

Generalized Vehicle Routing Problem for Reverse Logistics Aiming at Low Carbon Transportation

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(Received: March 4, 2013 / Revised: May 21, 2013; accepted May 30, 2013)

ABSTRACT

Deployment of green transportation in reverse logistics is a key issue for low carbon technologies. To cope with such logistic innovation, this paper proposes a hybrid approach to solve practical vehicle routing problem (VRP) of pickup type that is common when considering the reverse logistics. Noticing that transportation cost depends not only on distance traveled but also on weight loaded, we propose a hierarchical procedure that can design an economically efficient reverse logistics network even when the scale of the problem becomes very large. Since environmental concerns are of growing importance in the reverse logistics field, we need to reveal some prospects that can reduce CO₂ emissions from the economically optimized VRP in the same framework. In order to cope with manifold circumstances, the above idea has been deployed by extending the Weber model to the generalized Weber model and to the case with an intermediate destination. Numerical experiments are carried out to validate the effectiveness of the proposed approach and to explore the prospects for future green reverse logistics.

Keywords: Vehicle Routing Problem, Low Carbon Logistics, Hybrid Metaheuristic Method, Modified Saving Method

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1. INTRODUCTION

Recently, low carbon technologies have attracted a great interest in Japan under the provision for essential infrastructure aligned with sustainable development. Deployment of green transportation in reverse logistics is a key issue for such technologies. As a synchronized topic with such logistic innovation, the vehicle routing problem (VRP) has been widely studied from various aspects. It tries to optimize total transportation cost for the circular routes of vehicles that start the depot, deliver products to customers one after another and return to the original depot under certain constants.

Since transportation cost depends not only on distance traveled but also on load, it is practical to consider these two factors in parallel or to adopt the Weber model

(a bilinear model of distance and load). However, this approach has not been considered in previous studies. Moreover, most studies concerned with the delivery type problems that are popular in manufacturing. However, in this paper, we pay our attention on the VRP of pickup type so that we can evaluate various scenarios regarding reverse logistics.

In addition to the economic issue, environmental issues are growing in importance in the reverse logistics. As a result, we can evaluate the CO₂ emissions from the transportation in the same framework since the emission amount also depends both on distance and load. To make a rational decision that can reduce CO₂ emissions from the economically optimized VRP, we engage in analyzing some relations between the transport cost and the released CO₂ under some possible and promising scenarios for low

carbon logistics (Shimizu, 2012).

For this purpose, we used a hierarchical procedure that applies the modified saving method and the modified tabu search developed by the author. By using this procedure, we can optimize an economically efficient reverse logistics network design even when the scale of the problem becomes extremely large. Moreover, the above idea has been deployed by extending the Weber model to the generalized Weber model (power model of distance and load) and to the case with an intermediate destination such as disposal site before returning to the depot. Numerical experiments are carried out to validate the effectiveness of the proposed approach and to explore the prospects for future green reverse logistics.

The rest of the paper is organized as follows. In Section 2, we formulate the problem after giving a brief review of the associated studies. Then, we present the variants of the modified saving method in Section 3. Section 4 outlines the proposed solution procedure. Numerical experiments are provided in Section 5. Finally, we give conclusions.

2. PROBLEM STATEMENT

2.1 Brief Review

Let us consider such a logistic network design problem as illustrated in Figure 1 where each vehicle must take a circular route from its depot that is to be a starting and a destination point at the same time. This generic problem has been studied popularly as VRP. The VRP is a well-known combinatorial optimization problem, which minimizes the total distance traveled by a fleet of delivery vehicles under various constraints. Recent studies on VRP which aim at application can be classified into the following four kinds.

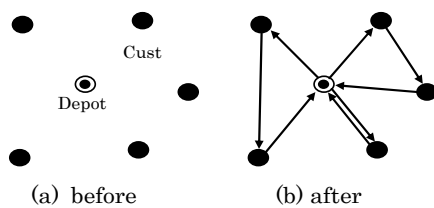


Figure 1. Solution image of vehicle routing problem.

One of them is an extension from the generic customer demand satisfaction and vehicle payload limit. For example, practical conditions such as customer availability or time window (Hashimoto *et al.*, 2006; Mester *et al.*, 2007), pickup (Gribkovskaia *et al.*, 2007), split and mixed deliveries (Mota *et al.*, 2007) are concerned not only separately but together (Zhong and Cole, 2005). The second is known as the multi-depot problem that tries to deliver from multiple depots (Chen *et al.*, 2005; Crevier *et al.*, 2007; Wu *et al.*, 2002). The thirds are interested in the multi-objective formulation for the single depot and multi-

depot problems (Bou and Arakawa, 2010; Geiger, 2010; Jozefowicz *et al.*, 2008; Murata and Itai, 2005; Pasia *et al.*, 2007; Tan *et al.*, 2006). The decision on the locations of depot is involved besides VRP in the last one (Albareda-Sambola *et al.*, 2005; Prins *et al.*, 2006; Tuzun and Burke, 1999; Zhao *et al.*, 2008).

