmental, cost and safety concerns. The solution lies not just in more concrete and signs, but in smarter, intelligent transport systems and better informed commuters so they can travel faster and safer- and with greater energy efficiency than ever.

For instance, according to a research conducted on behalf National Transportation Commission (NTC), Australia, the Australian public is not satisfied with the passenger transport system (Figures 1 and 2). The average rating of the overall transport system in helping people to get around was 4.9 out of 10, reflecting a raft of challenges, issues and growing tensions. In terms of the public's perceptions of the transport system against the five most common policy objectives across the country's jurisdictions, ratings were quite similar. The lowest rated area was being green and environmentally sustainable (4.7 out of 10), and the highest rated was being fair and accessible for people from all walks of life (5.2 out of 10). Public transport tended to be the first thing research participants thought of in relation to the transport system, even though they were asked to consider all aspects of the system including roads and driving. Public transport received a similar overall rating of 4.8. Roads were rated significantly higher at 5.6 out of 10 on average.

The key attribute driving overall perceptions of public transport is the frequency of services (rated 4.7 out of 10 on average). While reliability and overcrowding of public transport are issues for many people, quite a few participants in the qualitative research spoke of their experiences with overseas transport systems being much more frequent and how in effect this reduces the importance of reliability.

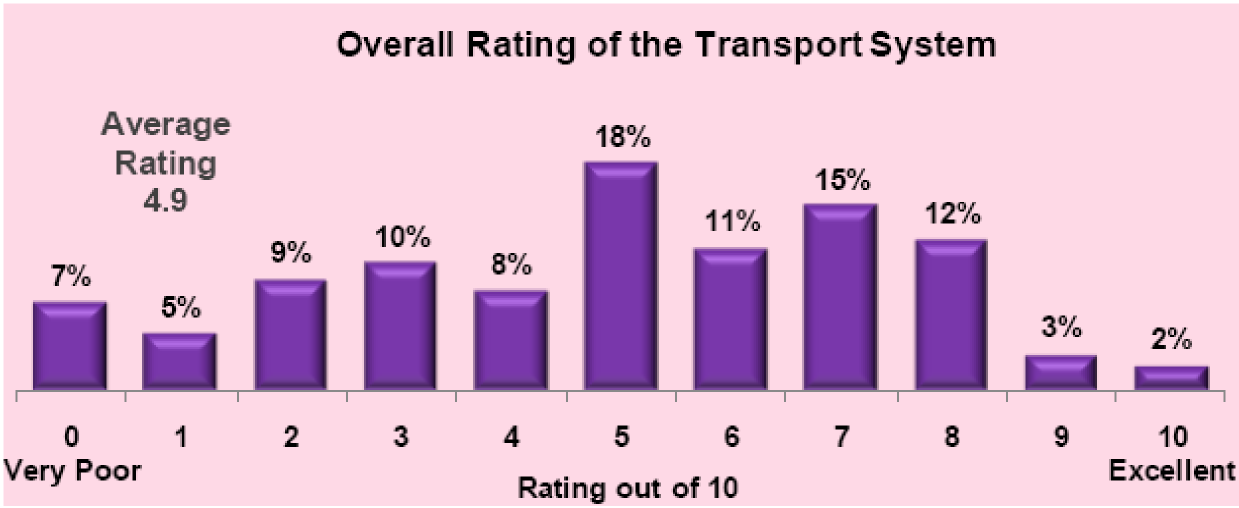


Figure 1. Overall rating of the transportation system (Source: National Survey, Australia)

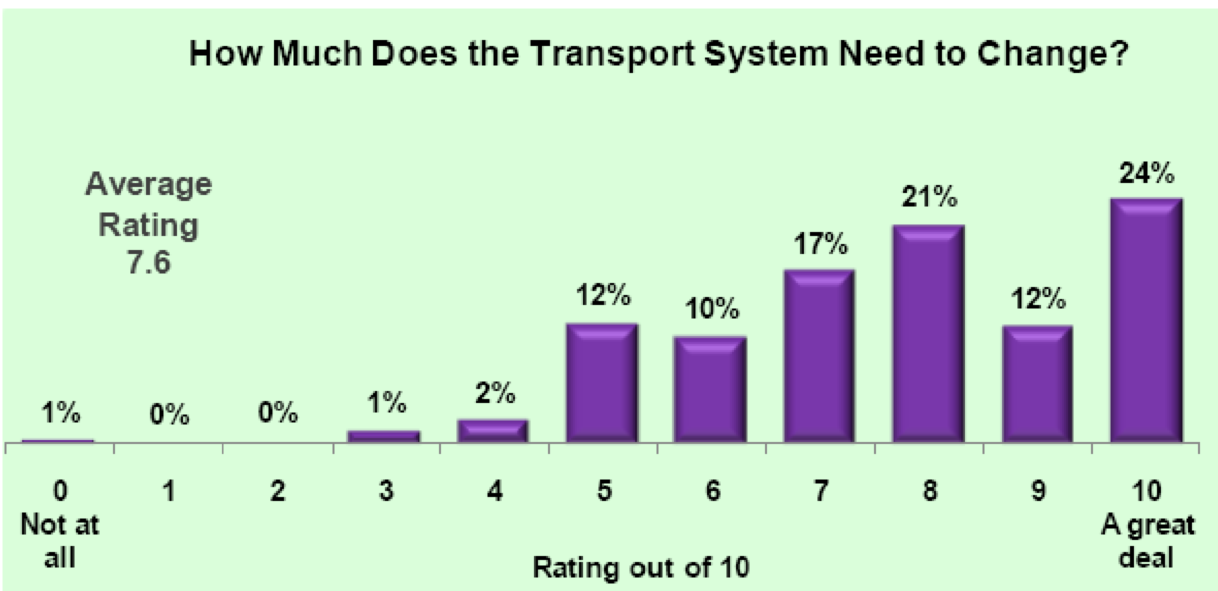


Figure 2. People's thought regarding what extent the transportation should be changed

According to the same survey, when asked how much people think the transport system needs to change on a 0-10 scale where ten meant "a great deal", the national average rating was quite a high 7.6 out of 10. Significantly, around one in four (24%) gave a rating of 10.

2. Smart transport system

2.1. Outline

With the recent development of intelligent system, we can infuse intelligence into our entire transportation system – streets, bridges, intersections, ports, rail, signs, signals and tolls – which can all be interconnected and made smarter. With smart transport we can achieve:

- Improved productivity
- Fewer accidents
- Reduced greenhouse emissions

Now we will consider several aspects of intelligent transportation system

2.2. Traffic Congestion

If we consider the case to cut traffic congestion with intelligent transport solutions that monitor, manage and predict traffic, working the whole system to prevent gridlock. Short-term solutions to eliminating congestion often merely shift the problem, such as from freeways to city streets; from city centres to suburbs. But the whole scenario becomes critical because we simply don’t have room to build more roads. However, we do have room to build efficient and smart intelligence into them. Where the intelligence comes into play:

- Making real time adjustments to traffic lights to ease congestion.
- Electronic tolls with flexible tolling options.

- Predicting what will happen to traffic congestion as well as air pollution, traffic accidents and safely during new construction and better planning roads and public transport in that area.
- Integrating ports with smart road infrastructure and phasing out manual processes for shipping documentation.

