A Hierarchical Hybrid Approach for Rich VRP Studies through Elaborate Cost Accounting Considering Various Driving Conditions

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Abstract— **Today global and dynamic markets require us to provide cooperative and competitive logistics so that we can build a sustainable manufacturing system amenable to sales and operations planning. As a deployment for such practice, keen interests have been paid at logistics optimization known as vehicle routing problem (VRP). Noticing that fuel consumption and/or CO_2 emission actually depend not only on distance traveled but also weight loaded (Weber basis), we concerned with large-scale VRP from various aspects. To provide a unified framework for such problems, we first overview manifold or rich VRP studies following certain classifications and claim our hierarchical hybrid approach is commonly available for solving manifold variants of VRP. Then, as an emerging and relevant issue to make such framework more fruitful associated with green and/or economic logistics, in this study, we aim at considering some real-world situations elaborately. Actually, we try to introduce a scalable cost accounting depending on the several driving conditions such as slope, traffic jam and so on. Such concern owes to the recent amazing progresses of information and communication technologies. Finally, through numerical experiments, we show our approach is able to practically solve such large problems that have been never solved elsewhere. Moreover, based on the broad comparison covering transportation types, depot number and kind of cost accounting, we examine the solution abilities and also discuss some prospects towards the scalable cost accounting.**

Keywords— ***hierarchical approach, rich VRP studies, hybrid evolutionary algorithm, elaborate cost accounting***

I. INTRODUCTION

Facing with rising markets and various demands on qualified service in competitive transportation system, logistic optimization is becoming a keen interest to provide a sustainable infrastructure aligning to modern societal prospects. As a key technology for such deployment, we have been engaged in the practical studies on vehicle routing problem (VRP) noticing that the fuel consumption and/or CO_2 emission surely depend not only distance but also loading weight (tonnage-kilo meter basis). This cost accounting is known as Weber basis and has been applied popularly in a strategic planning like allocation/location problems. Based on this cost accounting, we have developed a hybrid approach that can cope with various VRPs efficiently as well as practically.

In this paper, we will provide a more general approach so that we can expand our framework of VRP studies. In fact, we know the cost accounting depends on the degree of traffic jam, uphill, flat or downhill driving, city, suburb or highway driving, etc. Accordingly, we need to consider a certain scalable factor for elaborate and realistic evaluation depending on such driving conditions. Then, to validate the significance of introducing such idea, we carry out a few numerical experiments.

The rest of the paper is organized as follows. In Section 2, we briefly overview manifold or rich VRP studies in terms of certain classifications. Then, we outline the proposed solution procedure in Section 3. Numerical experiments are provided in Section 4. Finally, we give some conclusions.

II. OVERVIEW OF RICH VRP STUDIES

A logistic network problem known as VRP is a combinatorial optimization problem on minimizing the total distance traveled by a fleet of vehicles under various constraints. This transportation of goods from depots to all customers must be considered under the condition that each vehicle must take a circular route with the depot as its starting point and destination as well. Due to NP-hardness as a nature of problem, it is almost impossible to rigidly solve real world problems through any optimization methods. In contrast, by virtue of amazing progress of meta-heuristic methods, we can cope with such situation reasonably if only near optimal solution is satisfactory. Now, let us review rich VRP studies briefly,

A. *Conventional and Weber Basis Transportation Cost Accounting*

Even from our daily experience, we know the cost accounting obeys Weber basis that is a bilinear model of distance and weight, i.e., (Distance)*(Weight). A power model of those two quantities is known as the generalized Weber basis and it can give a more rigid cost accounting [1]. It is described as $\gamma\cdot(\text{distance})^{\alpha}\cdot(\text{weight})^{\beta}$ where γ denotes a constant and α and β elastic coefficients for the distance and weight, respectively. From this fact, reducing weight of vehicle itself has been a keen engineering interest in every car industry. It means we should use either of these Weber bases to evaluate burden instead of the conventional non-Weber basis, i.e., kilo-meter basis.

As pointed out already, the Weber basis has been popularly applied to the location problems while not to VRP so far. Hence, if we apply this basis in VRP, we can evaluate the transportation costs on the same basis both for location and routing problems as discussed in our study on location-routing problem [2]. This is another significance of using the Weber bases instead of the conventional one.