Though many of those studies belong to delivery type problem and are solved by using certain metaheuristic method (Kubiak and Wesolek, 2007; Prins, 2004), another local search is applied in the literature. Due to the difficulty of the solution, in the numerical experiment, only small problems given by no more than 200 customers are solved to validate the effectiveness except for the literature (Kytojoki *et al.*, 2007). Moreover, they have never noted to account for the transportation cost by the Weber model (Shimizu, 2011a, 2011b).

2.2 Problem Formulation

Being different from the conventional formulations or delivery type VRP, it is common that the reverse logistic collects garbage and/or spent products from a number of distributed disposal/recycle points. Roughly speaking, this pickup type VRP is stated as follows.

The objective function is to minimize the total cost that is composed of transportation cost for every routing and fixed operational charge of vehicle. Then, it tries to decide the circular routes of vehicle necessary to pickup every quantity under the condition regarding available payload of the vehicle.

This basic VRP is formulated by the following combinatorial optimization problem.

(p.1) Minimize

$$\sum_{v \in V} \sum_{p \in P} \sum_{p' \in P} c_v d_{pp'} g_{pp'v} z_{pp'v} + \sum_{v \in V} F_v y_v$$

subject to

$$\sum_{p \in P} z_{kp v} \leq 1, \quad \forall k \in K; \forall v \in V \quad (1)$$

$$\sum_{p' \in P} z_{pp'v} - \sum_{p' \in P} z_{p'pv} = 0, \quad \forall p \in P; \forall v \in V \quad (2)$$

$$g_{pp'v} \leq W_v z_{pp'v}, \quad \forall p \in P; \forall p' \in P; \forall v \in V \quad (3)$$

$$\sum_{p \in P} \sum_{p' \in P} z_{pp'v} \leq M y_v, \quad \forall v \in V \quad (4)$$

$$\sum_{k \in K} g_{jkv} = 0, \quad \forall j \in J; \forall v \in V \quad (5)$$

$$\sum_{v \in V} \sum_{p \in P} g_{kp v} - \sum_{v \in V} \sum_{p \in P} g_{p k v} = D_k, \quad \forall k \in K \quad (6)$$

$$\sum_{j \in J} \sum_{k \in K} z_{jkv} = y_v, \quad \forall v \in V \quad (7)$$

$$\sum_{j \in J} \sum_{k \in K} z_{kjv} = y_v, \quad \forall v \in V \quad (8)$$

$$\sum_{p \in \Omega} \sum_{p' \in \Omega} z_{pp'v} \leq |\Omega| - 1, \quad \forall \Omega \subseteq P \setminus \{1\}; |\Omega| \geq 2, \forall v \in V \quad (9)$$

$$y_v \in \{0, 1\}, \forall v \in V; z_{pp'v} \in \{0, 1\}, \forall p \in P; \forall p' \in P; \forall v \in V$$

$$g_{pp'v} \geq 0, \forall p \in P; \forall p' \in P; \forall v \in V$$

Notation of this problem is shown below.

Variables

- $y_v = 1$ if vehicle v is used; otherwise 0
- $z_{pp'v} = 1$ if vehicle v travels on the path from $p \in P$ to $p' \in P$; otherwise 0
- $g_{pp'v}$: load of vehicle v on the path from $p \in P$ to $p' \in P$

Parameters

- c_v : transportation cost per unit load per unit distance of vehicle v
- D_k : pickup quantity at service point k
- $d_{pp'}$: path distance between $p \in P$ and $p' \in P$
- F_v : fixed charge of vehicle v
- M : auxiliary constant (Large real number)
- W_v : maximum capacity of vehicle v

Index set

- J : depot; K : pickup service point; V : vehicle; $P = J \cup K$;
- Ω : sub-tour candidate

Here, objective function is composed of routing transportation cost and fixed charges of used vehicles. On the other hand, each constraint means such as

- Eq. (1): that each vehicle cannot visit the customer twice;
- Eq. (2): that coming in vehicle must leave out;
- Eq. (3): upper bound load capacity for vehicle;
- Eq. (4): that vehicle must travel on a certain path;
- Eq. (5): that load must be empty for departing truck;
- Eq. (6): pickup satisfaction at service point;
- Eqs. (7) and (8): that each vehicle leaves only one depot and return there;
- Eq. (9): subtour elimination.