To point some successful cases, in London, a smart congestion management system has lowered traffic volume to mid-1980s levels. In Singapore, a system can predict traffic speeds with nearly 90% accuracy. With future enhancements, the system will help predict—rather than merely monitor other traffic conditions, as well.

2.3. Empowering Consumers

Another aspect of smart and intelligent transportation can be achieved by empowering consumers. Which tells by giving them real time information on traffic problems, suggesting alternative routes and offering better public transport options. In an urbanized society, traffic congestion and poor public transport leaves the commuters stressed and angry. They come to work less productive because of their challenging journey to work.

Research shows most commuters would be happy to switch from cars to public transport – if the system actually worked. So, we can induce smartness as

- Using new sensor technologies, GPS and satellites to tell motorists about the best routes and parking during rush hours.
- Helping commuters make more informed choices about public transport, telecommuting or driving in non-peak periods.
- An integrated public transport system that tracks and adjusts services to meet changing commuter needs.
- Fleets of smaller buses that change route on the fly and go where they are needed most.

On the same note, we can point out some successful cases studies such as:

- **Changing commuter habits:** In London, investing revenues raised by the Road-User Charge solution into other public transportation improvements increased inbound bus passenger numbers by 37% in the first year.

- **Integrating public transport:** In Shanghai, Singapore, Hong Kong Special Administrative Region of China and, most recently, Dublin, people can now use the same smart cards on buses, trains and ferries. Some of these cards will even work for taxis and parking lots.

- **Keeping traffic moving:** In Brisbane, the Queensland government has implemented a smart tolling project, using cashless billing options and license plate recognition technology. The project will give Queensland's motorists substantial benefits in time savings, reliability and improved safety.

2.4. Air Pollutions

Intelligent transportation system can actively help to reduce air pollution specially green house gas (GHG) emission. Since the world is moving towards a low carbon society, reduction GHG should rightfully be one of the utmost priorities of policy. As one of the measures for ICT (Information and Communication Technology), ITS indeed can help reduce the GHG (Figure 3).

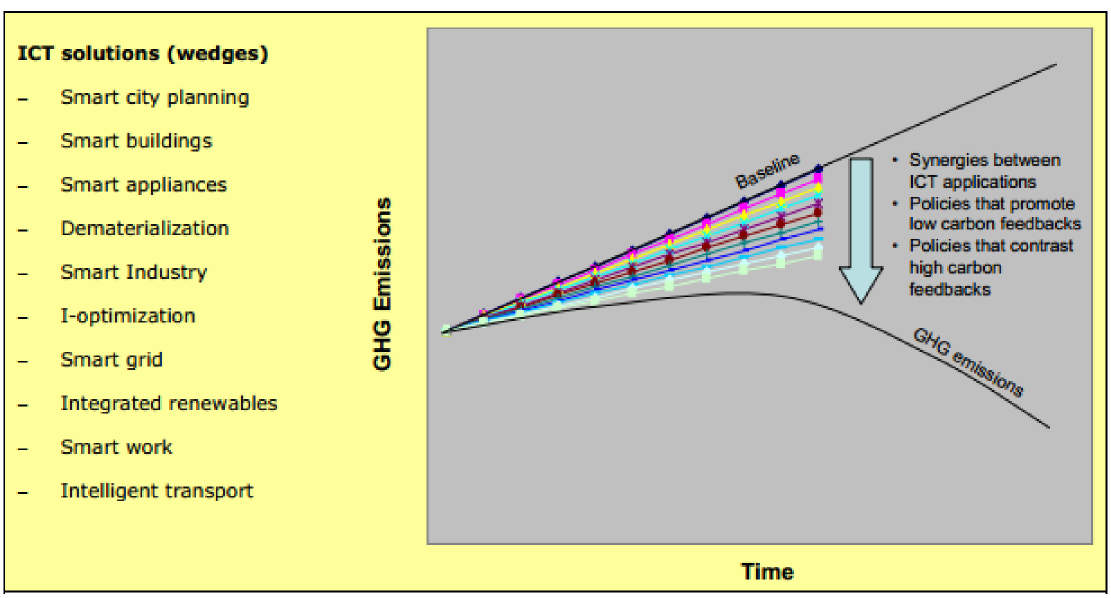


Figure 3: ICT solutions for the first billion ton of GHG emission reductions and to achieve systemic change

2.5. Traffic Accidents and Safety

ITS, which are based on intelligence placed at the roadside and in the vehicle can be designed efficiently to reduce accidents and increase safely. By means of communication between these systems and road users (primarily drivers), various road safety problems can be solved more easily. These can be societal problems such as speed adaptation as well as individual problems such as a call for help in an emergency.

2.6. Integrating Environmental Friendly Electric Vehicle (EV)

Electricity and transportation industries are the main sources of greenhouse gas emissions on earth. One of the main aspects of designing intelligent and smart transportation system is reducing green house gas emission. Today electric vehicles (EV) and plug-in hybrid EVs (PHEVs) do not claim a significant share of the automotive market, but that will change rapidly. Aggressive EV pilot programs are underway in Denmark, Israel, Hawaii, San Francisco and elsewhere. Every utility needs to begin understanding how it will handle the opportunities and challenges EVs will create. On the other hand, Renewable energy, mainly wind and solar, can reduce emission from the electricity industry (mainly from power plants). Likewise, next generation plug-in vehicles which include PHEVs with vehicle-togrid capability, can reduce emission from the transportation industry. PHEVs can be used as loads, energy sources (small portable power plants) and energy storages in a smart grid integrated with renewable energy sources (RESs). Smart grid operation to reduce both cost and emission simultaneously is a very complex task considering smart charging and discharging of gridable vehicles in a distributed energy source and load environment.

PHEVs can be an important part of intelligent transportation system if they are properly managed and operated in accordance with renewable sources. Smart grid connected parking lot can be developed for parking and charging PHEVs. The charging park will be connected with renewable sources (such as Photovoltaic, PV power).

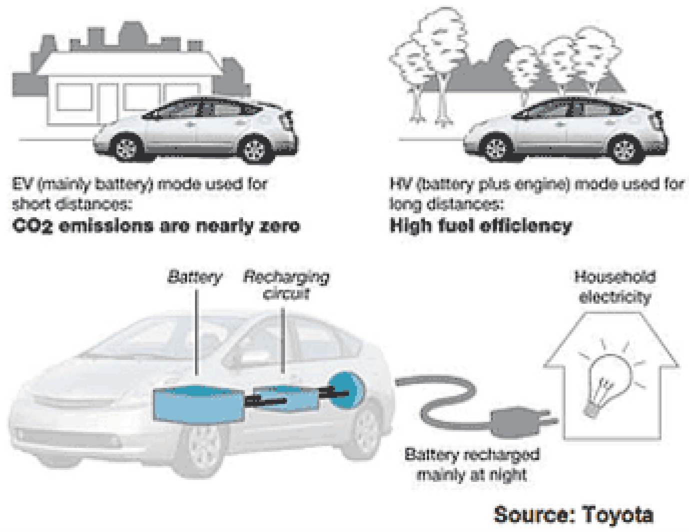


Figure 4: Electric vehicles in operation

Figure 5 shows such a setting. However, efficient energy management systems should be implemented to properly manage the energy status of each PHEV and charging stations.

