Probabilistic Vehicle Routing and Scheduling Based on Probe Vehicle Data

Eiichi Taniguchi[*1] Naoki Ando[*2]
Professor, Department of Urban Management, Kyoto University[*1]
(Yoshidahonmachi, Sakyo-ku, Kyoto 606-8501 Japan, TEL: +81-75-753-4789,
E-mail: taniguchi@kiban.kuciv.kyoto-u.ac.jp)
PhD Student, Department of Urban Management, Kyoto University[*2]
(Yoshidahonmachi, Sakyo-ku, Kyoto 606-8501 Japan, TEL:+81-75-753-4788,
E-mail:n-ando@kiban.kuciv.kyoto-u.ac.jp)

Abstract: This paper presents the Probabilistic Vehicle Routing and scheduling Problem with Time Windows (VRPTW-P) model which takes into account the uncertainty of travel times. Probe vehicle data of travel times were obtained from actual operation of pickup-delivery truck in Osaka-Kobe area. The optimal solution of VRPTW-P resulted in considerably reducing total cost, travel times and CO_2, NOx 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.

Keywords: *Freight transport, Vehicle routing and scheduling, Travel time, Intelligent transport systems, Optimisation*

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 [1][2][3][4] 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.* [5] 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.* [6] and Malandraki and Daskin [7] 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 Osaka-Kobe 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. Estimating the distribution of travel times using probe vehicle data

The measurement system shown in Figure 1 was installed in a small pickup-delivery truck (load capacity = 2 ton) which delivers electronic products to retail shops in Osaka-Kobe 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 month during 7 months (25th July 2003 – 28 February 2004). This study used a single pickup-delivery truck and the data were taken for 151 days.

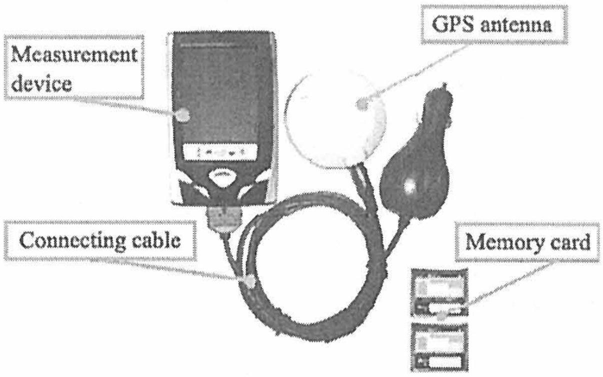

Figure 1 Measurement system

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 Osaka-Kobe area. The road network only represents trunk roads and urban streets which are associated with visiting customers in this area. This road network contains 292 links and 89 nodes, where one depot and 37 customer nodes are located. A pickup-delivery truck leaves the depot to deliver goods to some of 37 customers and returns to the same depot.

The road network contains trunk roads of National Highways Route 2 and 43, which run in east-west direction in Osaka-Kobe area as well as urban streets with lower traffic capacity, which mainly run in north-south direction. These roads within the network were classified into 7 groups based on the class of roads and area as shown in Figure 3. The historical data of link travel times have been accumulated at each road group to analyse the distribution.

Figure 4 illustrates the frequency of probe vehicle running within the network during 7 months. There were only 9 links where the probe vehicle did not run and 75 links where the probe vehicle ran 1- 20 times.

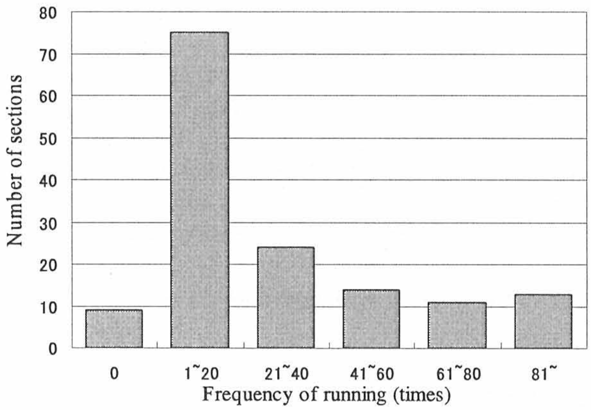

Figure 4 Frequency of probe vehicle running

Since the VRPTW-P model requires the distribution of travel times, we analysed travel times data by the probe vehicle in each road group. Figure 5 shows an example of travel time distribution at link 161. The travel time distribution looks like a triangular shape.

