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AN EXPERIMENTAL ANALYSIS ON PROBABILISTIC VEHICLE ROUTING AND SCHEDULING WITH ITS

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Abstract: This paper presents the performance of the Probabilistic Vehicle Routing and scheduling Problem with Time Windows (VRPTW-P) model which takes into account the uncertainty of travel times through case studies. Probe vehicle data of travel times were obtained from actual operation of pickup-delivery truck in South-Osaka area. VICS (Vehicle Information Communication System) also provides travel times for some links in the same area. With these travel time information, the optimal solution of VRPTW-P resulted in considerably reducing total costs, travel times and CO_2, NO_X and SPM emissions compared with expected average case based on the real operation. This is attributed to better routing of VRPTW-P to choose more reliable roads. Therefore, VRPTW-P can contribute to establish efficient and environmentally friendly delivery systems in urban area. In particular delay penalty was considerably reduced.

Key Words: Urban freight transport, ITS, Optimization, City logistics

1.INTRODUCTION

Urban freight transport is faced with difficult problems of traffic congestion and negative environmental impacts by heavy freight vehicles. As well reducing logistics costs is a key issue for shippers in the competitive global market. Although these issues should be promptly solved, there is difficulty to take drastic measures of building new roads.

Some researchers (Ruske, 1994; Kohler, 1997; Taniguchi and Heijden, 2000a; Taniguchi *et al*., 2001; Taniguchi and Thompson, 2002; Taniguchi *et al.*, 2003: Crainic *et al*., 2004) proposed city logistics measures to cope with these complicated freight problems in urban areas including: (a)Application of ITS (Intelligent Transport Systems) or advanced information systems, (b)Co-operative freight transport systems, (c)Public logistics terminals, (d)Load factor controls, (d)Underground freight transport systems. Among these measures the application of ITS to vehicle routing and scheduling planning is most promising to establish efficient and environmentally friendly logistics systems. Taniguchi *et al*. (2000b) pointed out that probabilistic vehicle routing and scheduling with time windows incorporating the uncertainty of travel times can reduce total costs as well as negative environmental impacts. ITS allows us to obtain change of link travel times on road network. The historical travel time data can be used for probabilistic vehicle routing and scheduling.

Laporte *et al.* (1992), Malandraki and Daskin (1992), Taniguchi *et al.* (2000b) and Kenyon and Morton (2003) investigated probabilistic vehicle routing and scheduling with time windows. However, these papers do not explicitly take into account real change of travel times on road network.

Recently probe vehicle techniques have been available for measuring current position of vehicles, travel times and travel routes using in-vehicle sensors and GPS (Global Positioning Systems). Prove vehicle techniques allow us to obtain accurate travel time data, since measurement devices are installed in real running vehicles.

This study investigates probe vehicle data on link travel times. We installed sensors and recording systems in an urban pickup-delivery truck in South-Osaka area in Japan and examined following two points using probe vehicle data:

(a) Method for obtaining the distribution of travel time on real urban roads
(b) Comparison between optimal probabilistic vehicle routing and scheduling based on probe vehicle data and real operation of vehicle routing and scheduling.

The study uses Probabilistic Vehicle Routing and scheduling Problems with Time Windows (VRPTW-P) model which will be formulated later. It also analyses the possibility to establish efficient and environmentally friendly logistics systems in urban areas.

2. PROBABILISTIC VEHICLE ROUTING AND SCHEDULING MODEL

This study adopted Probabilistic Vehicle Routing and scheduling Problems with Time Windows (VRPTW-P) model. The VRPTW-P model is defined as follows. A depot and a number of customers are defined for each freight carrier. A fleet of identical vehicles collects goods from customers and deliver them to the depot or deliver goods to customers from the depot. For each customer a designated time window, specifying the desired time period to be visited is also specified. The VRPTW-P model minimises the total cost of distributing goods with truck capacity and designated time constraints. The total cost is composed of three components; (a) fixed cost of vehicles, (b) vehicle operating cost that is proportional to time travelled and spent waiting at customers, (c) delay penalty for designated pickup/delivery time at customers. The VRPTW-P model takes into account the uncertainty of link travel times on road network to identify the optimal solution. Taniguchi *et al.* (1999) formed Vehicle Routing and scheduling Problem with Time Windows- Probabilistic (VRPTW-P) model for minimising the total costs, which is comprised of fixed cost, operation cost and early arrival and delay penalty. The conditions for vehicle routing and scheduling are given below.

a) A vehicle is allowed to make multiple routes per day.
b) Each customer must be assigned to exactly one route of a vehicle and all the goods from each customer must be loaded on the vehicle at the same time.
c) The total weight of the goods for a route must not exceed the capacity of the vehicle.
d) A vehicle should be operated within the designated time of operation, for instance from 8 a.m. to 5 p.m.