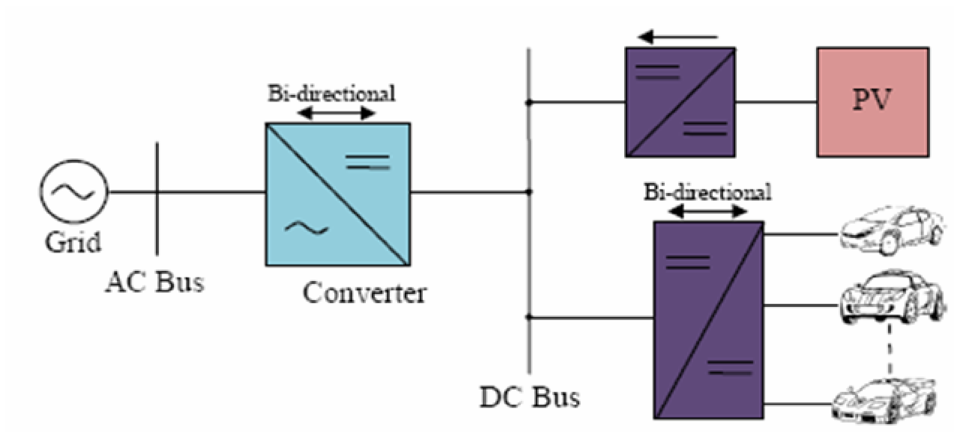


Figure 5: One-line diagram of PHEV charging park with PV power

3. ITS in Japan

In Japan, 20th ITS World Congress is going to be held at Tokyo on October 14-18, 2013 (see: http://www.itsworldcongress.jp/) , and this is 3rd ITS World Congress that is held in Japan. This year's congress focuses on the next stage of ITS including three new domains energy management, personalized mobility services navigated by big data, and resilient transport systems. When 2nd ITS World Congress was held in Yokohama in 1995, Japanese Ministries (Co-organized by National Policy Agency, Ministry of Posts and Telecommunications, Ministry of Economy, Trade and Industry, Ministry of Transport, and Ministry of Construction) started to jointly generate a policy called "The comprehensive vision of ITS promotion", and drew it up in 1996 (http://www.mlit.go.jp/road/ITS/j-html/5Ministries/).

In this policy, the following 9 fields were selected as the significant fields that should be focused for development and implementation.

1. Navigation Systems
2. Electronic Toll Collection Systems
3. Safety Driving Support
4. Transporting Management Optimization
5. Effective Load Management
6. Public Transportation Support
7. Effective Commercial Vehicles
8. Pedestrian Support
9. Emergency Vehicle Operation Support

These developments and implementations had made progress for each topic. In 2004, World Congress on ITS was held in Nagoya. This was 2nd Congress in Japan. This event made very positive effect to penetrate car navigation systems, vehicle information and transportation systems (VICSs) and Electronic Toll Collection (ETC) systems.

Before helding the Congress in Nagoya 2004, the ITS promotion conference that consisted by Industry, Government, and Academia, re-organize the ITS policy to make it more objective-oriented. Then, they agreed on "ITS promotion policy" that is based on the following 5 significant fields:

1. Increasing Safety of Load Transportation
2. Smoothing Transportation and Reducing Environmental Cost

3. Increasing Convenience of Individuals
4. Activating Local Regions
5. Improving and International Standarding Common Infrastructures and Policy making on International Criteria, etc.

In 2006, the IT strategic headquarters of the Japanese government proposed *"IT new revolution strategy 2006 – 2010".* It contained 7 important fields, and one of the fields was *"Most Safety Load Transportation Society in the World"*. This provided effective fields that realized the above *"ITS promotion policy"*, and this extended the promotion of ITS in Japan.

In 2008, the Council for Science and Technology Policy proposed "Society Restration Accelration Project (2008-2012)" that contains 6 significant themes. One of those themes is "Safe and Efficient Load Transportation Systems by using ITS." This theme focused on mainly low-carbon transportation systems. Aomori-city, Kashiwa-city, Yokohama-city, and Toyota-city have been acting as model cities about this theme. So far, such initiatives brought very promising results while reducing CO_2 emission to these model cities. For instance, Toyota Motor Corp. started operating the Ha:mo Harmonious Mobility Network transportation support system on October 1st, 2012. This system is comprised of two services, which include the Ha:mo Navi information provision system supporting low-carbon and seamless movement, and the Ha:mo RIDE compact EV sharing system that assumes short traveling distances between points within the city. This system not only aims at the adoption of environmentally-friendly next-generation vehicles, but also combines optimal combinations of automobiles and public transport in order to attain levels of movement within the city that are user-friendly, city-friendly and society-friendly by eradicating traffic congestion and cutting down on CO_2 emissions, etc.

Currently, ITS-Japan is proposing "ITS-Longterm Vision 2030" from 2008 based on the above developments and implementations. In ITS-Japan's middle term plan (2011-2015), the following 3 targets are proposed:

- Transportation system that can handle revolutional enery-supply methods.
- Next generationl cooperative drinving supporting system.
- Constructing transportation systems in information sharing society.

Japan is one of the top countries that can pursue next generation ITS, and now the main players are considering a variety of mobility such as enjoyable, environmental, clean, electricity-based, personalized, etc.

4. Research on Smart Transportation System

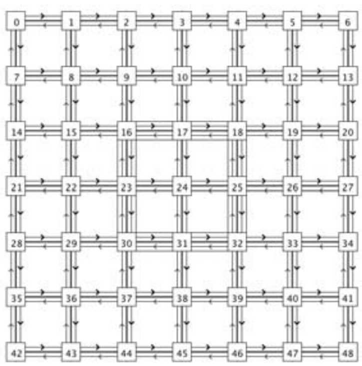
We have been actively involve developing multi agent based intelligent strategies for smart society optimization. This research tackles the grand challenge on establishing multi-agent based computational social mechanism design theories, in which we focus on developing novel social systems and mechanisms that are globally optimized by using computers and networks, and apply them to society simulations and real world applications. This research tries to enable to construct a globally-optimized social systems, which have not been realized yet, by using new multi-agent algorithms that employ pricing mechanisms, matching mechanisms, and scoring mechanisms with the computing power and network infrastructures. This research has been supported by the Funding Program for Next Generation World-Leading Researchers (NEXT Program) of the Japan Cabinet Office.