B. Single and Multi-Depot Networks

When we consider only one depot in logistic network, the problem is called single-depot problem or simply VRP. Meanwhile, it is called multi-depot VRP when we consider multiple depots. Multi-depot VRP is viewed as a variant of location-routing problem since it involves another decision how to allocate the client customers for each depot. Due to such integrated difficulties in solution, previous studies [3] basically solved only small benchmark problems under the non-Weber basis cost accounting to validate the effectiveness of the proposed method. From a practical point of view, therefore, those studies are said to be quite insufficient.

C. Mono Mode and Multi-Mode Transportations

Conventionally, VRP has mainly concerned delivery problems. According to the increasing interests in green logistics, however, pickup type is often considered recently. In contrast to delivery, it collects garbage and/or spent products from the distributed pickup points as commonly seen in reverse logistic. Such pickup problem is further classified into direct and drop-by types. The former is just the dual of the delivery and the later need to drop by another destination to dump the debris collected over the route before returning to the starting depot.

Besides such mono-mode VRP, some researchers have been recently interested in VRP with varying pickup and delivery configurations or multi-mode VRP. This mode seems to be the most practical and suitable idea to consider reverse logistics. They are classified into three categories known as delivery with backhauls (VRPB), mixed pickup and delivery (MVRP) and simultaneous pickup and delivery (VRPSPD) [4].

Here, VRPB can be managed by applying the mono mode cases separately in order of delivery and pickup. VRPSPD [5] turns to MVRP when either of pickup demand or delivery demand is placed at each customer. In this sense, VRPSPD is considered as the most practical and general when we discuss on the cooperative and competitive logistics in modern society.

By the simultaneous delivery and pickup (SPD), we can expect to realize a higher loading ratio of vehicle compared with the mono mode. Besides such higher loading ratio of vehicle, it is meaningful to ascertain the merit of SPD from the saving rate against the separate transportations, i.e., independent delivery and pickup transportations [6].

D. Single and Multi-Objective Evaluations

Duo to diversified value system, we should notice manifold objectives realizing environmentally benign (low carbon), elaborate (agile service) and/or confidential (low risk) achievements. Generally speaking, there exists a trade-off between anyone of those objectives and the economy (cost). Hence, multi-objective optimization is more suitable to cope with such situations [7].

Regarding the recent report on CO_2 emission, transportation sector occupies a rather higher portion among all sectors of society. Hence, aiming at realizing sustainable logistics, we considered a bi-objective location–routing problem considering trade-off between low carbon and cost [8]. Actually, it was solved by introducing a coefficient known as the emission trading rate on CO_2 and transforming the original bi-objective problem into scalar one.

Besides the concerns discussed above, sophisticated deployments have been known in this area. For example, in addition to generic customer demand satisfaction and vehicle payload limit conditions, including some practical concerns such as customer availability or time windows and split and mixed delivery are very popular. These extensions are considered both separately and in combined manners.

III. HIERARCHICAL HYBRID APPROACH ASSOCIATED WITH SCALABLE FACTOR

A. Scalable Factor on Driving Conditions

To evaluate the cost more elaborately depending on various driving conditions as mentioned in Introduction, we should consider a scalable option. For this purpose, today, we can easily retrieve the necessary information due to great progress of ITC technologies, e.g., Elevation API of Google map, VICS (Vehicle Information and Communication System) and so on.

Factor G_{ij} is defined as a scale to account such driving condition between two site i and j. Actually, to get the revised cost $\mathrm{Cost_H}(\boldsymbol{x})$, this scalable factor is multiplied with the nominal $\mathrm{Cost}(\boldsymbol{x})$ as $\mathrm{Cost_H}(\boldsymbol{x}) = G_{ij} \cdot \mathrm{Cost}(\boldsymbol{x})$. To evaluate this effect practically in real world applications, we divide the route into sub-routes where this scale is possible to be almost constant. Then, we compute the revised factor for the scalable case by Eq.(1).

$$\tilde{G}_{ij} = \Big(\sum_{\forall(m,n)} \delta_{mn}^{ij} G_{mn}^{ij} \Big) / d_{ij} \qquad (1)$$

where δ^{ij}_{mn} denotes a distance of sub-route involved in route i-j. Hence, distance d_{ij} is given by $\sum_{\forall(m,n)} \delta_{mn}^{ij} = d_{ij}$. Finally, we use this scale for the cost accounting between two sites. Such generalization from our conventional approach is directly available for rich VRP studies mentioned above.