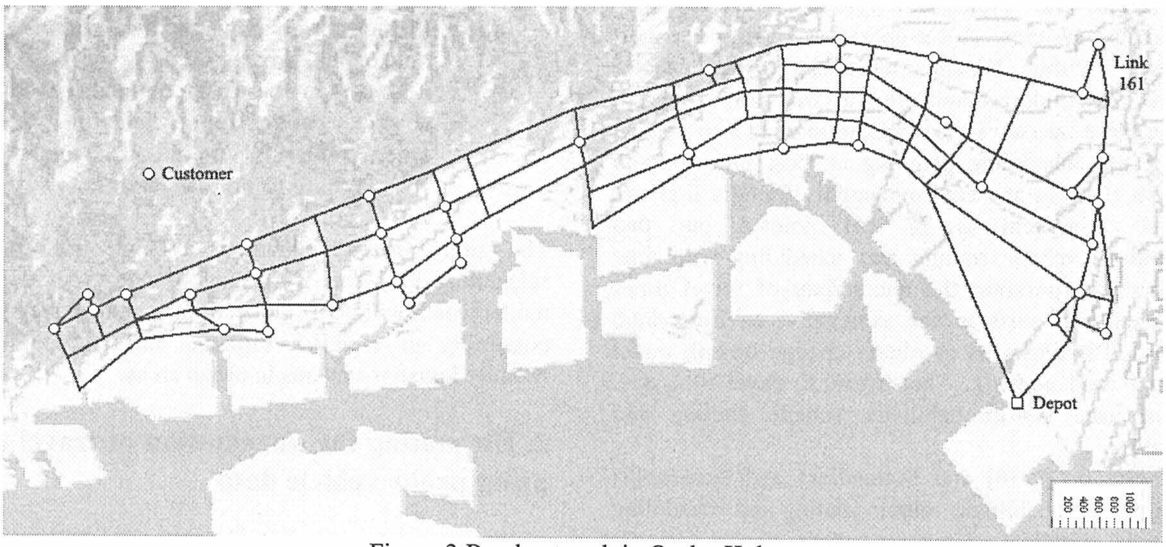

Figure 2 Road network in Osaka-Kobe area

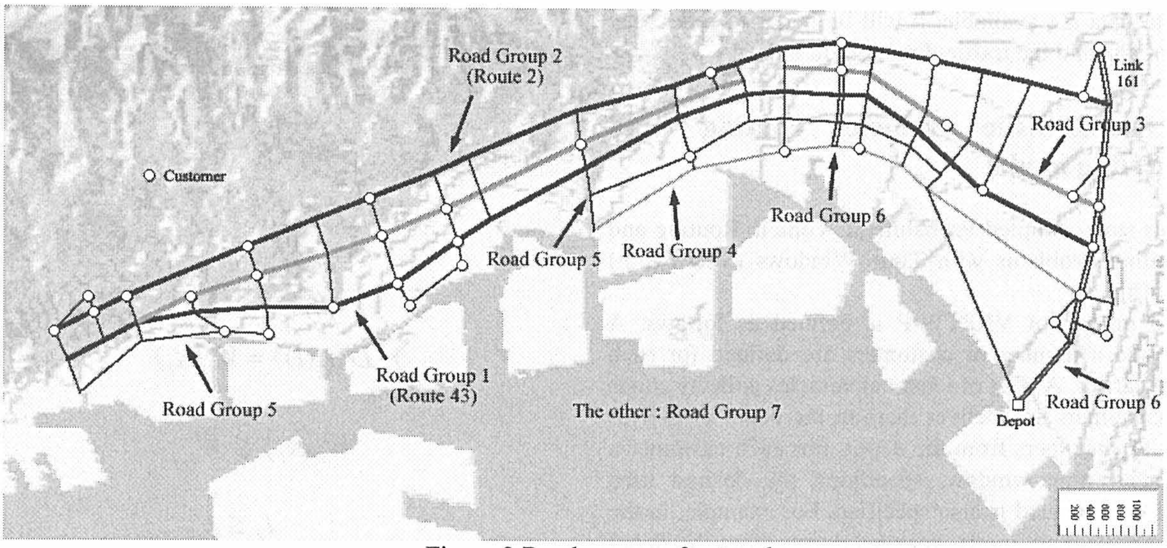

Figure 3 Road groups of network

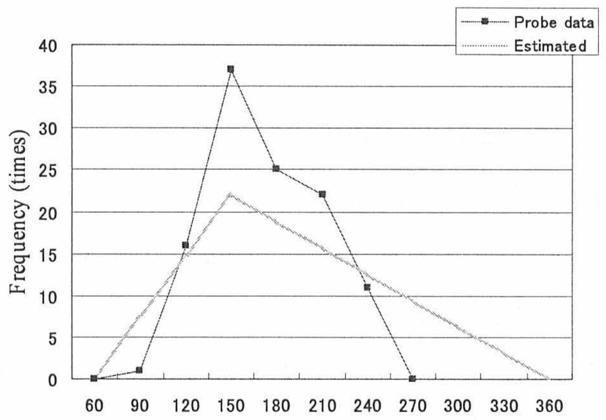

Figure 5 An example of travel time distribution (Link 161 (see Figure 2))

Analysing travel time data of each link gave the maximum, minimum and average value of travel times for each road group. Figure 6 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 shows the maximum, minimum and average travel speeds and their fluctuation for each road group. This table indicates that trunk roads in the road group 1, 2 and 4 account for higher average travel speed and lower fluctuation. It means that these roads are relatively reliable in terms of travel speed. In contrast roads in the road group 5, 6 and 7 account for lower average travel speed and higher fluctuation.