- Traffic management strategies with Stigmergy
- Emission reduction by PHEV and renewable sources
- Reservation based online mechanism (useful for smart parking system)

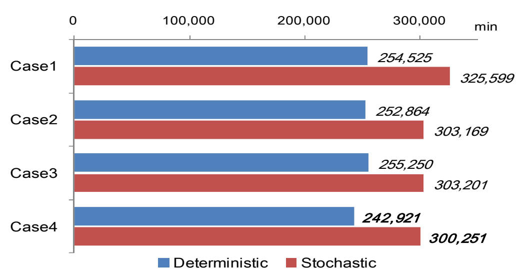
4.1 Traffic management strategies with Stigmergy

Researches in the field of transportation and multi-agent systems have been focusing on dynamic short-term memory. Vehicles share this dynamic information, and drivers can choose their routes more dynamically based on real-time information. This short-term traffic information is usually modeled as a stigmergy. Stigmergy has been used for indirect communication for cooperation among agents. For example, ants' pheromone is a kind of stigmergy for cooperation among them. In this case, ants are modeled as agents in multi-agent models and also as vehicles in traffic situations. Vehicles can estimate their nearest future situation based these stigmergies. One drawback of these stigmergies approaches is that handling near-future congestion remains problematic because stigmergies are basically of past information. In our model, each vehicle submits its near-future location based on the result of car-navigation as anticipatory stigmergy, and recalculates its shortest path based on predicted traffic volume that is summation of the submitted anticipatory stigmergies. And in order to avoid hunting or oscillation, which means another congestion occurs if all drivers follow the recommended link, we introduce some strategies to assign a driver appropriately. In addition, we analyze impacts of driver's route choice behavior to follow the recommended link because it is difficult to control all vehicles automatically. Several case studies based on the traffic information have been conducted.

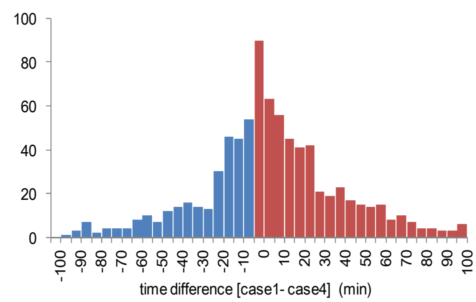
- Case 0: No Information (No traffic information is gathered and provided)
- Case 1: Combined Long- and Short-Term Stigmergy
- Case 2: Anticipatory Stigmergy without Assignment Strategy
- Case 3: Anticipatory Stigmergy with Assignment Strategy considering Residual Distance
- Case 4: Anticipatory Stigmergy with Assignment Strategy considering Lost Time of Traffic Congestion



Road network



Total Travel Time

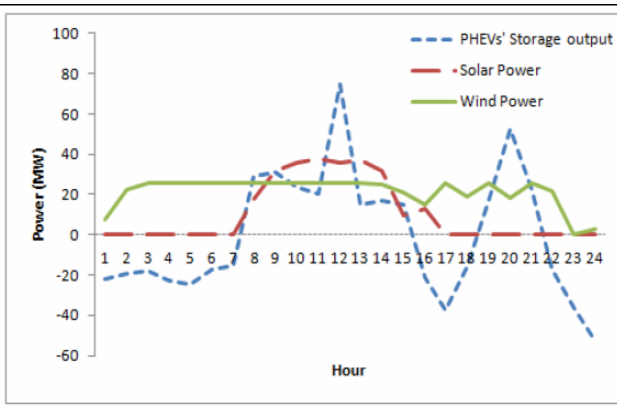


Histogram of Time Differences

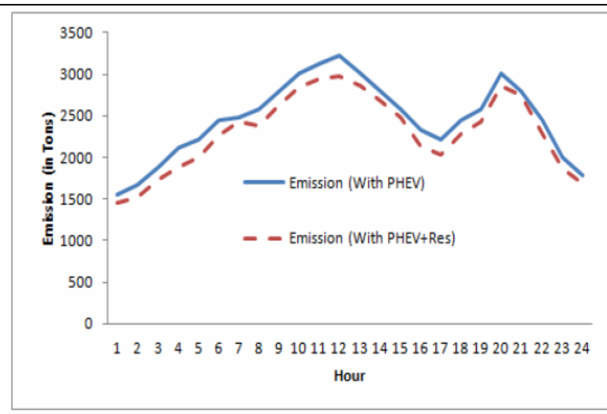
Here we present some results of our analysis. The left figure shows the road network with 49 nodes. The middle one compares the time consumption in travelling using different cases. Note that, deterministic is *without driver's route choice model* and stochastic is *with driver's route choice model.* The rightmost figure presents the histogram of time differences in congestion.

4.2 Emission reduction by PHEV and renewable sources

We have developed a strategy which will perform intelligent economic operation in smart grid with PHEV, thermal generators and renewable sources. Introducing PHEVs will increase the emission from traditional power plant since, the battery installed in them will require more energy from the grid. Although it will reduce NOx and CO2 from the environment. Therefore, efficient utilization of energy is required to reduce emission as well as energy consumption. An intelligent quantum inspired evolutionary algorithm (IQEA) is proposed and applied in this model to perform the intelligent economic scheduling operation concerning scheduling and dispatching energy sources and loads. IQEA features intelligent operators such as sophisticated rotation operator, differential operator, etc. The method is tested on a hypothetical power system with 10 thermal units, equivalent number of PHEVs, equivalent solar and wind farm. The simulation results will show the effectiveness of IQEA that provides excellent operational resource scheduling while reducing the production cost and emission.



The output from renewables and PHEVs' batteries



Emission reduction in smart-grid model

Emission can be effectively reduced by using the proposed method.

4.3 Reservation based online mechanism (useful for smart parking system)

We also presented online mechanisms with reservation capability. These mechanisms can be effectively applied in real world situation involving smart parking system intelligent transportation. Online mechanism design focuses on the design of mechanisms for online scheduling in which agents (or vehicles) bid for access to a resource such as wireless network access or smart parking system. Each vehicle (agents in this context) is supposed to arrive and depart dynamically. The main challenge of online mechanism design is that the mechanism needs to make allocation decisions without knowledge about future (arrived) types of agents. In addition, we are trying to design mechanisms that are truthful in the sense that truthful reporting of arrival, departure, and valuation is a dominant strategy for every agent. In real-world situations, if there is no knowledge about future types, it is very common to use a reservation mechanism to know the future arrivals of customers. Thus, this paper models a new online mechanism that includes a reservation mechanism as an online mechanism. To do so, we extend the model of an agent's arrival time. In the basic online mechanism design, the definition of arrival time has several meanings, in which the arrival time is defined as the time when the agent appears physically or the time the agent knows the mechanism and its type. We try to define these two meanings separately as virtual arrival times and physical arrival times. Our preliminary result demonstrates that our proposed mechanism ensures dominant strategy incentive compatibility.