Moreover, to evaluate such elaboration, we give an index called gap that is given by $(\mathrm{Cost_H}(\boldsymbol{x}_L^*) - \mathrm{Cost_H}(\boldsymbol{x}_H^*))/\mathrm{Cost_H}(\boldsymbol{x}_H^*)$ where $\mathrm{Cost_H}(\boldsymbol{x}_H^*)$ and $\mathrm{Cost_H}(\boldsymbol{x}_L^*)$ denote the revised cost by its optimal solution $\boldsymbol{x}_H^*$ (under higher reality or elabrate cost accounting) and the re-evaluated revised cost by the nominal solution $\boldsymbol{x}_L^*$ (under lower reality or conventional cost accounting), respectively. It represents a loss that we will suffer if we evaluate the costs without using more realistic basis or scalable one.

B. Hierarchical Hybrid Approach

Any of the above problems formulated mathematically belong to an NP-hard class and become almost impossible to obtain an exact optimal solution for real-world problems. Hence, instead of any commercial solvers, it is meaningful to provide a practical method that can derive a near optimum solution with an acceptable computational effort. For this purpose, we can apply our hierarchical hybrid approach whose flowchart is shown in Fig.1, Thereat, we use three major components, i.e., graph algorithm to solve minimum cost flow (MCF) problem, Weber basis saving method and modified tabu search (hybrid). The graph algorithm is used for multi-depot problems to allocate the client customers for each depot (first level), Weber basis saving method to derive an initial solution of VRP in the

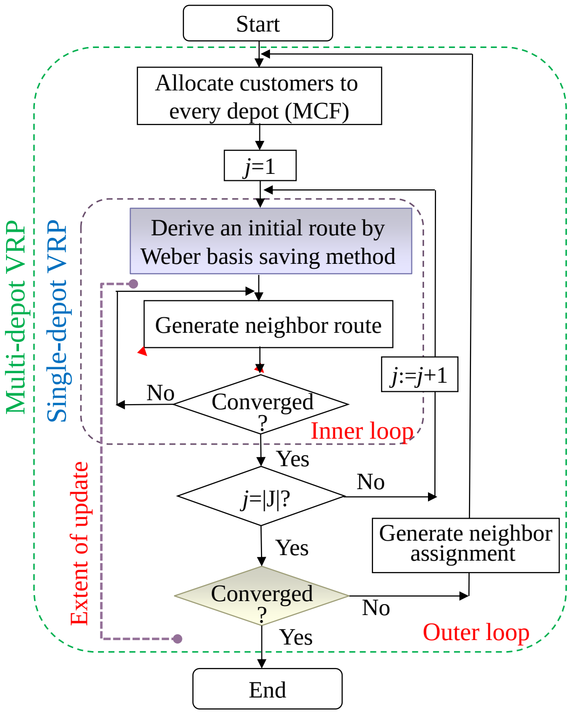


Fig. 1. Flowchart of the proposed hierarchical hybrid approach

inner loop search (second level) and the modified tabu search to improve the tentative solution both in the inner loop search and outer one (third level), respectively. Hence, the allocation problem and outer loop search are to be skipped for single depot problems. Actually, we can cope with every variant just by replacing the value of cost accounting with the relevant one for the problem under consideration. Below, major components in the procedure are explained briefly.