Integrality conditions and positive conditions are imposed on the respective variables.

It is well known that this kind of problem belongs to an NP-hard class, and becomes extremely difficult to obtain a rigid optimal solution for real-world size problems. Hence, it is desirable for applications to provide a practical method that can derive a near optimum solution with reasonable computational efforts. To practically work with this problem, we first derive an approach named modified saving method. It is able to generally solve new VRPs described by Weber model and generalized Weber model. Eventually, we used a hierarchical procedure that applies the modified saving method and the modified tabu search developed for this purpose.

3. VARIANTS OF MODIFIED SAVING METHODS

3.1 In the Case of Direct Pickup

Here, every vehicle visits the pickup points and re-

turn the depot directly. Since the transportation cost depends not only on the distance traveled (kilometer) but also on the weight (ton) as mentioned already, it is practical to consider these two factors in parallel if compared with the distance only. Noticing this ton-kilo basis, we can generally describe the transportation cost C_{trans} as Eq. (10), and call this the generalized Weber model.

$$C_{trans} = c_{tr} \gamma d_{i,j}^\alpha Q_{i,j}^\beta \tag{10}$$

where c_{tr} , $d_{i,j}$ and $Q_{i,j}$ denote transportation cost unit, traveling distance between customer i and j , and its weight, respectively. Moreover, α and β denote the elastic coefficients for distance and weight, respectively, and γ is a constant.

Then, referring to Figure 2, the saving value is obtained as Eq. (11).

$$s_{ij} / (\gamma c_{tr}) = w^\alpha d_{0j}^\beta + (w+q_i)^\alpha d_{i0}^\beta + (w+q_j)^\alpha d_{j0}^\beta - (w+q_i)^\alpha d_{ij}^\beta - (w+q_i+q_j)^\alpha d_{j0}^\beta \tag{11}$$

$i, j = 1, 2, \dots, n, i \neq j$

where w and q_j are weight of the vehicle itself and demand of customer j , respectively. On the other hand, n means the total number of customers, and let the suffix be 0 for the depot. Also it is apparent $s_{i,i} = 0$.

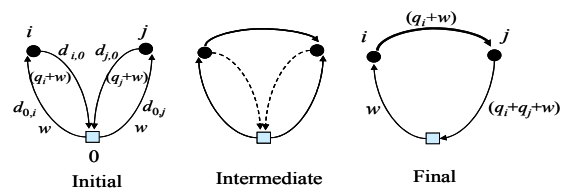


Figure 2. Scheme to compute the saving value (direct pickup).

When $\alpha = \beta = \gamma = 1$, these equations refer to those of the Weber model (a bilinear model of distance and load).

For a practical evaluation of the economy, it is desirable to account for the fixed-charge of vehicle C_{fix} beside the transportation cost. This comes to the assertion that it is more economical to visit the new customer even if its saving value ($\gamma c_{tr} s_{i,j}$) would become negative as long as its absolute value stays within the fixed charge. Applying these ideas to the original saving method, we can derive the ton-kilo based routes, and evaluate the cost TC by Eq. (12).

$$TC = c_{tr} \sum_{i=1}^l D_i + L \cdot C_{fix} \tag{12}$$

where D_i denotes the ton-kilo value of root i , and L the total number of roots (necessary vehicle number).

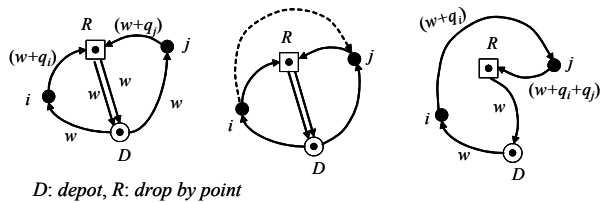
3.2 In the Case of Drop by Pickup

In order to evaluate the scenario from another view-

point, the foregoing idea can be extended to the case where vehicle drops by an intermediate destination before returning to the depot. This is the case where vehicle visits a disposal site to dump the debris, for example. Referring to Figure 3, we can modify Eq. (11) as follows.

$$s_{ij}/(\gamma c_r) = (w+q_i)^\alpha d_{Ri}^\beta + w^\alpha d_{R0}^\beta + w^\alpha d_{0j}^\beta + (w+q_j)^\alpha d_{Rj}^\beta - (w+q_i)^\alpha d_{ij}^\beta - (w+q_i+q_j)^\alpha d_{Rj}^\beta \quad (13)$$

where subscript R denotes the intermediate destination. We can apply the same procedure as before to derive the routes just by using the saving value given by Eq. (13).