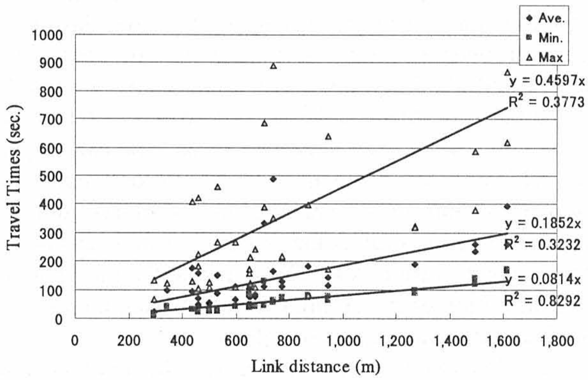

Figure 6 Travel time and link distance (Road group 2)

Table 1 Maximum, minimum and average travel speeds and their fluctuation

Road Group		Number of Lane	Travel speeds (km/h)			Fluctuation ((a)-(c))/(b)
			Maximum (a)	Average (b)	Minimum (c)	
1	Route 43	8	50.3	25.2	12.0	1.52
2	Route 2	4	44.2	19.4	7.8	1.87
3	East-west street	2	24.0	12.9	6.8	1.34
4	Bay area 1	2	26.0	17.0	12.2	0.81
5	Bay area 2	2	39.0	12.2	5.9	2.71
6	North-south streets 1	4	47.6	16.2	6.7	2.52
7	North-south streets 2	2	31.3	11.6	4.4	2.32

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 6, (b) form a triangular shape distribution to let the area of triangle be 1. Figure 5 shows an example of the estimated triangular shape distribution for link 161. Because of the limited number of data, we used whole data of the link during the measurement period to produce travel time distribution.