1) Allocation of Customers for Multi-Depot Problems

Deciding the client customers to each depot in a suitable manner, we can move on the next step to solve the multiple single-depot problems in turn. This allocation problem for delivery problem is equivalent to solve the following linear programming problem (LP).

$$\text{(p.1)}\ \min \sum_{j\in J}\sum_{k\in K}\phi_{jk}c_v d_{jk} g_{jk} + \sum_{j\in J} H_j \sum_{k\in K} g_{jk} \quad \text{subject to}$$

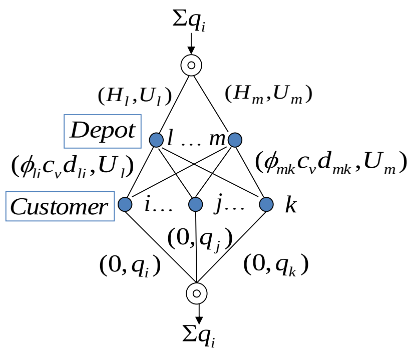
$$\sum_{k\in K} g_{jk} \le U_j, \quad \forall j \in J \tag{2}$$

$$\sum_{j\in J} g_{jk} = q_k, \quad \forall k \in K \tag{3}$$

$$g_{jk} \ge 0, \quad \forall j \in J, \forall k \in K \tag{4}$$

where g_{jk} denotes the burden allocated from depot k to customer j [ton]; c_v: transportation cost per unit load per unit distance of vehicle v [cost unit /ton/km]; d_{jk}: path distance between $j \in J$ and $k \in K$ [km]; H_j: handling cost of depot j [cost unit /ton], q_k: delivery demand of customer k [ton]; U_j: maximum capacity of depot j [ton]; J: index set of depot; K: index set of customer. Moreover, ϕ_{jk} is a scale depending on the adopted accounting and given at the bottom of table in Fig.2.

Actually, to enhance the solution ability, we apply the graph algorithm of MCF problem instead of solving the above LP directly. We show this graph and label information on the edge of graph in Fig.2. Here, the depot with no inflow from the source in the MCF graph will not be opened. After all, we can allocate every customer to each depot efficiently and practically as well.



ϕ_{ij}	Delivery	Pickup	SPD
Bi-linear	G_{ij}		
Power*	$G_{ij}\gamma q_j^{\alpha-1} d_{ij}^{\beta-1}$	$G_{ij}\gamma p_j^{\alpha-1} d_{ij}^{\beta-1}$	$G_{ij}\gamma r_j^{\alpha-1} d_{ij}^{\beta-1}$

**Approximated by apparent linearization*, $r_k = \max\{q_k, p_k\}$

Fig. 2. MCF graph for allocation for delivery problem.

In the cases of pickup or SPD, the above Eq.(3) might be replaced with Eq.(5) or Eq.(6), respectively.

$$\sum_{j\in J} g_{jk} = p_k, \quad \forall k \in K \tag{5}$$

$$\sum_{j\in J} g_{jk} = r_k = \max(q_k, p_k), \quad \forall k \in K \tag{6}$$

where p_k denotes pickup demand of customer k.

This approach is suitable compared with the other methods such as Voronoi diagram, cluster divisions, polar angles between the depot and the customers, etc. These methods just claim their rationality only from a certain geometric reason respectively, and neglect almost every condition given in the mathematical formulation. For example, those never consider capacity constraint of each depot, Eq.(2) and the handling cost and the practical transportation cost accounting in the objective function. Against this, since the above auxiliary problem (p.1) considers all these key conditions that are involved in the generic mathematical formulation, we can assert its rationality more relevantly.

2) Scable Weber Basis Saving Method

Saving method is a popularly known heuristic method for solving the generic VRP. Thereat, saving value that is the reward from merging the redundant paths plays a key role to drive the algorithm. Letting the suffix be 0 for depot and $s_{ii} = 0$, it is given only on distance (kilo-meter) basis as follows.

$$s_{ij} = d_{i0} + d_{0j} - d_{ij}, \quad i, j = 1,2,..,|K|, i \ne j \tag{7}$$

If we will not pay attention to the special conditions on forward and backward paths, the above conventional saving values becomes always same regardless of the problem type, i.e., either delivery or pickup or SPD. Against this, it is not true when we take Weber basis. Here, we also try to account the unladen weight of vehicle v, w_v. After all, consulting the

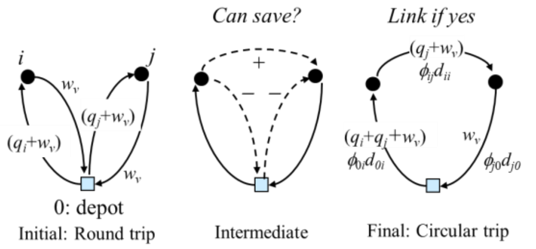


Fig. 3. Scheme available for deriving the scalable Weber saving value (delivery).

scheme depicted in Fig.3 for delivery problem, we summarize the present scalable Weber basis saving values s'_{ij} for various modes in Table 1.