The problem is to determine the optimal assignment of vehicles to customers and the departure time as well as the order of visiting customers for a freight carrier. The model was formulated as follows.

Minimise

$$C(\boldsymbol{t}_0, \mathbf{X}) = \sum_{l=1}^{m} c_{f,l} \cdot \delta_l(\mathbf{x}_l) + \sum_{l=1}^{m} E\left[C_{t,l}(t_{l,0}, \mathbf{x}_l)\right] + \sum_{l=1}^{m} E\left[C_{p,l}(t_{l,0}, \mathbf{x}_l)\right] \tag{1}$$

where,

$$E\left[C_{t,l}(t_{l,0},\mathbf{x}_l)\right] = c_{t,l}\sum_{i=0}^{N_l}\left\{\overline{T}(\bar{t}_{l,n(i)},n(i),n(i+1)) + t_{c,n(i+1)}\right\} \tag{2}$$

$$E\left[C_{p,l}(t_{l,0},\mathbf{x}_l)\right] = \sum_{i=0}^{N_l}\int_0^{\infty} p_{l,n(i)}(t_{l,0},t,\mathbf{x}_l)\left\{c_{d,n(i)}(t)+c_{e,n(i)}(t)\right\}dt \tag{3}$$

Subject to

$$n_0 \geq 2 \tag{4}$$

$$n(0) = 0 \tag{5}$$

$$n(N_l) = 0 \tag{6}$$

$$\prod_{l=1}^{m}\prod_{i=1}^{N_l}\{n(i)-k\} = 0 \qquad \forall k = 1,2,\cdots,N \tag{7}$$

$$\sum_{l=1}^{m} N_l = N \tag{8}$$

$$\sum_{n(i)\in\mathbf{x}_l} D(n(i)) = W_l(\mathbf{x}_l) \tag{9}$$

$$W_l(\mathbf{x}_l) \leq W_{c,l} \tag{10}$$

$$t_s \leq t_{l,0} \tag{11}$$

$$t'_{l,0} \leq t_e \tag{12}$$

where

$$t'_{l,0} = t_{l,0} + \sum_{i=0}^{N_l}\left\{\overline{T}(\bar{t}_{l,n(i)},n(i),n(i+1)) + t_{c,n(i+1)}\right\} \tag{13}$$

$C(\boldsymbol{t}_0,\mathbf{X})$: total cost (yen)

$\boldsymbol{t}_0$: departure time vector for all vehicles at the depot

$\boldsymbol{t}_0 = \{t_{l,0} \mid l = 1, m\}$

$\mathbf{X}$: assignment and order of visiting customers for all vehicles

$\mathbf{X} = \{\mathbf{x}_l \mid l = 1, m\}$

$\mathbf{x}_l$: assignment and order of visiting customers for vehicle l

$\mathbf{x}_l = \{n(i) \mid i = 1, N_l\}$

$n(i)$: node number of i th customer visited by a vehicle

$d(j)$: number of depot (= 0)

N_l : total number of customers visited by vehicle l

n_0 : total number of $d(j)$ in $\mathbf{x}_l$

m : maximum number of vehicles available

$c_{f,l}$: fixed cost for vehicle l (yen /vehicle)

$\delta_l(\mathbf{x}_l)$: = 1; if vehicle l is used, = 0; otherwise

$C_{t,l}(t_{l,0},\mathbf{x}_l)$: operating cost for vehicle l (yen)

$C_{p,l}(t_{l,0},\mathbf{x}_l)$: penalty cost for vehicle l (yen)

$c_{t,l}$: operating cost per minute for vehicle l (yen /min)

$t_{l,n(i)}$: departure time of vehicle l at customer $n(i)$

$\overline{T}(\bar{t}_{l,n(i)},n(i),n(i+1))$: average travel time of vehicle l between customer $n(i)$ and