If more data are available, it will be better to reflect the hour of day and the traffic direction on link.

3. Probabilistic vehicle routing and scheduling model

This study adopted Probabilistic Vehicle Routing and scheduling Problems with Time Windows (VRPTW-P) model [5].

The model for VRPTW-P 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. For example, in the case of collecting goods, vehicles depart from the depot and visit a subset of customers for picking up goods in sequence and return to the depot to unload them. A vehicle is allowed to make multiple trips per day. 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. The total weight of the goods in a route must not exceed the capacity of the vehicle. This problem is used 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. VRPTW-P explicitly incorporates the distribution of travel times for identifying the optimal routes and departure times of vehicles.

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 model can be formulated as follows.

Minimise

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

where,

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

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

Subject to

$$n_0 \geq 2 \quad (4)$$

$$\sum_{l=1}^{m} N_l = N \quad (5)$$

$$\sum_{n(i) \in \mathbf{x}_l} D(n(i)) = W_l(\mathbf{x}_l) \quad (6)$$

$$W_l(\mathbf{x}_l) \leq W_{c,l} \quad (7)$$

$$t_s \leq t_{l,0} \quad (8)$$

$$t'_{l,0} \leq t_e \quad (9)$$

where

$$t'_{l,0} = t_{l,0} + \sum_{i=0}^{N_l} \left\{\bar{T}(\bar{t}_{l,n(i)}, n(i), n(i+1)) + t_{c,n(i+1)}\right\} \quad (10)$$

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

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

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

$\mathbf{X}$: 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 $n(i)$

$\bar{T}(\bar{t}_{l,n(i)}, n(i), n(i+1))$: 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) – (10) involves determining the variable $\mathbf{X}$, that is, the assignment of vehicles and the visiting order of customers and the variable 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 7 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 7 can identify the penalty of early arrivals and delay at customers for the probabilistic model.

The problem described herewith is a NP-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.

The parameters of GA were determined for several test cases as follows:

Number of individuals = 300
Number of generations = 1,000
Number of elite individuals = 30
Crossover rate = 0.8
Mutation rate = 0.02

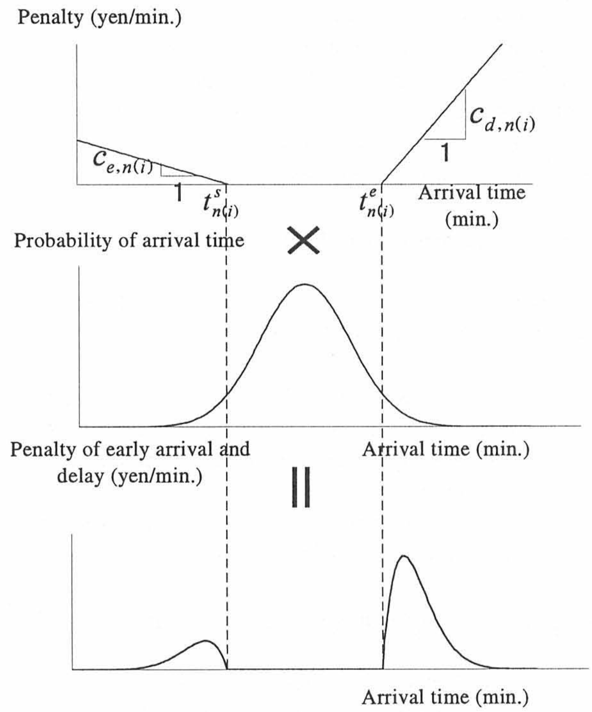

Figure 7 Delay and early arrival penalty

4. Case study in Osaka-Kobe area

4.1. Overview

This study measured precise movements of a pickup-delivery truck using the measurement device with GPS. The truck visited over 20 customers for delivering electronic products per day in Osaka-Kobe area and the total distance travelled was 40-50 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, NOx and SPM (Suspended Particle Materials) emissions of optimal solution of VRPTW-P.