Though the algorithm is basically same as the original one, the proposed method also takes the fixed-charge of vehicle C_{fix} into account besides the routing cost. This procedure is outlined as follows.

Step 1: Create round trip routes from the depot for every pair, and compute the scalable Weber basis savings value.

Step 2: Order these pairs in descending order of such saving values.

Step 3: Merge the path in turn following the order obtained from Step 2 as long as it is feasible and the savings value is greater than $-F_v/c_v$, where F_v denotes the fixed operational cost of vehicle v.

The above Step 3 modifies the original idea in terms of such assertion that visiting the new customer is more economical even if its saving cost would become negative as long as its absolute value stays within the fixed operational cost of the additional vehicle. Including such fixed charge and weight of unladen vehicle in evaluations are our original ideas. Through this method, we can derive the initial routes more practically and consistently compared with the conventional one. Finally, we can evaluate the total transportation cost by Eq.(8).

$$TC = \sum_{i=1}^{L} TR_i + L_R \cdot F_v \tag{8}$$

where TR_i denotes routing cost of root i, and L_R total number of routs (necessary vehicle number).

3) Modified Tabu Search

Since the Weber basis saving method derives only an approximated solution, we try to improve it by applying the modified tabu search. The tabu search is a simple but powerful heuristic method that refers to a local search with certain memory structure. In its local search applied in the inner loop, we generate a neighbour solution from either of insert, swap or 2-opt operations within the route and either of insert, swap or cross operations between the routes by randomly selecting every candidate. On the other hand, in the outer loop search, an extended swap [6] is used to generate a neighbour solution. To avoid trapping into a local minimum, our modified method allows even a degraded neighbour solution to be a new tentative solution as long as it would be feasible and not be involved in the tabu list. Such decision is made in terms of the probability whose distribution obeys the Maxwell-Boltzmann function as used in simulated annealing.

IV. NUMERICAL EXPERIMENT

We prepared benchmark problems for numerical experiments as follows. We randomly generated the prescribed numbers of customers within a rectangular region. On the other hand, depot is placed at the centre for single-depot problem while they are distributed randomly within the smaller region involved in the entire region for multi-depot problem. The distances between depot and customers for multi-depot problem and also between every customer are given by Euclidian basis (See Fig.4). For scalable problems, scaling data as the weighted average factor defined by Eq.(1) are randomly given within a certain range, i.e., [0.75, 1.5]. Likewise, each demand of customer is randomly given within a certain prescribed range.

Moreover, for the generalized problems, we set α=0.894, β=0.750, γ=1.726 referring to Ref. [1]. Convergence condition is given by either total number of generation or

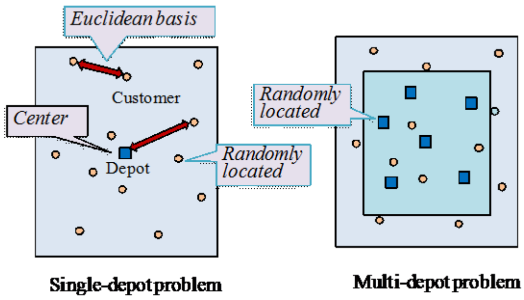


Fig. 4. Scheme for problem generation

TABLE I. SCALABLE WEBER BASIS SAVING VALUES s'_{ij} FOR VARIOUS MODES OF VRP.