5. ITS in Developing Countries and Conclusion

As a concluding note we will point some critical issues in developing countries while combining ITS with the economic growth in developing countries. Usually economic growth and rise of prosperity result in an increased volume of unsustainable private motorized transport. In the long term, this is not sustainable; congestion and air pollution hinder the quality of living and the economic development and prosperity of the cities. Extension of infrastructure for cars is expensive and space for unlimited growth is simply not available in most of the developing countries. Hence, sustainable and intelligent transport modes have to be made available and the right incentives to encourage their use have to be created. Investments in right transport modes can foster growth sustainably. Investments in public transport modes will improve the quality of living in cities and thereby increase its economic attractiveness. Another complex challenge is freight transport: freight transport works as a trade facilitator and thereby foster economic development but at the same time a big polluter. To find a solution, a relatively hostile approach: changing production chain and optimizing logics to avoid transport, shifting freight from road to rail or marine transport, as those have much lower emission per ton kilometer, and improving the operation and vehicles. This includes simple measure like tire pressure or roof spoiler but include advanced options like diesel-electric hybrid vehicles. Apart from the effects of transportation system, there is a challenge to "green" the production of vehicles. However, the question remains, whether vehicle manufacturing really should play the role of key industry in economic growth policies. People's Republic of China is a good example for such an approach. Other policies can be:

- Fostering employment--green jobs
- Enabling the poor--provide high quality infrastructure and operations for less-privileged
- Incentivizing mass to participate in green and intelligent movement towards transportation

Appendix

ANNEX: Innovating Multiagent Algorithms for Smart City: An Overview

Innovating Multiagent Algorithms for Smart City: An Overview

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Abstract

This research tackles the grand challenge on establishing multi-agent based computational social mechanism design theories, in which we focus on developing novel social systems and mechanisms that are globally optimized by using computers and networks, and apply them to society simulations and real world applications. This research tries to enable to construct a globally-optimized social systems, which have not been realized yet, by using new multi-agent algorithms that employ pricing mechanisms, matching mechanisms, and scoring mechanisms with the computing power and network infrastructures. In this paper, we introduce the overall vision of this project and present some of the current research results. This research has been supported by the Funding Program for Next Generation World-Leading Researchers (NEXT Program) of the Japan Cabinet Office.

1 Introduction

It is the world-wide most important problem that the existing social systems and mechanisms fail to harness and manage environmental changes. This is because the existing social systems and mechanisms are not *globally* optimized by effectively using computers and networks although many efforts have been done against some *parts* of the social systems and mechanisms has been partially optimized. This research tackles the grand challenge on establishing multi-agent based computational social mechanism design theories, in which we focus on developing novel social systems and mechanisms that are globally optimized by using computers and networks, and apply them to society simulations and real world applications. This research tries to enable to construct a globally-optimized social systems, which have not been realized yet, by using new multi-agent algorithms that employ the pricing mechanisms, the matching mechanisms, and the scoring mechanisms with the computing power and network infrastructures. The methodology developed by this research will be able to be applied to smart grids, congestion management, sensor networks with the computing power and network infrastructures. Further, we can anticipate that the result will be applicable to recovering planning systems against huge scale disasters. In this paper, we introduce the overall vision of this project and present some of the current research results. This research has been supported by Funding Program for Next Generation World-Leading Researchers (NEXT Program) of the Japan Cabinet Office.

2 Overview of Intelligent Transport System (ITS)

In this paper, we propose a traffic management with anticipatory stigmergy to solve traffic congestion. Recently, there are several studies and practices for observing traffic flow and providing information on traffic condition. These are usually done by counting the vehicles that pass particular locations using sensing gates that are usually placed on the arterial roads. Such information is broadcasted as current information to vehicles. It is rarely stored and cannot work as shared memory.

More sophisticated coordination methods are becoming feasible by utilizing the current traffic information. More precise traffic information can be provided by car-navigation systems with GPS or probe-vehicle's information. These data are stored in central servers as long-term memory that can provide stochastic travel time information to vehicles. Such information technologies have been already applied in the real world.

Researches in the field of transportation and multi-agent systems have been focusing on dynamic short-term memory. Vehicles share this dynamic information, and drivers can choose their routes more dynamically based on real-time information. This short-term traffic information is usually modeled as a stigmergy. *Stigmergy* has been used for indirect communication for cooperation among agents [Dorigo and Gambardella, 1997]. For example, ants' pheromone is a kind of stigmergy for cooperation among them. In this case, ants are modeled as agents in multi-agent models and also as vehicles in traffic situations. Vehicles can estimate their nearest future situation based these stigmergies.

One drawback of these stigmergies approaches is that handling near-future congestion remains problematic because stigmergies are basically of past information. In this paper, we propose anticipatory stigmergy for sharing information on near-future traffic condition. In our model, each vehicle submits its near-future location based on the result of car-navigation as anticipatory stigmergy, and recalculates its shortest path based on predicted traffic volume that is summation of the submitted anticipatory stigmergies. And in order to avoid hunting or oscillation, which means another congestion occurs if all drivers follow the recommended link, we introduce some strategies to assign a driver appropriately. In addition, we analyze impacts of driver's route choice behavior to follow the recommended link because it is difficult to control all vehicles automatically.

In this paper, we evaluate the following types of stigmergies with a custom simulator: combined long- and short-term stigmergy as a conventional method, and anticipatory stigmergy with assignment strategies. We conducted several experiments to compare the different kinds, and evaluate impacts of driver's route choice behavior as sensitivity analysis. Our preliminary results demonstrate that the anticipatory stigmergy works especially well by considering each driver's time loss in congestion, and that it is important to introduce incentive mechanisms for drivers to follow information.

2 Traffic Management Strategies with Stigmergy

We set the following five cases (case0 – case4) for traffic simulation, and explain how to collect and provide traffic information in each case to evaluate and compare the effect of stigmergies. And logit model is introduced to describe driver's decision-making of whether to follow route information.

2.1 How to collect and Provide Traffic Information

Case0: No Information

No traffic information is gathered and provided. Each vehicle finds the best path by Dijkstra search before it departs. We assume several different starting and end points since drivers have different origins and destinations. The cost of link *l* can be shown in Eq. (1):

$$v_0 = t_0(l) = int\left(\frac{|l|}{v_{max}(l)}\right) \quad (1)$$

where $\tau_0(l)$ defines a free flow travel time, and $v_{max}(l)$ defines the maximum speed and |*l*| is distance of link *l*.

Case1: Combined Long- and Short-Term Stigmergy

First we define historical travel time data as two stigmergy; long-term stigmergy and short-term stigmergy.

A road (link) stores and manages long-term stigmergy (historical) information forever. As long-term stigmergy information, the each link stores the travel time from the vehicles equipped with GPS (i.e., probe cars), and provides them a long-term stigmergy value $v_l = ave + \rho \times sd$, where *ave* is the average, *sd* is the standard deviation of all stored data of each link, and ρ is the weight of standard deviation (in this paper, this value is set in 0.01). Each probe vehicle utilizes this long-term stigmergy information to make a new plan by Dijkstra search before its department. Long-term stigmergy is updated every day (i.e., daily update).

As short-term stigmergy information, the each link keeps storing data about the travel time of probe cars for only the most recent a few minutes, and provides short-term stigmergy value v_s which is the average of the most recent ten minutes stored data in this study.

In this case, we consider the traffic information which combined long- and short-term stigmergies. As mentioned before, the long-term stigmergy information is the value of v_l that is updated daily, the short-term stigmergy information is the value of v_s that is updated every ten minutes. Each probe vehicle utilizes combined long- and short-term stigmergy information to make a new route plan by Dijkstra search every ten minutes. Eq. (2) shows how to combine long- and short-term stigmergies, and v_{ls} is the combined stigmergy information:

$$v_{ls} = \omega \times v_l + (1 - \omega) \times v_s \quad (2)$$

where v_l is the long-term stigmergy value, v_s is the short-term stigmergy value, and ω is the weight of the long-term stigmergy ($0 \le \omega \le 1$). Each probe vehicle utilizes this combined stigmergy information to search new route by Dijkstra algorithm every ten minutes in this study.