$n(i+1)$ at time $\bar{t}_{l,n(i)}$

$t_{c,n(i)}$: loading/unloading time at customer $n(i)$

$p_{l,n(i)}(t_{l,0}, t, \mathbf{x}_l)$: probability in which a vehicle that departs the depots at time $t_{l,0}$ arrives at customer $n(i)$ at time t

$c_{d,n(i)}(t)$: delay penalty cost per minute at customer $n(i)$ (yen/min)

$c_{e,n(i)}(t)$: early arrival penalty cost per minute at customer $n(i)$ (yen/min)

N : total number of customers

$D(n(i))$: demand of customer $n(i)$ (kg)

$t'_{l,0}$: last arrival time of vehicle l at the depot

t_s : starting of possible operation time of trucks

t_e : end of possible operation time of trucks

$W_l(\mathbf{x}_l)$: load of vehicle l (kg)

$W_{c,l}$: capacity of vehicle l (kg).

The problem specified by equations (1) – (13) involves determining the variable $\mathbf{X}$, that is, the assignment of vehicles and the visiting order of customers and the variable $\boldsymbol{t}_0$, the departure time of vehicles from the depot. Note, that $n(0)$ and $n(N_l+1)$ represent the depot in equations (2) and (3).

Figure 1 shows the penalty for vehicle delay and early arrivals at customers. The time period $(t^e_{n(i)} - t^s_{n(i)})$ of the penalty function defines the width of the soft time window in which vehicles are requested to arrive at customers. If a vehicle arrives at a customer earlier than $t^s_{n(i)}$, it must wait until the start of the designated time window and a cost is incurred during waiting. If a vehicle is delayed, it must pay a penalty proportional to the amount of time it was delayed. This type of penalty is typically observed in goods distribution to shops and supermarkets in urban areas. Multiplying the penalty function and the probability of arrival time as shown in Figure 1 can identify the penalty of early arrivals and delay at customers for the probabilistic model.

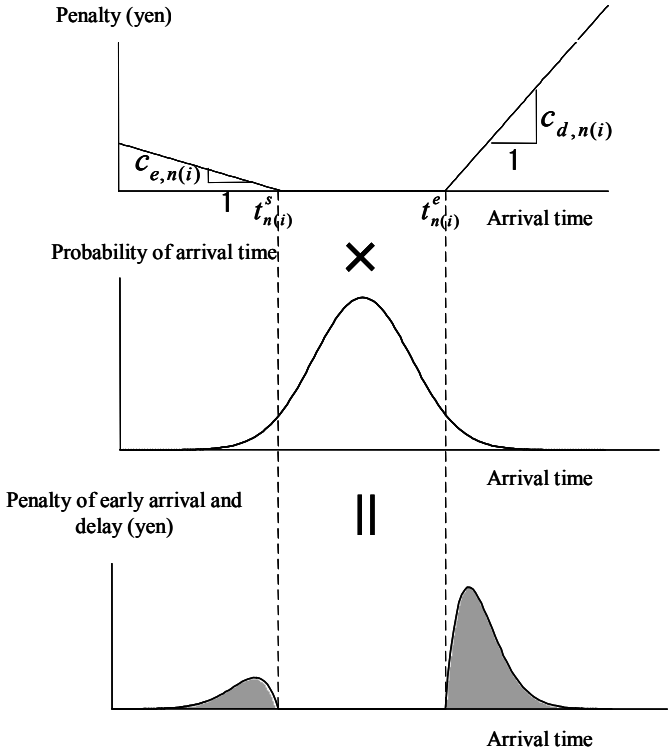

Figure 1. Early arrival and delay penalty

The problem described herewith is a NP-hard (Non-deterministic Polynomial-hard) combinatorial optimisation problem. It requires heuristic methods to efficiently obtain a good solution. The model described in this paper uses a Genetic Algorithms (GA) to solve the VRPTW-P. GA was selected because it is a heuristic procedure that can simultaneously determine the departure time and the assignment of vehicles as well as the visiting order of customers.

3. CASE STUDIES IN SOUTH-OSAKA AREA

3.1 Overview

In order to show the effectiveness of VRPTW-P model in real delivery systems, we performed case studies in South Osaka area, Japan. These studies measured precise movements of a pickup-delivery truck using the measurement device with GPS (Global Positioning System). The truck visited about 10 customers for delivering electronic products per day in South Osaka area and the total distance travelled was about 30 km per day. It used wide range of roads including trunk roads and urban streets.