Type		**Weber model (s'_{ij}/c_v)**	**Generalized Weber model ($s'_{ij}/\gamma/c_v$)**
Cost accounting between i & j		***Bilinear: $G_{ij}c_v g_{ij} d_{ij}$***	***Power: $G_{ij}c_v\gamma g_{ij}^{\alpha} d_{ij}^{\beta}$***
Delivery		$q_j(G_{0j}d_{0j} - G_{0i}d_{0i} - G_{ij}d_{ij})$ $+ w_v(G_{0j}d_{0j} + G_{i0}d_{i0} - G_{ij}d_{ij})$	$\{(w_v+q_i)^{\alpha} - (w_v+q_i+q_j)^{\alpha}\}G_{0i}d_{0i}^{\beta}$ $+(w_v+q_j)^{\alpha}(G_{0j}d_{0j}^{\beta} - G_{ij}d_{ij}^{\beta}) + w_v{}^{\alpha}G_{i0}d_{i0}^{\beta}$
Pick up	Direct	$p_i(G_{i0}d_{i0} - G_{j0}d_{j0} - G_{ij}d_{ij})$ $+ w_v(G_{0j}d_{0j} + G_{i0}d_{i0} - G_{ij}d_{ij})$	$\{(w_v+p_j)^{\alpha} - (w_v+p_i+p_j)^{\alpha}\}G_{j0}d_{j0}^{\beta}$ $+(w_v+p_i)^{\alpha}(G_{i0}d_{i0}^{\beta} - G_{ij}d_{ij}^{\beta}) + w_v{}^{\alpha}G_{0j}d_{0j}^{\beta}$
	Drop by	$(p_i+w_v)(G_{iR}d_{iR} - G_{ij}d_{ij})$ $+ w_v(G_{R0}d_{R0} + G_{0j}d_{0j}) - p_iG_{jR}d_{jR}$ Here, suffix R denotes drop-by site.	$\{(w_v+p_i)^{\alpha}(G_{iR}d_{iR}^{\beta} - G_{ij}d_{ij}^{\beta}) + w_v{}^{\alpha}(G_{R0}d_{R0}^{\beta} + G_{0j}d_{0j}^{\beta})$ $+\{(w_v+p_j)^{\alpha} - (w_v+p_i+p_j)^{\alpha}\}G_{jR}d_{jR}^{\beta}$
SPD		$(w_v+p_i-q_j)G_{0i}d_{0i} + (w_v-p_i+q_j)G_{0j}d_{0j}$ $-(w_v+p_i+q_j)G_{ij}d_{ij}$	$(w_v+q_i)^{\alpha}G_{0i}d_{0i}^{\beta} + (w_v+p_i)^{\alpha}G_{0i}d_{0i}^{\beta} + (w_v+q_j)^{\alpha}G_{0j}d_{0j}^{\beta}$ $+(w_v+p_j)^{\alpha}G_{0j}d_{0j}^{\beta} - (w_v+q_i+q_j)^{\alpha}G_{0i}d_{0i}^{\beta}$ $-(w_v+p_i+q_j)^{\alpha}G_{ij}d_{ij}^{\beta} - (w_v+p_i+p_j)^{\alpha}G_{0j}d_{0j}^{\beta}$

TABLE II. SUMMARY OF RESULTS FOR THE PLAIN CASE WHERE G_{ij} =1 ([6],[9])

Mode	Type	Size: [J, K]	Bilinear		Power	
			Up-rate [a]	*CPU [s]*	*Up-rate*	*CPU [s]*
Mono	Single-Deliver	[1, 1000]	0.285	38.1	0.149	207.2
	Single-Pick(Direct)	[1, 1000]	0.290	40.1	0.113	210.2
	Single-Pick(Drop-by)	[1, 1000]	0.214	41.5	0.111	208.5
	Multi-Deliver	[10, 1000]	0.037	230.1	0.046	977.4
	Multi-Pick(Direct)	[10, 1000]	0.041	277.2	0.035	1701.4
Multi	Single-SPD	[1, 1000]	0.804	133.9	0.611	289.7
	Multi-SPD	[10, 1000]	0.621	309.2	0.601	1986.6

a. Improved rate of the final solution from the initial, i.e., 1.0- Cost(final)/Cost(first)