Case2: Anticipatory Stigmergy without Assignment Strategy

Every ten minutes, all probe vehicles find the best route to their destination node based on long- and short-term stigmergy, as in case 1. Here, they submit (as a link) where they will be in the next ten minutes. This is how we define anticipatory stigmergy. Then they can confirm the traffic situation in future and search the best route based on the anticipatory stigmergies. Eq. (3) shows the heuristic cost of link *l* by using anticipatory stigmergies, which are average travel time calculated by link performance function defined by Bureau of Public Road (BPR) in U.S. [Sheffi, 1985]:

$$v_a = t_0(l) \cdot \left[1.0 + \alpha\left(\frac{Vol(l)}{Cap(l) \times 0.4}\right)^{\beta}\right] \quad (3)$$

$Vol(l)$ is the total number of probe vehicles in near-future on link *l* gathered as anticipatory stigmergy. Function $\tau_0(l)$ is a free flow travel time, and $Cap(l)$ is a capacity of link *l* that is adjusted adequately (in this study for the traffic simulation based on the cellular automaton model (see next subsection), the adjustment value is set in 0.4 because the condition to drive freely is a half of capacity). α = 0.48, and β =2.48. This cost function ν_a is a heuristic; if there are many vehicles, ν_a will be increased briefly.

In this case 2, there are concerns that it is efficient to navigate all probe vehicles to the path that is calculated based on information of anticipatory stigmergies (Eq. (3)). According to the results of sensitivity analysis [Ito *et al.*, 2012] [Kanamori *et al.*, 2012], we adopted 50% as a ratio of assigned drivers to the recommended link with anticipatory stigmergy. But in this case, there is no criterion of assignment (i.e., random assignment).

Case3: Anticipatory Stigmergy with Assignment Strategy considering Residual Distance

Every ten minutes, all probe vehicles search the best route to their destination node based on a link travel time with anticipatory stigmergy (Eq. (3)). In case 2, the route that a driver assigned actually is set randomly, so it might not be efficient. In this case 3, we introduce a strategy to assign drivers reasonably into the two routes, that one is a route searched with historical information (i.e., combined long- and short-term stigmergy in case 1) and the other is a route searched with near-future information (i.e., anticipatory stigmergy in case 2). Although there are various criteria of assignment, in this study, a rest of straight-line distance to his/her destination is adopted. A concrete procedure to assign drivers into two routes is as follows.

- If the number of drivers on the link searched with the traffic information of anticipatory stigmergy is larger than the congestion level, which is a half of capacity (i.e., $Cap(l) \times 0.5$) to drive freely in the cellular automaton model, drivers are sorted in descending order by a straight-line distance from the cell stayed to his/her destination.
- In the concentrated situation, the upper 50% drivers are assigned to the link that is recommended as the best route with anticipatory stigmergy as shown in case 2, and the rest of drivers are assigned to the link that is searched with combined long- and short-term stigmergy as shown in case 1. Otherwise, all drivers choose the link on a route calculated in case1.

In this study, we set two situation considering driver's travel behavior; one is deterministic case that all drivers follow travel information perfectly, another is stochastic case that drivers can choose a route by themselves because there is no penalty and incentive to obey this rule.

Case4: Anticipatory Stigmergy with Assignment Strategy considering Lost Time of Traffic Congestion

In this case 4, we adopt an assignment by a time involved in congestion so for. Although there are some definitions of traffic congestion [Marfia and Roccetti, 2011], we regard an extra time from a free flow time as a congestion time in this study. A concrete procedure to assign drivers into two routes is as follows.

- Firstly a time stayed in congestion from departure is calculated for each driver base on Eq. (4),

$$\tau_{congestion} = \sum (t_{travel}(l) - t_0(l)) \tag{4}$$

  where $\tau_{congestion}$ is a time involved in congestion from departure, $\tau_{travel}(l)$ is the driver's travel time on link *l*, and $\tau_0(l)$ is a free flow travel time calculated in Eq. (1).
- If the number of drivers on the link searched with the traffic information of anticipatory stigmergy is larger than the congestion level, drivers are sorted in ascending order by his/her time stayed in congestion ($\tau_{congestion}$) and then the upper 50% drivers are assigned to the link that is recommended as the best route with anticipatory stigmergy in the same way of case3.

2.2 Driver's Route Choice Behavior

Logit Model

Logit model is one of a discrete choice model, and this model has been widely used in transportation planning field. In this study, logit model is introduced to describe each driver's decision-making of whether to follow route information because it is not realistic that all drivers follow the provided travel information.

We assume that a driver is a rational individual and a driver's route choice behavior is expressed as logit model. According to famous textbooks [Ben-akiva and Lerman, 1985],[Train, 2003], logit model is formulated as follows; The utility that the decision-maker obtains from alternative *j* is decomposed into (a) a part labeled V_j that is known by the researcher up to some parameters, and (b) an unknown part ε_j that is treated by the researcher as random: $U_j = V_j + \varepsilon_j, \forall j$. The logit model is obtained by assuming that each ε_j is distributed independently, identically extreme value. The distribution is also called Gumbel. Then representative utility is usually specified to be linear in parameters: $V_j = \beta x_j$ where x_j is a vector of observed variables relating to alternative *j* and β is a vector of parameter. With this specification, the logit probabilities become:

$$P_i = \frac{\exp(\beta x_i)}{\sum_j \exp(\beta x_j)} \tag{5}$$

Route Choice Model

All drivers have a chance to make a decision whether to follow the travel information or not. Most of drivers believe that it is efficient to obey the result of route search by car-navigation, but a few drivers would change a route by one's own judgment. In order to represent these drivers' route choice behavior, we develop a route choice model, which is expressed as logit model.

As a systematic component in a driver's utility function, three variables are considered; a) reliability to traffic information (x_1), b) regret based on his/her own past experience

(x_2), and c)

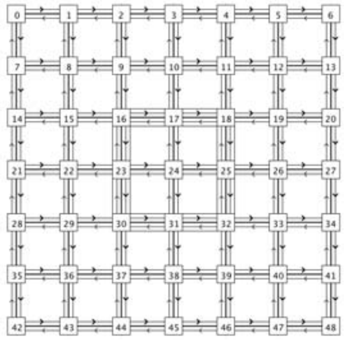


Figure 1. Road network

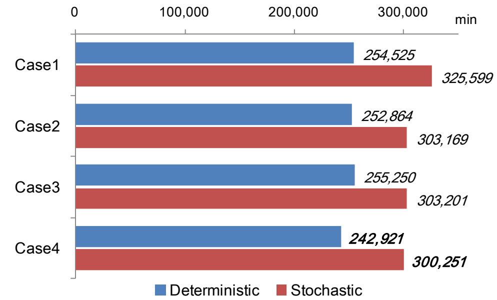


Figure 2. Total travel time

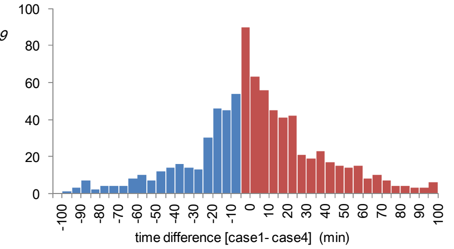


Figure 3. Histogram of time difference in congestion [case1-case4]

short-sighted present situation (x_3). We define each variable as follows;

$$x_1 = \begin{cases} 1 & \text{if link is on a shortest path (provide information)} \\ 0 & \text{if otherwise} \end{cases},$$

$$x_2 = \frac{\tau_{travel}^{yesterday}(l) - \tau_0(l)}{\tau_0(l)},$$

$$x_3 = \frac{Vol^{now}(l)}{Cap(l)},$$

where $\tau_{travel}^{yesterday}(l)$ is a past link travel time that each driver uses yesterday, $\tau_0(l)$ is a a free flow travel time calculated in Eq. (1), $Vol^{now}(l)$ is current link traffic volumes, and $Cap(l)$ is a capacity. So x_2 means a delay from a free flow travel time, and x_3 means congestion rate that each driver can visually judge.