D: depot, R: drop by point

Figure 3. Scheme to compute saving value (drop by pickup).

4. PROPOSED IDEAS

4.1 Hybrid Approach to Practical Solution

Since the (modified) saving method derives only an approximated solution, we try to improve it by applying a modified tabu search. In its original algorithm, only the improved neighboring solution can survive as long as it would not be involved in the tabu lists. In the modified method (Shimizu and Wada, 2004; Wada and Shimizu, 2006), however, even a degraded neighboring solution can be allowed to be a new tentative solution. This decision is made based on the probability whose function is known as Maxwell-Boltzmann and used in simulated annealing.

$$p = \begin{cases} 1 & \text{if } \Delta e \leq 0 \\ \exp(-\Delta e/T) & \text{if } \Delta e > 0 \end{cases} \quad (14)$$

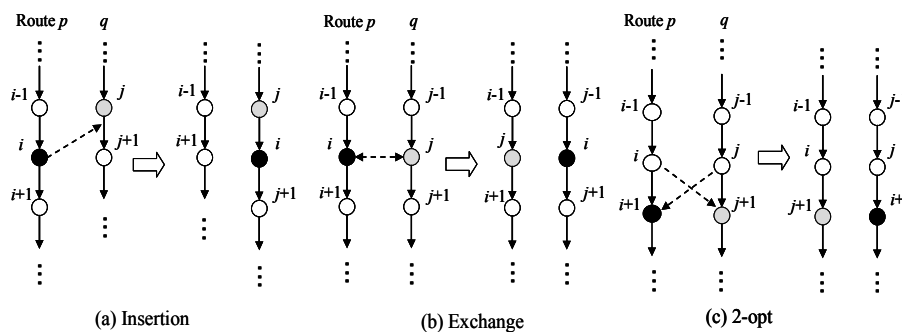


Figure 6. Neighborhood operations between loop.

where Δe denotes the difference of objective value from the best at hand.

We also introduce a few tactics when implementing the algorithm (Shimizu, 2011 b). They are listed below.

- (1) When the center angle made by the candidate customers from the depot is greater than the prescribed value, we withdraw its selection and move on to the next one. Here, the center angle θ is derived from the following formula if we denote the two candidates A and B and depot O as depicted in Figure 4.

$$\cos \theta = \frac{|AO|^2 + |OB|^2 - |AB|^2}{2|AO||OB|} \quad (15)$$

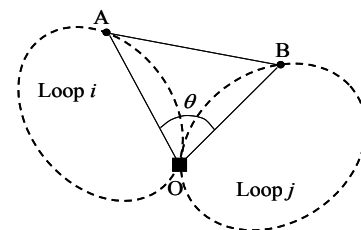


Figure 4. Center angle of a pair of candidates from depot.

- (2) During a certain *front uni-mode interval*, we urge to use only the operations within the loop (Figure 5). After that, its usage is decreased gradually and shifts to the dual operation, i.e., between the loops (Figure 6) and within the loop (Figure 7).
- (3) The thresholds to decide the modes introduced in the above (1) and (2) are changed exponentially along with the iteration. Such update is commonly taken place by Eq. (16).

$$r = a \exp(-k/b) + c \quad (16)$$

where a , b , and c denote appropriate constants and k iteration number. That is to say, according to the increase in iteration, the sharp angled neighbor is likely to be selected to weigh more the near neighbor. On the other hand, to reserve the near optimal structure derived from the modified saving method, it is plausible to take such a strategy that the *within-loop-search* comes first and then the *be-*

tween-loop-search follows. What are intended in these treatments stand for a rationale that is found in our foregoing experience (Shimizu, 2011a). This policy is illustrated in Figure 5.

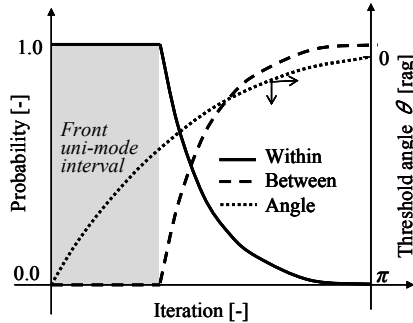


Figure 5. Illustration of selection rate of neighbor operations.