Therefore, this paper compares the optimal solution of VRPTW-P using historical link travel time data given by a probe vehicle with expected average case based on the actual operation of the pickup-delivery truck in terms of total costs and CO_2, NOx and SPM (Suspended Particle Materials) emissions.

4.2. Delivery

The case study evaluates delivery activities on two days of 8th and 9th December 2003. The pickup-delivery truck visited 21 customers on 8th December and 24 customers on 9th December, 16 customers of which were same. Figures 8 and 9 show the actual routing of the pickup-delivery truck. A single two-ton truck started the depot at 10 a.m. and returned to the same depot after delivering goods to customers.

4.3. 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.

4.4. Identifying the optimal solution

The VRPTW-P model identified the optimal visiting order of customers and departure time of depot for two days of 8th and 9th December. 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 6 and Table 1.Thus expected average costs for Case (EA) can be calculated.

In this research, the delay and early arrival penalties do not represent real penalties of that day, but expectations of penalties in each routing with assumed travel time distributions. Optimal solutions are identified for 2 cases; Case (a) the unit delay penalty is set equal to the unit early arrival penalty and Case (b) the unit delay penalty is set 5 times larger than the unit early arrival penalty. Results showed that the same visiting order of customers and departure time are determined for optimal solution in both cases. Then results Case (a) are discussed as follows.

Table 2 shows the comparison of costs for Case (EA) and optimal solution of VRPTW-P. The table indicates that the total cost of the optimal solution of VRPTW-P was reduced by 13.4-24.7% compared with that of Case (EA). In particular, the operation cost of the optimal solution of VRPTW-P was reduced by 8.5-12.8% 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 greatly decreased to zero for both two days. The early arrival penalty was slightly increased for the optimal solution of VRPTW-P. 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.

Table 2(a) Comparison of costs (Case (a))

	8th December		
	Case (EA) (Yen)	Optimal solution (Yen)	Change (%)
Fixed cost	10,417	10,417	0.0
Operation cost	16,488	14,383	-12.8
Delay penalty	7,236	0	-100.0
Early arrival penalty	0	906	-
Total cost	34,141	25,706	-24.7

Table 2(b) Comparison of costs (Case (a))

	9th December		
	Case (EA) (Yen)	Optimal solution (Yen)	Change (%)
Fixed cost	10,417	10,417	0.0
Operation cost	16,575	15,172	-8.5
Delay penalty	4,039	0	-100.0
Early arrival penalty	0	1,288	-
Total cost	31,031	26,877	-13.4