The best approach to show the effectiveness of VRPTW-P is to compare total costs of the optimal solution of VRPTW-P with those of real operation. However, because of lack of link travel time information except links where a probe vehicle runs, it is difficult to identify total costs and CO_2, NO_X and SPM (Suspended Particle Materials) emissions of optimal solution of VRPTW-P. Therefore, we will use historical data of travel times given by VICS (Vehicle Information Communication Systems) as well as probe vehicle data.

3.2 Estimating Travel Time Distribution Using Probe Vehicle Data

The measurement system was installed in a small pickup-delivery truck (load capacity = 2 tons) which delivers electronic products to retail shops in South Osaka area. The measurement device can record the current position of a vehicle at the interval of 1 second receiving GPS signals from satellites. Data were recorded in a memory card and collected every day via Internet during 3 months (13th March 2004 – 2nd June 2004). This study used a single pickup-delivery truck and the data were taken for 66 days.

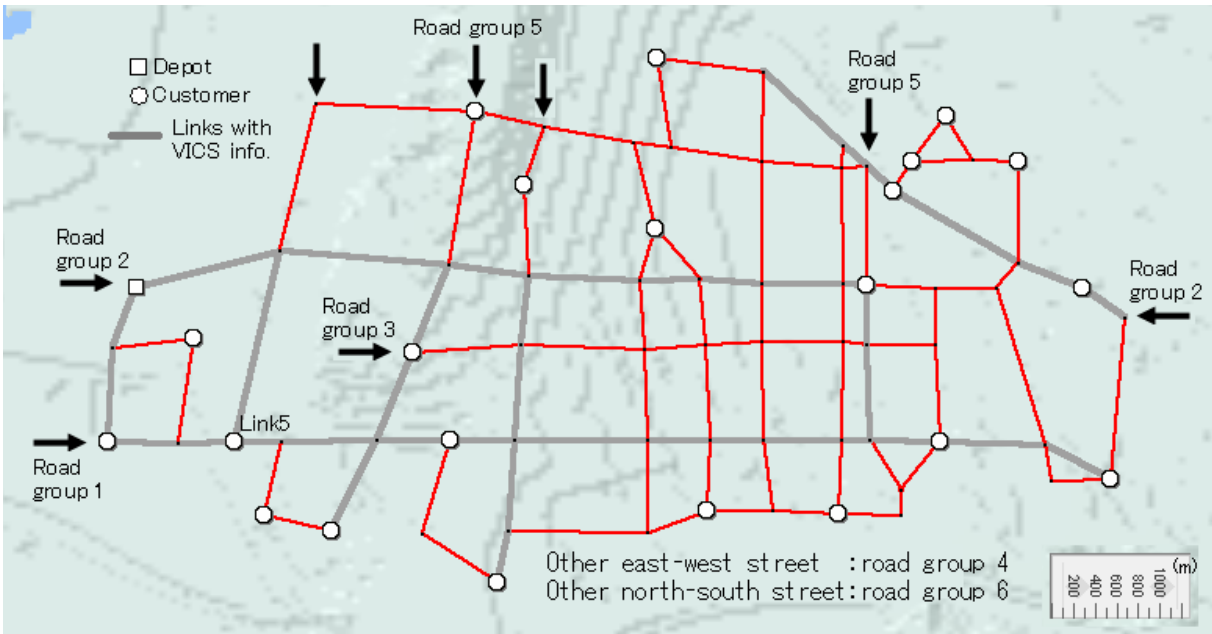

Figure 2. South Osaka Road Network

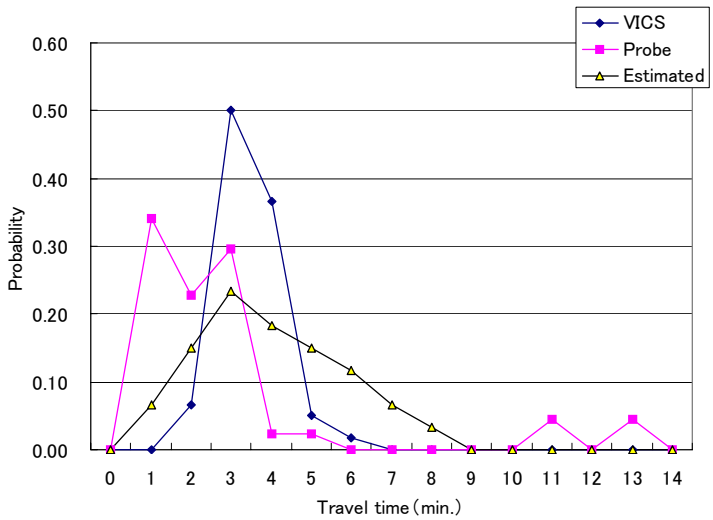

Figure 3. An Example of Travel Time Distribution (Link 5 (See Figure 2))