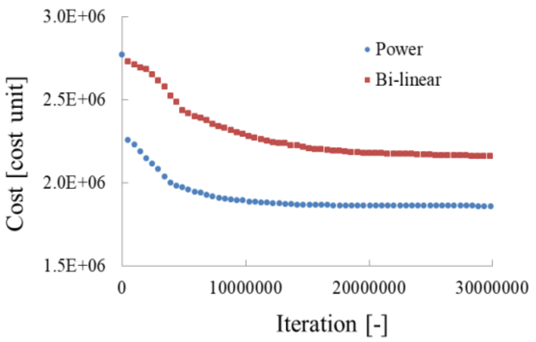


Fig. 6. Profiles of convergence

number of successive failures in local search. Those values and size of tabu list are changed depending on the problem size. We used PC with CPU: Intel(R) Core(TM)2 Quad Processor Q6600 2.4GHz, and RAM: 3GB. The following discussions are made based on the results averaged over 10 runs per each problem.

In Table 2, we summarized a part of the results solved for plain cases to show the overall evaluation. First, we know it possible to solve all within acceptable computation times even for such large problems that have never been solved elsewhere. Here, 'Up-rate' denotes the improved rate of the final solution from the initial one by Weber basis saving method (Refer to Fig.1 also). In other words, it stands for the merit of the new heuristics employed in our

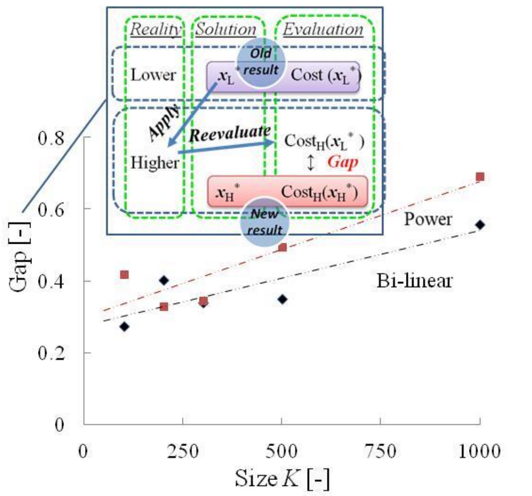


Fig. 5. Profiles of the gap for each cost accounting along with problem size both for Weber (bi-linear) and the generalized one (power).

TABLE III. RESULTS OF SCALABLE CASE WHERE $G_{ij}=\tilde{G}_{ij}$ (MONO-MODE SINGLE DELIVERY)

Size	Bilinear		Power	
	Up-rate	*CPU [s]*	*Up-rate*	*CPU [s]*
100	0.230	2.4	0.222	5.0
200	0.179	12.0	0.183	22.6
300	0.263	32.5	0.181	64.8
500	0.228	109.8	0.205	202.7
1000	0.302	514.5	0.243	1038.6

framework over the classical one. After all, we obtained the following results:

- Considerable improvements are possible by the proposed approach except for the 'mono-mode multi-depot' problems since its average number of customers is one tenth (smaller room for the further improvement). Also, neighbor assignment in the outer loop search should be considered more extensively.
- Multi-mode case (SPD) gets larger improvement compared with the mono-mode. In turn, it might suggest the poor performance of Weber basis saving method for the SPD problems. However, its poor performance is recovered by the modified tabu search.

Next, we show the result of the scalable case in Table 3. Though we solved only the single-depot delivery problem, we know its performance is pretty good and equivalent to the ordinal case as a whole. As shown in Fig.5, we also confirmed the sufficient convergence both for the ordinal and the generalized Weber model with 1000 customers. These facts still claim the high performance of the proposed approach.

Both for Weber and its generalized bases, in Fig.6, we illustrate the profiles of the gap defined earlier, i.e., Gap = (Cost$_H$($\boldsymbol{x}_L^*$) – Cost$_H$($\boldsymbol{x}_H^*$))/Cost$_H$($\boldsymbol{x}_H^*$) and shown there schematically. It evaluates the relative cost difference between two solutions ($\boldsymbol{x}_H^*$ and $\boldsymbol{x}_L^*$) in the higher realistic environment (denoted by Subscript H). Since every value takes positive value, we know it possible to reduce the actual cost by introducing the scalable data. As it were, it represents a rate of opportunity loss due to missing available more correct data in cost evaluation. Moreover, its magnitude is pretty large and increases along with the problem size. Thus, considering the qualified data has a great advantage over the conventional dealing that has ignored it and promises a certain deployment towards innovative logistics in future real-world applications.