Then the probability of choosing the route i is expressed by the following logit model;

$$P_i = \frac{\exp(\theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3)}{\sum \exp(\theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3)} \quad (6)$$

Unfortunately, the parameters are not able to estimate from real data, so we examine the effect of each parameter on the results of driver's route choice as sensitivity analysis.

3 Traffic Simulator

3.1 Cellular Automaton Model

In order to treat each vehicle as a discrete one (not continuous), our developed traffic simulation model is one of a cellular automaton model. A vehicle can move from a current cell $cell_{current}$ to next cell $cell_{next}$ at time *t+1* if there is no other vehicle at cell $cell_{next}$ at current time *t*. If there is a vehicle at cell $cell_{next}$ at current time *t*, then it stops at current cell $cell_{current}$. This simple rule is famous as a "Rule 184" [Wolfram, 1986].

3.2 Road Network

We model a road network as a graph. Let directed graph *G* = (*N*, *E*, *Cap*, τ_0) serve as a model of the road network, where *N* is a finite set of nodes that model intersections, and *E* is a set of links that model one-way roads among intersections. Link *l* = (*n*, *n'*) in *E* if and only if there is a link that permits traffic to flow from intersections n to *n'*. Function *Cap*(*l*) defines the capacity on link *l*. Function $\tau_0(l)$ defines a free flow travel time of link *l*. Each vehicle *i* has origin node n_i^o and destination node n_i^d. |*l*| is the length of link *l*.

We assume two road classifications: arterial and ordinary. Arterial roads have two lanes while ordinary roads have one lane. The following is the procedure to determine the characteristic values for each link in this paper.

- The links in road network are classified into an arterial road or an ordinary road.
- If a link is an arterial road, the number of lanes of link *l* is two. Otherwise, it is one.
- If a link is an arterial road, the maximum speed of link *l*, $v_{max}(l)$, is sampled from *Uniform*(20,30) km/h. Otherwise, it is sampled from *Uniform*(15,25) km/h.
- Every link is divided into some cells. The number of cells for one lane in *l* is defined by $int(|l|/v_{max}(l))$.
- We call one unit-time for passing one cell. The number of cells equals to a free flow travel time $\tau_0(l)$. One unit-time is supposed one minute in this paper.

Table 1. Average of each driver's time loss in congestion

		Time Loss in Congestion [min]
Case1	Deterministic	48.7
	Stochastic	36.4
Case2	Deterministic	54.2
	Stochastic	31.9
Case3	Deterministic	56.0
	Stochastic	33.7
Case4	Deterministic	47.6
	Stochastic	28.5

Figure 4. Sensitivity Analysis ($\beta_2 = \beta_3 = 1.0$)

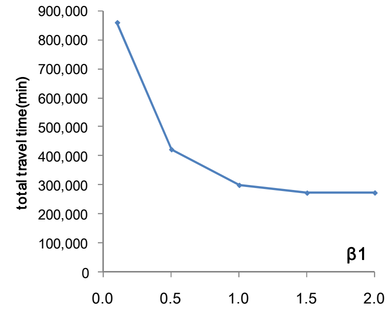


Figure 5. Sensitivity Analysis ($\beta_1 = 1.0$)

- The capacity *Cap*(*l*) is calculated from the number of cells and lanes.

In this study, we use a simple road network (Figure. 1), where 16-17, 17-18, 16-23, 18-25, 23-30, 25-32, 30-31, and 31-32 are set arterial roads (the number of lane is two), and the others are the ordinary roads (the number of lane is one).

3.3 Origin-Destination Traffic Volume

OD (origin-destination) traffic volumes are 800 vehicles. The 200 vehicles start from nodes 0 to 48 (i.e., OD is 0->48). Another 200 vehicles start from nodes 2 to 45 (i.e., OD is 2->45), and start from nodes 4 to 45 (i.e., OD is 4->45). The Last 200 vehicles start from nodes 6 to 42 (i.e., OD is 6->42). Every minute, each vehicle starts from origin node 0, node 2, node 4 and node 6. Also, we assume that all vehicles in each OD pair have a device to send and receive information (i.e., probe car like car-navigation systems that can handle stigmergies).

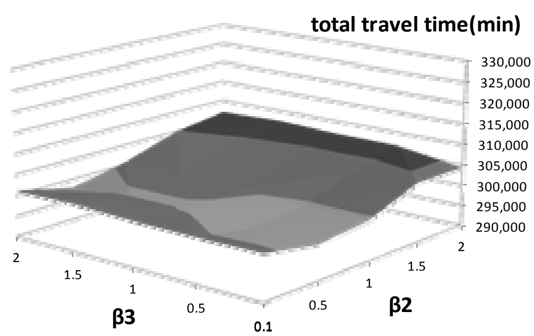
4 Experimental Results

Results of Total Travel Time

Figure 2 compares total travel times in all cases (case1 – 4 and with/without driver's route choice behavior). The following summarizes the strategies for managing traffic congestion.

- Case 0: No information
- Case 1: Combined Long- and Short-Term Stigmergy
- Case 2: Anticipatory Stigmergy without Assignment Strategy
- Case 3: Anticipatory Stigmergy with Assignment Strategy considering Residual Distance
- Case 4: Anticipatory Stigmergy with Assignment Strategy considering Lost Time of Traffic Congestion
- [Deterministic]: Without driver's route choice model
- [Stochastic]: With driver's route choice model

In case0 [deterministic], total travel time is 484,306 minutes, which is the worst results because all vehicles in each OD pair use the same route and do not share any traffic information. The result of case1 [deterministic] (i.e., long- and short-term stigmergy is combined) is one under the condition that the weight of the long-term stigmergy ω in Eq. (2) is 0.7. The total travel time in case1 is almost half of one in case0 since both characteristics are harnessed by integrating long- and short-term stigmergy. Similarly from the result of case2 [deterministic], we can confirm that anticipatory stigmergy (i.e., near-future traffic information) is effective. As one of a management to assign drivers to network, we proposed in case3 to judge by the level of the rest of straight-line distance to his/her destination, and in case4 to judge by the level of the time involved in congestion after departure. From Figure 2, the result of case4 [deterministic] is better than case1 and case2, but the total travel time in case3 [deterministic] is not improved. In this study, the assignment ratio to the link which is recommended as the best route with anticipatory stigmergy is simply fixed top 50%, it would be desirable to explore an optimal assignment ratio with learning day-to-day results. From the comparison of the results of the total travel time in each deterministic case, a car-navigation services, which have been introduced already in real world and utilize the historical traffic information maximally as in case1, is one of the effective traffic management. In order to increase efficiency more, it is better to gather the near-future traffic information as anticipatory stigmergy and to assign drivers appropriately.