We formed a road network for the analysis of vehicle routing and scheduling based on the actual running path of probe vehicle. Figure 2 indicates the road network in South Osaka area. The road network only represents trunk roads and urban streets which are associated with

visiting customers in this area. This road network contains 218 links and 69 nodes, where one depot and 22 customer nodes are located. A pickup-delivery truck leaves the depot to deliver goods to some of 22 customers and returns to the same depot.

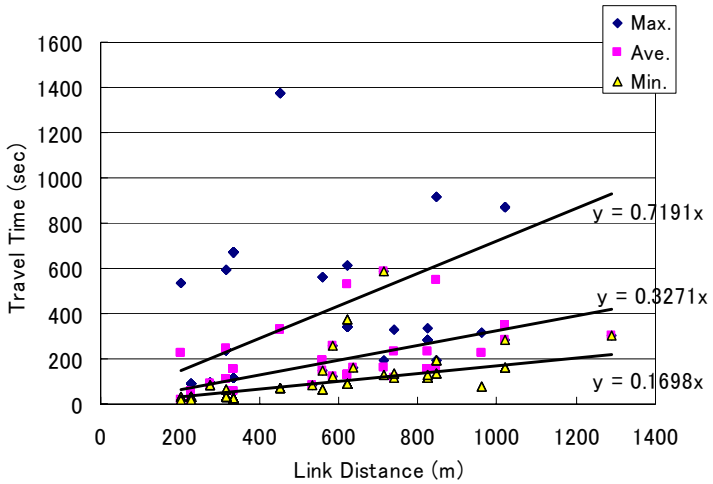

Figure 4. Travel Time and Link Distance (Road Group 2)

The road network contains trunk roads of National Highways as well as urban streets with lower traffic capacity. These roads within the network were classified into 6 groups based on the class of roads and area. The historical data of link travel times have been accumulated at each road group to analyse the distribution.

Since the VRPTW-P model requires the distribution of travel times, we collected travel times by VICS for some of links which are shown by bold line in Figure 2. Travel times data we used were recorded by VICS during 14 months (1st February 2001 – 31st March 2002). For the other links, where VICS data are not available, we analysed travel times data by the probe vehicle in each road group. Figure 3 shows an example of travel time distribution at link 5. We approximate the travel time distribution to a triangular shape.

Analysing travel time data of each link gave the maximum, minimum and average value of travel times for each road group. Figure 4 shows the relationship of these values and the link distance for road group 2. A linear regression analysis was performed and the maximum, minimum and average travel speeds were identified from the inclination of the approximated line.

Table 1. Maximum, Minimum and Average Travel Speeds and Their Fluctuation

Road Group	Travel Speeds(km/h)			Fluctuation ((a)-(c))/(b)
	Max. (a)	Ave. (b)	Min. (c)	
1(E-W st.1)	18.0	6.9	3.1	2.17
2(E-W st.2)	21.2	11.0	5.0	1.47
3(E-W st.3)	20.1	9.0	3.1	1.89
4(E-W st.4)	11.3	6.8	4.6	0.99
5(N-S st.1)	17.4	6.5	2.3	2.32
6(N-S st.2)	21.3	10.7	4.1	1.62

A triangular shape distribution of travel times was used for VRPTW-P model. It can be produced as follows: (a) Determine the maximum, minimum and average travel times using the relationship of travel time and link distance as shown in Figure 4, (b) Form a triangular shape distribution to let the area of triangle be 1. Figure 3 shows an example of the estimated triangular shape distribution for link 5.

3.3 Delivery

The case studies evaluate delivery activities on two days of 7th and 10th April 2004. The pickup-delivery truck visited 9 customers on 7th April and 11 customers on 10th April, 6 customers of which were same. A single two-ton truck started the depot at 8 a.m. and returned to the same depot after delivering goods to customers.

3.4 Assumptions For VRPTW-P

There are some assumptions for calculating the optimal solution of VRPTW-P:

(a) A single two-ton truck is allowed to be used
(b) Each customer sets soft time window of 3 hours (1.5 hours before and after the actual arrival at customer)
(c) The configuration of link travel time distribution during delivery is same for a specific link.