V. CONCLUSION

As a key technology for logistics optimization under global manufacturing and demand on qualified service, this study considers a general and practical framework of the effective algorithm for VRP to cope with various real world applications.

Through numerical experiments, we claim the great possibility and practice of our framework. Depending on the available information or the decision environment, it is easy to extend to more practical power model and/or scalable formulation. Moreover, it has a flexibility to straightforwardly import some new findings on heuristics in local search to improve the solution ability and cope with other variants. Those are some topics in future studies.

ACKNOWLEDGMENT

A part of this research was supported by Grant-in-Aid for Research of JSPS, 17K01250

APPENDIX TWO-DIMENSIONAL AND THREE-DIMENSIONAL TRANSPORTATIONS

As a typical example of driving conditions mentioned in the text, we show a 3-dimensional option (slope) to evaluate the cost more correctly. For this purpose, we are now ready for retrieving such geographic data through Elevation API of Google map, for example. In fact, we know vehicle uses more fuel when driving the upward route while less for the downward compared with the flat. Factor $G(z_{ij})$ is defined as a scale to adjust such driving condition depending on the difference of elevation between two site i and j, h_{ij}. Actually, it is given as the value of $z_{ij} = \tan\theta_{ij} = h_{ij}/d_{ij}$. To get the revised cost Cost(3D), this factor is multiplied with the usual 2-dimensional one, Cost(2D) as Cost(3D) = $G(z_{ij})$*Cost(2D).

Since we could not find an appropriate mathematical model to work with this idea, we assume a sigmoid function referring to the literature that discussed on this issue [10], i.e., $a+b/(1+e^{-cz})$. The profile described in Fig.A-1 is reasonable since it suites to our empirical knowledge such that: the factor exceeds 1 for the upward and falls below 1 for the downward; upward band is greater than that of downward; and the factor will be saturated at both edges of range z. To evaluate this effect practically in real world applications, we divide the route into sub-routes according to the feature such as upward, flat and downward, respectively. Then we compute the revised distance for 3-dimensional

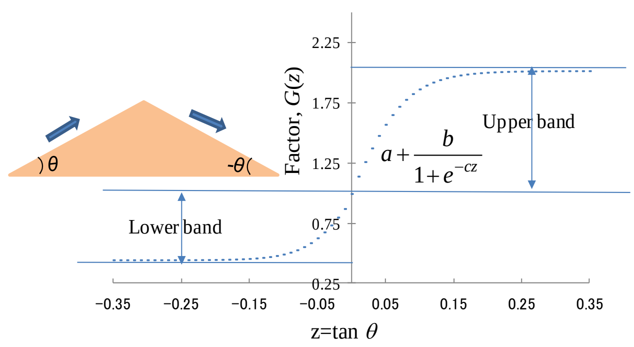


Fig. A-1 A scheme of adjusting factor with slope angle; Factor increases over 1 for the upward and decreases below 1 before saturation at both ends of z

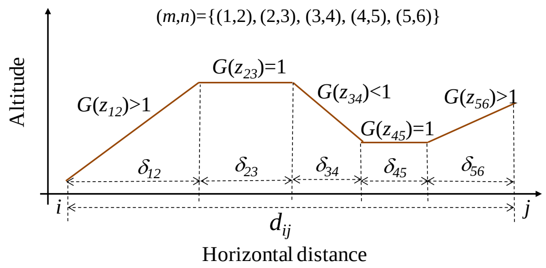


Fig. A-2 A scheme to compute the revised distance for complex configuration of slope: Dividing the route from i to j into sub-routes, we obtain the factor $\tilde{G}$ as the weighted average of each factor with sub-distances δ_{ij}.

case by Eq.(A-1).

$$\tilde{G}(z_{ij})d_{ij} = \sum_{\forall(m,n)} \delta_{mn} G(z_{mn}) \tag{A-1}$$

Here δ_{mn} denotes a distance of sub-route involved in the route as shown in Fig.A-2. Finally, we use this value as the premium or discount factor to compute the transportation cost between two sites.

By gathering relevant information, it is possible to consider the other driving conditions for the elaborate cost accounting just following the similar manner described here.

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