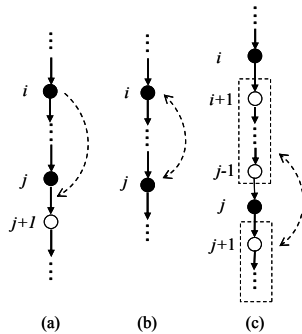


Figure 7. Neighborhood operations within loop.

Table 1. Specification of minimum cost flow graph

Edge	Cost	Capacity
Inlet	-	ΣD_j
Source-Depot _i	H_i	U_i
Depot _i -Customer _j	$c_0 d_{ij} (c_0 \gamma D_j^{\alpha-1} d_{ij}^\beta)$	U_j
Customer _j -Depot _i	0	D_j
Outlet	-	ΣD_j

c_0 [¥/(ton · km)]: unit transportation cost
 d_{ij} [km]: distance between depot i and customer j
 D_j [ton]: demand of customer j
 H_i [¥/ton]: operation cost at depot i
 U_i [ton]: capacity at depot i

4.2 Extension to Multi-Depot Problems

According to the increase in the problem size, it is more suitable to formulate the problem associated with multiple depots.

To cope with this aspect, we need to first decide the client customers to each depot in a suitable manner. Being different from the conventional kilo base case, however, no ideas such as ton-kilo base under consideration have been previously known. That is why we proposed a prac-

tical two-level approach (Shimizu, 2011b). In its upper level, the minimum cost flow (MCF) problem is favorably used to work with this assignment matter. By providing such a graph as shown in Figure 8, we can allocate every customer to each depot efficiently and practically as well. In Table 1, we summarize the labeling information of edges.

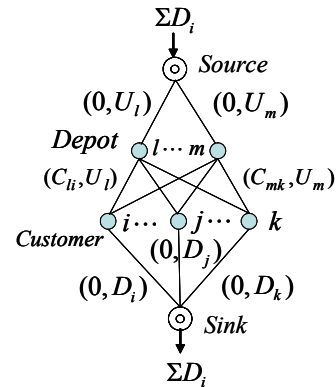


Figure 8. Minimum cost flow graph for allocation problem edge label denotes (cost, capacity).

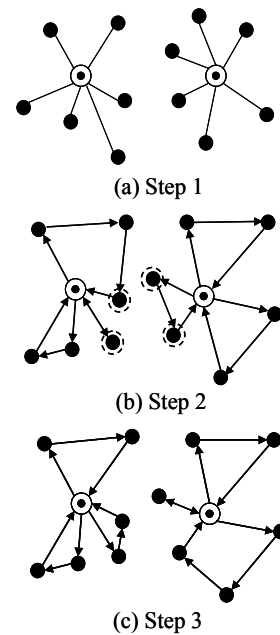


Figure 9. Idea of proposed procedure for multi-depot problem. (a) Allocation, (b) saving method, and (c) tabu search.

In the above, cost between depot and customer in the generalized case, which is described in the parenthesis, is derived as follows:

$$c_0 \gamma W_i^{\alpha-1} d_{ij}^\beta = c_0 \gamma w_i^{\alpha-1} d_{ij}^\beta \cdot w_i = (c_0 \gamma D_j^{\alpha-1} d_{ij}^\beta) w_i \cdot$$

Finally, we provide a solution image in Figure 9 and outline the procedures as follows.

- Step 1: Define the assignment problem in terms of MCF problem assuming each depot $\forall j \in J$ has an available capacity $U_j \in J$ and need a certain operational cost C_{jk} , $\forall j \in J, k \in K$.
- Step 2: Per every depot, derive the initial solution of VRP by applying the modified saving method.
- Step 3: Improve the above solutions by the modified tabu search.

Here the depot with no inflow from the source in the MCF graph will not be opened. Though the result presents an approximated solution, we can expect the high performance due to the optimal assignment procedure in Step 1. Of course, another evolutionary search is able to improve this result in advance.

4.3 Evaluation of CO₂ Emission under Cost Minimum Strategy

In addition to the economical aspects, environmental issues in the reverse logistics are growing its importance as a major part of realizing the low carbon supply system. It is meaningful, therefore, to consider certain effective measures that can reduce CO₂ emissions from the economically optimized VRP.