3.5 Identifying The Optimal Solution

Table 2. Comparison of Costs

7th April	Case (EA) (Yen)	Optimal solution (Yen)	Change (%)	10th April	Case (EA) (Yen)	Optimal solution (Yen)	Change (%)
Fixed cost	10,417	10,417	0	Fixed cost	10,417	10,417	0
Operation cost	26,310	20,083	-24	Operation cost	26,924	21,925	-19
Delay Penalty	16,662	17	-100	Delay Penalty	5,018	2,661	-47
Early arrival penalty	89	538	504	Early arrival penalty	923	923	0
Total cost	53,478	31,055	-42	Total cost	43,282	35,926	-17

The VRPTW-P model identified the optimal visiting order of customers and departure time of depot for two days of 7th and 10th April. It also determined the shortest path between customers using the average travel times. Here we assume expected average case based on the real operation (Case (EA)): (a) A pickup-delivery truck follows the same roads of real operation, but (b) It runs at the estimated average travel time by the regression model as shown in Figure 4 and Table 1. Thus expected average costs for Case (EA) can be calculated.

Table 2 shows the comparison of costs for Case (EA) and optimal solution of VRPTW-P. The table indicates that the total costs of the optimal solution of VRPTW-P were reduced by 17-42% compared with that of Case (EA). In particular, the operation cost of the optimal solution of VRPTW-P was reduced by 19-24% compared with Case (EA). This is attributed to

choosing better visiting order of customers and roads used. The delay penalty for the optimal solution of VRPTW-P was also decreased for both two days. The early arrival penalty was increased for the optimal solution of VRPTW-P on 7th April. The results represent the characteristics of VRPTW-P model that tends to arrive earlier avoiding any delay at customers considering the uncertainty of travel times. Therefore, VRPTW-P can contribute to provide better service to customers by decreasing an opportunity to arrive late at customers.

3.6 Negative Environmental Impacts

It is important to look into the improvement of negative environmental impacts of VRPTW-P as well as cost reduction. Figure 5 compares travel times of pickup-delivery truck, CO_2, NO_X and SPM (Suspended Particle Materials) emissions of the Case (EA) and the optimal solution of VRPTW-P. The figure indicates that travel times of pickup-delivery truck for the optimal solution of VRPTW-P compared with those of Case (EA). This reduction of travel times can contribute to alleviate traffic congestion. The emissions of CO_2, NO_X and SPM for the optimal solution of VRPTW-P were also reduced by 10.1-16.5%, 6.1-13.2%, and 5.3-12.4%, respectively. Therefore, VRPTW-P can contribute not only to decrease total costs but also to decrease traffic congestion and negative environmental impacts.

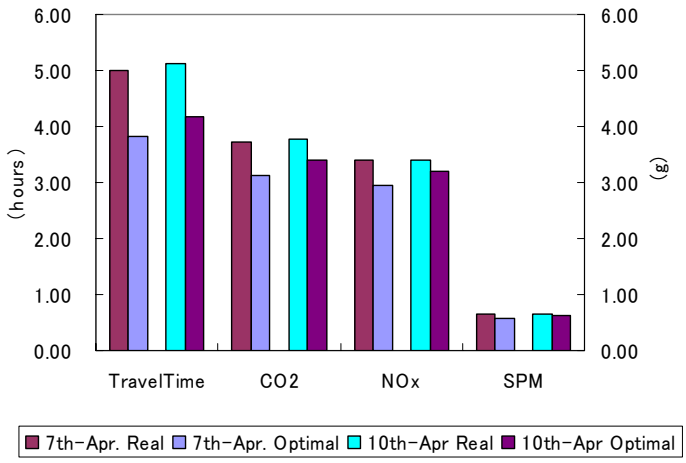

Figure 5. Environmental Impacts

4. CONCLUSIONS

This study derived following findings.

(a) Total costs of the optimal solution of VRPTW-P were reduced by 17-42% compared with that of the expected average case based on the real operation of pickup-delivery truck. In particular the operation cost and the delay penalty were considerably decreased due to better routing.

(b) The VRPTW-P also resulted in reducing the travel times and CO_2, NO_X and SPM emissions compared with those of the expected average case based on the real operation. Therefore, the VRPTW-P can contribute to decrease traffic congestion and negative environmental impacts.

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