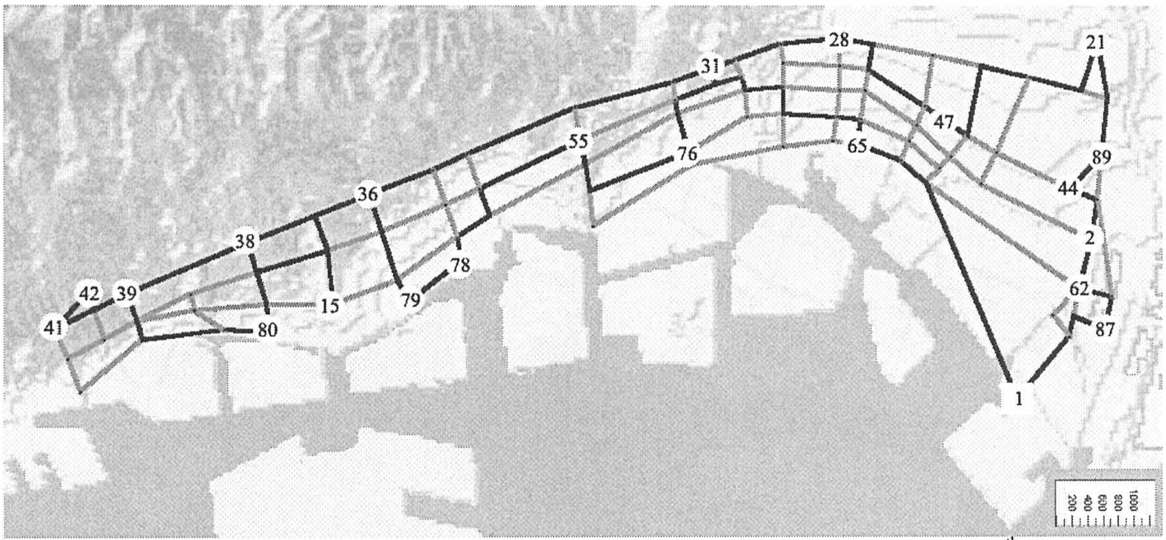

Figure 8 Routing of Case (EA), same as actual routing of the pickup-delivery truck on 8th December

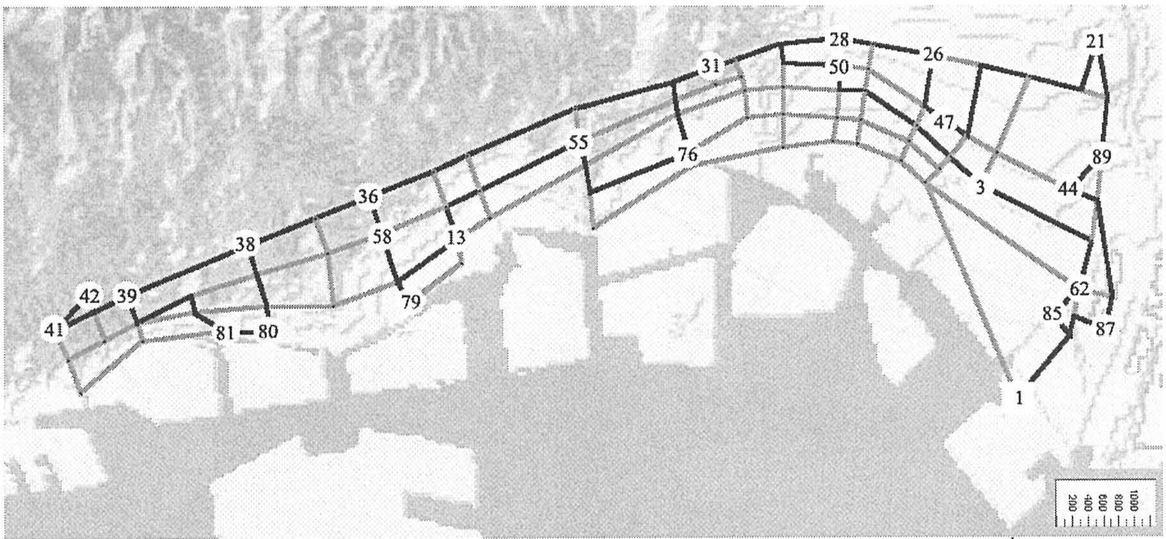

Figure 9 Routing of Case (EA), same as actual routing of the pickup-delivery truck on 9th December

Figures 10 and 11 demonstrate the routing of optimal solution of VRPTW-P. With the comparison of Case (EA) in Figures 8 and 9, these figures indicate that the optimal solution is likely to use trunk roads (Route 2 and 43) rather than urban streets. This is due to the characteristics that the trunk roads are more reliable in terms of travel times than urban streets.

Table 3 shows the visiting order of both Case (EA) and the optimal solution of VRPTW-P. The visiting order of customers for both cases is quite similar, because the time windows of 3 hours at customers make it difficult to largely change the visiting order of pickup-delivery truck.