To facilitate this idea, the Ministry of Economy, Trade and Industry in Japan published a new guide line (<http://www.meti.go.jp/>) together with the Ministry of Land, Infrastructure, Transport and Tourism (METI and MLIT, 2006). In it, they recommend that we calculate the amount of CO₂ emission from the vehicle using the improved ton-kilo basis. Actually, the following formula is applied to calculate the emission amount depending on the payload and kind of vehicle.

$$\text{Emission amount [t-CO}_2\text{]} = \text{Weight [t]} \times \text{Distance [km]} \times \text{Unit t-km mileage [l/t/km]} \times 1/1000 \text{ [l/kl]} \times \text{Unit fever cal-orie [GJ/kl]} \times \text{Emission coefficient [t-C/GJ]} \times 44/12 \text{ [t-CO}_2\text{/t-C]}$$

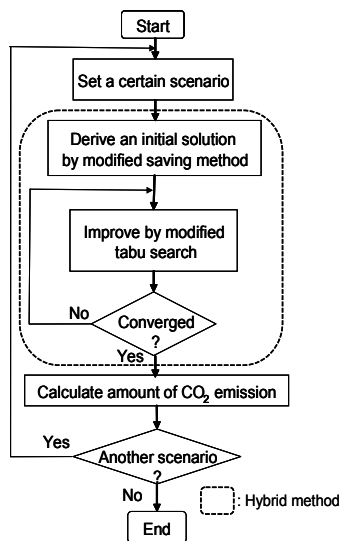


Figure 10. Procedure for scenario-based analysis.

In terms of the above guideline, we can also derive the transportation costs for various vehicles in terms of the ton-kilo basis. Now, it is possible for us to provide the same basis when evaluating the cost and the CO₂ emission. Then, we intend to carry out a what-if analysis between the total cost and the released CO₂ following the scenario-based approach shown in Figure 10. For the economically optimized reverse logistics, we can involve the concerns associated with a variety of low carbon scenarios.

5. NUMERICAL EXPERIMENT

Numerical experiments were carried out to validate the effectiveness of the proposed method and to explore some prospects for the reverse logistics. The following discussions are made by averaging the results over 10 samples.

We randomly generated the prescribed number of customers around the center at which the depot locates. The distances between depot and customers and also between the customers are given by Euclidian basis. Moreover, demand of each customer is randomly given within certain prescribed ranges. The coefficients introduced in the generalized Weber model are set as $\alpha = 0.894$, $\beta = 0.750$, $\gamma = 1.726$ (Watanabe, 2010).

5.1 Results for Evaluating Performance of the Method

We prepared several benchmark problems with different customer number, and the results for the single and multi-depot problems are summarized in Tables 2 and 3, respectively. It involves very large problems that have not been solved previously. According to the increase in customer number or problem size, the improvement rate defined at the bottom of the table becomes higher both in Weber and the generalized Weber models only for the direct single depot problems. However, in the other cases, either the improvement rates stay almost constant or decrease a little.

Though we need several CPU time for the generalized Weber model, its improved rate stays considerably lower compared with the Weber model. This might be due to the highly nonlinear cost function.

Regarding the cost in itself, the generalized model derives the smaller value due to the scale merit or introduction of elastic coefficients in Eq. (10).

5.2 Results for Evaluating Low Carbon Transportation Scenarios

It is significant to evaluate the various prospects aiming at the low carbon reverse logistics. From this point of view, we have evaluated a few scenarios regarding popular pickup options under the economically optimized

Table 2. Results for single-depot problems

		Customer#	Cost unit	Rate (-)	CPU (s)	Loop#	Iteration#
Direct	Weber	100	0.3578E+06	0.196	0.182	4.000	0.68E+05
		200	0.5585E+06	0.223	0.875	6.300	0.27E+06
		500	0.1065E+07	0.247	7.469	12.100	0.17E+07
		1,000	0.1748E+07	0.290	40.116	20.200	0.69E+07
	Generalized Weber	100	0.2911E+06	0.085	1.011	4.100	0.68E+05
		200	0.4847E+06	0.063	4.963	6.400	0.27E+06
		500	0.9359E+07	0.099	41.135	12.300	0.17E+07
		1,000	0.1620E+07	0.113	210.19	19.900	0.68E+07
Drop by	Weber	100	0.3444E+06	0.220	0.188	4.000	0.68E+05
		200	0.5609E+06	0.219	0.885	6.300	0.26E+06
		500	0.1065E+07	0.224	7.549	12.800	0.17E+07
		1,000	0.1795E+07	0.214	41.448	20.200	0.68E+07
	Generalized Weber	100	0.2903E+06	0.106	1.028	4.100	0.68E+05
		200	0.4620E+06	0.123	5.215	6.300	0.27E+06
		500	0.9276E+07	0.106	41.482	12.400	0.17E+07
		1,000	0.1586E+07	0.111	208.48	20.500	0.68E+07

Rate = (1st stage cost – the final stage)/1st stage cost.

Loop#: number of routes = vehicle.