In more realistic situation, it is general to assume that all drivers do not follow the travel information, so we consider a driver's route choice model (see 2.2). "Stochastic" in Figure 2 (red bar) shows the results of each cases introduced route choice model, in which parameters (β_1, β_2, β_3) are set in 1.0 respectively[1]. From Figure 2, the result of case4 [stochastic] is best one, and a provision of information based on antici-

[1] If the number of alternative is three, this is a situation where 80% drivers follow the recommended link, and 20% drivers will choose the other link.

patory stigmergy (case2 - case4) reduces total travel time compared with only historical travel data (case1). However the results of case that all drivers follow the recommended link are better than the results of cases with drivers' route model, therefore, it is important to consider how to follow the specified route as travel information.

Results of Time Loss in Congestion

Here, time loss in congestion is compared as another index of total travel time which is calculated for each driver from Eq. (4). We consider that this index is one of a driver's levels of frustration with the danger of bringing about a traffic accident. The results of average of each driver's time loss in congestion are shown in Table 1. Table 1 demonstrates that case4 is the best result as well as the total travel time (see 4.1), and that the stochastic way is better than the deterministic way in all cases. From a viewpoint of efficiency, which is better if the total travel time is smaller, it is significant to obey the navigation's instructions (recommended route), but from a viewpoint of driver's frustration, it would be necessary to allow driver's deviation from the instructions.

Figure 3 is the histogram of lost time difference of case1 [stochastic] and case4 [stochastic]. The number of drivers in red part, in which time loss in case1 is bigger than case4, is 506, and the blue part is 294 drivers. We can confirm that time loss is increased for 37% of drivers (=294/800), although the average of time loss in traffic congestion is improved by introduction of the provision of information based on anticipatory with assignment strategy considering lost time of traffic congestion. So it is necessary to consider another strategy as future tasks.

Results of Sensitivity Analysis of Logit Model

In this paper, logit model is adopted to express driver's route choice behavior, but the parameters in this model are not estimated due to lack of real observed data of driver's behavior or psychological factors. Therefore we do sensitivity analysis of parameters in driver's route choice model to understand the impacts on total travel time.

Figure 4 and Figure 5 show the results of sensitivity analysis in case4 [stochastic] (i.e., anticipatory stigmergy with assignment strategy considering lost time of traffic congestion). Parameters (β_1, β_2 and β_3) in route choice model are coefficient of reliability to traffic information (x_1), regret based on his own past experience (x_2), and short-sighted present situation (x_3), respectively (see 2.2).

From Figure 4, we can understand that the reliability to traffic information (x_1) has a significant impact on total travel time, and that it is again important to enhance a belief in travel information. On the other hand, although the impacts of regret based on his own past experience (x_2) and short-sighted present situation (x_3) are limited as shown in Figure 5, the total travel time is relatively good when the parameter of the regret to his/her past behavior is small (β_2 0.5).

Discussion

Now we discuss an incentive for drivers to follow the travel information. First we introduce a point system, in which drivers can collect a point by choosing the link on a route of travel information and the criterion of assignment strategy in case4 is also converted to driver's cumulative points. In this point system, drivers have incentive to follow the recommended route because a driver who has more points could be assigned preferentially. The total travel time with this point system introduced is 302,458 minutes, which is about the same results of case3 (303,201 minutes) and worse than the results of case4 (300,251 minutes), because the maximum of collected points in one trip is proportional to the OD pair distance.

Traffic congestion is one of external diseconomy, therefore it is efficient to implement the road pricing which has been introduced in Singapore or London (e.g., [Verhoef *et al.*, 2008]). If road pricing is introduced, the point system is usable as "Credit Based Congestion Pricing" in which a point-based mechanism is adopted for exchanging the rights to pass a congested road during peak demand [Kockelman and Kalmanje, 2005]. Moreover the scoring rule [e.g., Gneiting and Raftery 2007] could be introduced as considered in electricity market [Robu *et al.*, 2012].

5 Related Works

Chen and Cheng review comprehensively some examples to which Agent Technology is applied as traffic management, and they show that provision of dynamic route information is an important research area [Chen and Cheng, 2011].

There are many researches on travel information, but most of them are intended for a use of historical travel time data. Narzt *et al.* deal with the link travel time of each vehicle as stigmergy [Narzt *et al.*, 2011], and Ando *et al.* deals with velocity passing through link as stigmergy [Ando *et al.*, 2006]. Moreover these papers validate how to provide the real-time traffic information. Similar to our study, Claes *et al* define the route information based on the traffic condition in near-future as anticipatory stigmergy, and introduce a reservation system as an assignment strategy for a usage of link in a few minutes [Claes *et al.*, 2011]. However if driver's route is changed, his reservation is only left not canceled in a moment, their strategy has much room of improvement. Recently Dallmeyer *et al.* uses an inverse ant colony optimization [Dallmeyer *et al.*, 2012]. It is inverse in the sense that a strong pheromone trace will influence following cars not to follow their predecessors but instead to avoid this road, taking a different route to their goals. As assignment strategy, a reservation system is adopt to controlling a traffic signal [Dresner and Stone, 2007], or the auction system to treat tradable permits to pass bottleneck, such as a bridge, is proposed [Akamatsu, 2007].

On the other hand, Morikawa and Miwa provide knowledge on drivers' dynamic route choice behavior using probe-vehicle data [Morikawa and Miwa, 2006]. Modeling route choice from real probe-vehicle data is essential because real route choices could be biased by habitual activities. Ther are some research related to drivers' dynamic routing modeling [Mahmassani, 2001] [Thomas and White III, 2004].

6 Conclusion

We proposed some provisions of travel information based on anticipatory stigmergy and evaluated the effect of anticipatory stigmergy with assignment strategy. Our preliminary results demonstrated that the anticipatory stigmergy with assignment strategy considering lost time in congestion works better than a conventional way with only historical travel time data.

Furthermore, in order to describe a driver's route choice behavior, logit model, in which the reliability to traffic information, the regret based on driver's own past experience, and the short-sighted present traffic situation are considered as explanatory variables, is introduced. After taking into account of drivers' travel behavior, it is also most effective method to provide information based on anticipatory stigmergy with assignment strategy considering lost time of traffic congestion. In addition, the same method is the best result in average of lost time in congestion.

From the results of sensitivity analysis of parameters in logit model, it is important to raise the reliability to traffic information for an improvement of efficiency. And we have a little discussion about an incentive for drivers to follow the travel information.

Future work will examine more types of stigmergies, larger maps, and dynamic environments including accidents and road construction. All of our analysis was based on the particular network we showed in this study. We have to investigate the effect of the shape of different networks.

Acknowledgments

This work is partially supported by the Funding Program for Next Generation World-Leading Researchers (NEXT Program) of the Japan Cabinet Office.

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