Table 3 Visiting order of customers for real operation and optimal solution of VRPTW-P

Date		Visiting order of customers
8th Dec.	Case (EA)	87,62,2,44,89,21,47,28,76,55,78,79, 36,15,38,80,39,42,41,31,65
	Optimal solution	87,62,2,89,21,44,47,28,55,78,79,36, 15,38,42,41,39,80,76,31,65
9th Dec.	Case (EA)	87,44,89,21,47,26,28,76,55,13,79,58, 36,38,80,81,39,41,42,31,50,3,62,85
	Optimal solution	87,62,44,89,21,47,28,76,55,79,36,13, 58,38,80,81,39,42,41,31,26,50,3,85

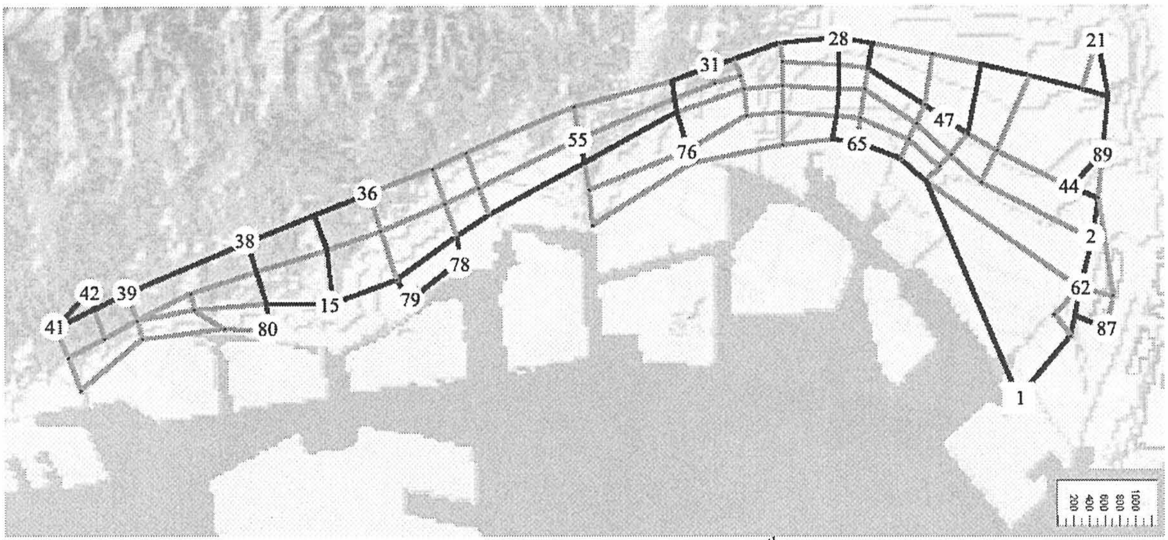

Figure 10 Routing of optimal solution on 8^{th} December

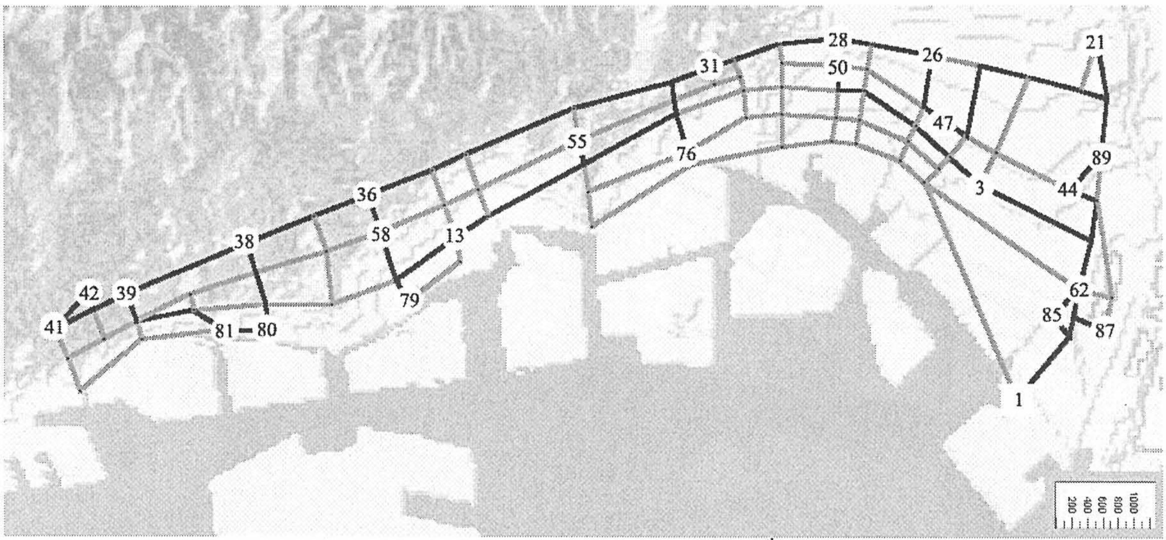

Figure 11 Routing of optimal solution on 9^{th} December

4.5. Negative environmental impacts

It is important to look into the improvement of negative environmental impacts of VRPTW-P as well as cost reduction. Figure 12 compares travel times of pickup-delivery truck, CO_2, NOx 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 were reduced by 8.2-12.7% compared with those of Case (EA). This reduction of travel times can contribute to alleviate traffic congestion. The emissions of CO_2, NOx and SPM for the optimal solution of VRPTW-P were also reduced by 4.3-10%, 3.5-10.7%, 3-9%, respectively. Therefore, VRPTW-P can contribute not only to decrease total costs but also to decrease traffic congestion and negative environmental impacts.

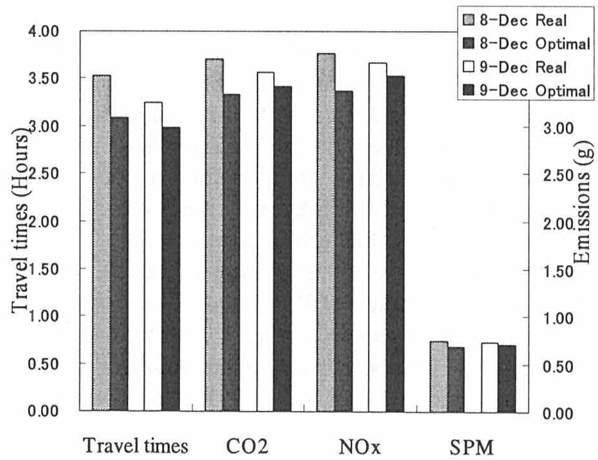

Figure 12 Environmental impacts

5. Conclusions

The study derived following findings.

(a) It is possible to obtain accurate data of travel times by analysing behaviour of probe vehicles of pickup-delivery trucks that run in urban areas.
(b) A classifying method of travel times data for appropriate road groups is useful for providing input data of travel times distribution to the VRPTW-P model.