Table 3. Results for multi-depot problems

		Size*	Cost	Rate (-)	CPU (s)	Loop#	Iteration#
Direct	Weber	(10, 1000)	0.1511E+08	0.052	6.822	11.44	0.32E+07
		(15, 2000)	0.2475E+08	0.067	20.050	14.70	0.89E+07
		(20, 2500)	0.3876E+08	0.082	25.964	13.04	0.11E+08
		(25, 3000)	0.4179E+08	0.067	27.623	12.92	0.12E+08
	Generalized Weber	(10, 1000)	0.7103E+07	0.025	24.237	12.48	0.41E+07
		(15, 2000)	0.1427E+08	0.025	64.391	15.26	0.89E+07
		(20, 2500)	0.2045E+08	0.021	83.189	14.09	0.12E+08
		(25, 3000)	0.2355E+08	0.023	91.597	15.27	0.13E+08
Drop by	Weber	(10, 1000)	0.8863E+07	0.213	7.233	12.46	0.35E+07
		(15, 2000)	0.1787E+08	0.293	20.314	14.19	0.95E+07
		(20, 2500)	0.2059E+08	0.279	23.564	15.25	0.12E+08
		(25, 3000)	0.2806E+08	0.268	29.047	15.03	0.14E+08
	Generalized Weber	(10, 1000)	0.6170E+07	0.307	24.614	11.27	0.37E+07
		(15, 2000)	0.1237E+08	0.295	76.489	15.19	0.11E+08
		(20, 2500)	0.1499E+08	0.270	96.203	16.17	0.14E+08
		(25, 3000)	0.1869E+08	0.273	94.236	14.45	0.13E+08

Rate = (1st stage cost – the final stage)/1st stage cost.

Loop#: Number of routes = vehicle, Size* = (Depot#, Customer#).

logistics following the procedure shown in Figure 10.

First, the effect of vehicle size or payload is considered using the specific data listed in Table 4 (Refer to the guide line mentioned already). Then, we obtained the

results as shown in Figures 11~13 for the direct pickup model.

In Figure 11, we show the relation between the cost and the payload of vehicle. We can observe the scale me-

rit against more apparent for the larger problem size.

Table 4. Specification of truck

Payload [t]	Weight [t]	Fixed charge [10^4 ¥]	Unit <i>t-km</i> mileage [l/t/km]
4	2.5	0.3	0.0844
8	3.5	0.4	0.0677
15	5.5	0.5	0.0575
20	7.5	0.6	0.0504
25	10.0	0.7	0.0421

From Figure 12 where the CO₂ emissions are related to the payload, the existence of the minimum is found around 8[t] though it is not so clear for every case. This suggests appropriate vehicle size exists for reducing CO₂ emission.

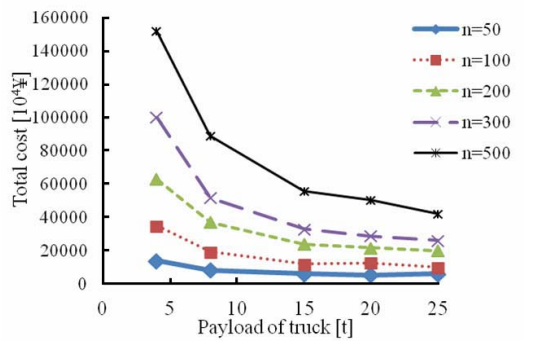


Figure 11. Effect of payload on total cost.

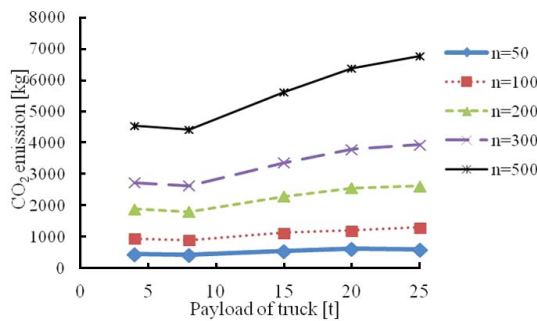


Figure 12. Effect of payload on CO₂ emission.

Moreover, it is interesting to see the trade-off relation between the CO₂ emission and the total cost shown in Figure 13. This means the comprehensive decision making is left in advance so that a better compromise will be attained by trading off either of the objectives to the other, i.e., compromise between economy and environmental issues.

In Figures 14 and 15, profiles of convergence of both models for the direct and drop by cases are shown for the direct case and the drop by case, respectively when $n = 300$. The trend of increase in CPU time is shown in Figure 16. It is a well-known profile that expands rapidly with problem sizes.

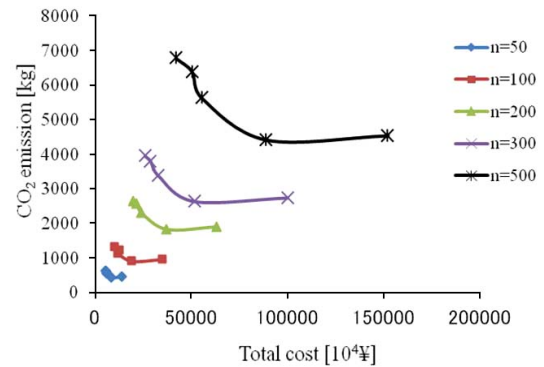


Figure 13. Trade-off relation between total cost & CO₂ emission.

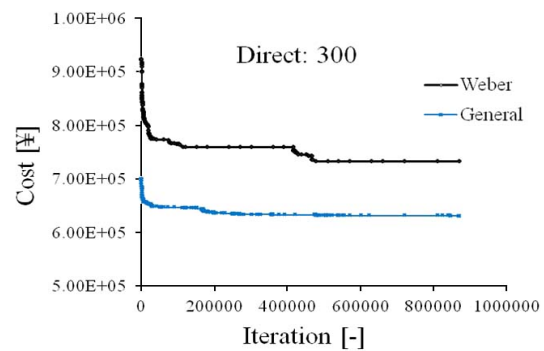


Figure 14. Convergence profile for direct pickup.

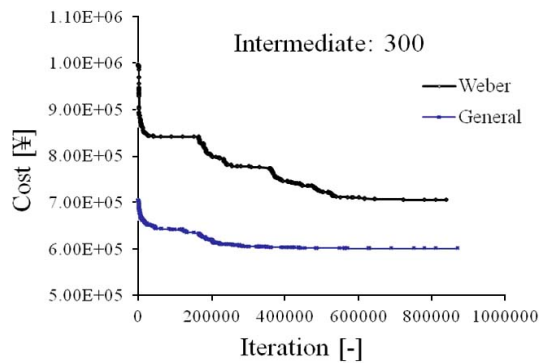


Figure 15. Convergence profile for drop-by pickup.

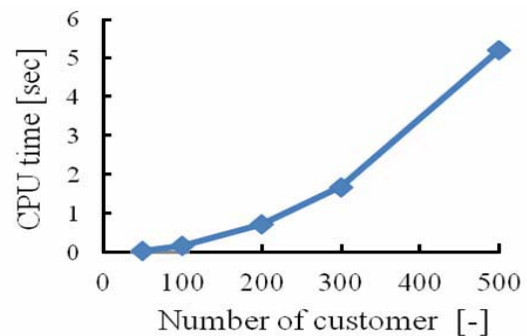


Figure 16. Profile of CPU time along problem size.

Since we could not find the elastic coefficient for the

CO₂ emission like the transportation cost, we used the same bilinear formula for the evaluation of the generalized model. Then, we have the similar results as shown already in Figures 11~13. The decision aiming at the scale merit for economy likely increases the ton-kilo values. This, in turn, makes the CO₂ emission larger compared with the case of Weber model. Accordingly, the CO₂ emission becomes greater than that of Weber model.

6. CONCLUSION

Low carbon technology is a key issue for green transportation in reverse logistics. To cope with the latest topic that involves logistics innovation, we have applied a hybrid approach proposed by one of the authors and engaged in scenario-based analysis toward the low carbon transportation. Thereat, we solve the practical VRP by the modified saving method and the modified tabu search. The idea relies on such a new aspect that transportation cost depends not only on distance traveled but also on load (ton-kilo basis). Since the pick-up problems are usual for reverse logistics, we deployed the idea to the two kinds of pickup problems, i.e., direct and drop by.

In addition to the economical aspects, the proposed idea is able to practically evaluate the CO₂ emission on the same ton-kilo basis. Accordingly, we discussed significant relations between the transport cost and the released CO₂ through a few scenarios for low carbon logistics.

Finally, through numerical experiment, we have verified that the proposed procedure can provide an economically efficient reverse logistics network even when the scale of the problem becomes extremely large. That enables us to explore some possible and promising prospects in the real world.

Real-world applications and deployment to multi-depot problem and bi-objective optimization between economy and environmental issue are left for future studies.

ACKNOWLEDGMENTS

This research was partially supported by the Ministry of Education, Science, Sports and Culture, Grant-in-Aid, 25350442, Japan.

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