(c) Total cost of the optimal solution of VRPTW-P was reduced by 13.4-24.7% 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. The optimal route of VRPTW-P was to choose more reliable trunk roads in terms of travel times than urban streets.
(d) The VRPTW-P also resulted in reducing the travel times and CO_2, NOx 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.

Further investigations are needed about following points.

(a) It is necessary to combine travel times data by VICS (Vehicle Information Communication Systems) with prove vehicles to improve the accuracy of link travel times distribution.
(b) Dynamic traffic simulation within road network is needed to compare details of the real operation and VRPTW-P.
(c) In order to compare the cost and negative environmental impacts of the optimal solution of VRPTW-P with those of real operation, a test truck running experiment will be required.

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Eiichi Taniguchi is a professor of transport and logistics at Kyoto University. He has performed intensive research on modeling city logistics and ITS based urban freight transport. He recently published a book entitled "Logistics systems for sustainable cities" (Elsevier, 2004) with many contributors. He also organized international conferences on city logistics at Cairns, Australia in 1999, at Okinawa, Japan in 2001 and at Madeira, Portugal in 2003.

Naoki Ando is a Ph.D student at Kyoto University. He received his Master degree from Kyoto University in 1995. He is still undergoing investigation of probabilistic vehicle routing and scheduling problems under supervision of Prof. Taniguchi.

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