Cost-Oriented Vehicle Routing and Cargo Allocation with Minimum CO$_2$ Emissions Based on Harmony Search Algorithm

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Abstract: Cargo carriers are obligated to reduce the CO$_2$ emissions that result from their cargo transportation activities. However, they tend to focus on reducing cargo transportation costs rather than CO$_2$ emissions. In addition, most cargo carriers entrust all their deliveries to subcontractors, and therefore, vehicle routing and cargo allocation that take only CO$_2$ emissions into consideration are not applicable for them. It is necessary to develop a method to determine cargo allocation and delivery routes for both the cargo carrier and their subcontractors. In our previous work, we proposed a method for solving a vehicle routing and cargo allocation problem where the cost and CO$_2$ emissions must be minimized. This method is not a global search but a hill-climbing method that adjusts a tentative cargo allocation with a low outsourcing fee, which is defined using a simple procedure. In this paper, we propose a method based on a harmony search algorithm. Experiments were conducted using both synthetic data and actual data provided by a cargo carrier in Japan. The results validate the utility of the proposed method.

Key Words: Vehicle Routing, Cargo Allocation, CO$_2$ Emissions, Harmony Search Algorithm

1. Introduction

Cargo carriers are obligated to reduce the CO$_2$ emissions that result from their cargo transportation activities. To achieve this, their policy is to use eco-friendly trucks and exploit the improved convenience of railroad and maritime transport, etc., by using modal shifts. In addition, their policy for improving the physical distribution system includes increasing the number of mixed-loading trucks, etc. As well as implementing these policies, it is indispensable to consider how to determine the route that produces the minimum CO$_2$ emissions.

The vehicle routing problem is used to improve the efficiency of delivery cargo from a depot to two or more delivery points. The objective is typically to minimize the transport distance. Some vehicle routing problems, such as the time window constrained problem [8], have been defined, and various algorithms using mathematical programming [1],[4] and heuristics [2] have been proposed to solve these problems. However, these methods are not applicable to minimizing CO$_2$ emissions. Because the shortest route is not necessarily the route with minimum CO$_2$ emissions in case of delivering cargos of different weights to various delivery points. In addition, CO$_2$ emissions can be decreased by assigning some cargos to a different series of delivery operations or delivering them with different trucks.

Some practical methods were proposed to solve the vehicle routing and cargo allocation problem where minimum CO$_2$ emissions must be considered [5],[6]. These are effective for cargo carriers that contract with senders to deliver cargos and deliver them themselves, but is not applicable for cargo carriers that entrust all the deliveries to subcontractors which at present is a common practice. In addition, both cargo carriers and subcontractors tend to focus on reducing cargo transportation costs rather than CO$_2$ emissions. It is necessary to develop a method to determine cargo allocation and delivery routes for both the cargo carrier and the subcontractors.

The outsourcing fee for cargo deliveries is based on many variables, such as the number of cargos, total weight of cargos, total volume of cargos, number of charter trucks available, time required to charter trucks, transport distance, and so on. The charter fee for a truck depends on the maximum load and the period for which it is chartered, however two small trucks cost more than a single large truck. To reduce the cost, cargo carriers typically allocate cargos to subcontractors to minimize the number of trucks required. Labor costs and fuel costs, which are directly linked to the number of trucks and CO$_2$ emissions, respectively, constitute the greatest transportation costs for the subcontractor. Subcontractors are able to reduce their costs by optimizing delivery routes to minimize CO$_2$ emissions. This leads to eco-friendly physical distribution and associates their company image with eco-friendly operations.

In our previous paper, we proposed a method for solving a vehicle routing and cargo allocation problem with minimum cost and minimum CO$_2$ emissions (VRCAP-MCMCE) that was defined such that it took into consideration not only the outsourcing fee for the cargo carrier, but also the transportation costs for the subcontractors [7]. First, a tentative cargo allocation with a low outsourcing fee is defined using a simple and easy procedure. Then, the cargo allocation is adjusted so that CO$_2$ emissions are reduced while the outsourcing fee is kept at or below the original tentative allocation. This method is not a global search but a hill-climbing method.

In this paper, we propose a method for solving VRCAP-
MCMCE in which a harmony search algorithm is applied. Harmony search is a music-based metaheuristic optimization algorithm that imitates the music improvisation process [3]. In the harmony search algorithm, diversification is controlled by a pitch adjustment and a randomization operation, and intensification is represented by the harmony memory. The proposed method makes it possible to search the optimal solution globally by using a harmony search algorithm.

2. VRCAP-MCMCE

2.1 Calculation Method of CO₂ Emissions

The revised Energy Conservation Law in Japan includes three calculation methods to measure and manage CO₂ emissions during transportation: the fuel consumption method, the fuel efficiency method, and the revised ton-kilometer method. The most accurate method is the fuel consumption method, which calculates CO₂ emissions according to fuel consumption. However, it is impossible for drivers to know the actual fuel consumption prior to transportation, and thus, they cannot use the fuel consumption method to plan their delivery route. Therefore, either the fuel efficiency method or revised ton-kilometer method is used as an alternative. When considering the load calculation methods to measure and manage CO₂ emissions, the harmony search algorithm is applied. Har

\[ e = w \times d \times y \times \alpha \times 10^{-3} \]  

where \( w \) (t) is the cargo weight, \( d \) (km) is the transport distance, \( y \) (L/h km) is the amount of fuel consumption per ton-kilometer, and \( \alpha \) (t-CO₂/kL) is the CO₂ emission factor, which is defined by fuel type in the bulletin of the Energy Conservation Law. The value of \( \alpha \) for light oil is 2.62 t-CO₂/kL. The 66th bulletin of the Japanese Ministry of Economy, Trade and Industry states that the value of \( y \) for a truck using light oil should be calculated as:

\[ \ln y = 2.71 - 0.812 \ln \frac{x}{100} - 0.654 \ln z \]  

where \( z \) (kg) is the maximum load of the truck and \( x \) (%) is the load efficiency. When the load efficiency is less than 10%, \( y \) is calculated using \( x = 10\% \).

2.2 Propositions

VRCAP-MCMCE is defined using the following propositions.

- The cost to charter a single truck depends on the maximum load of the truck. Larger trucks are more expensive, but two small trucks are more expensive than a single large truck. The standard fee is about 30,000 JPY for a 2 ton truck, 40,000 JPY for a 4 ton truck, and 50,000 JPY for a 10 ton truck.

- All cargos can be delivered without using any truck more than once in charter period.

- Delivery points are divided into groups called units. A series of delivery operations is performed for each unit. In other words, a truck is assigned and a corresponding route is determined for each unit.

- All routes start and finish at a depot. Trucks do not return to a depot during one delivery trip.

- The following data are given:
  - The total number of the trucks owned by the subcontractors and the variation in the maximum loads of those trucks.
  - The weight of the cargo to be delivered to each delivery point.
  - The symmetrical transport distances between all pairs of delivery points.
  - The symmetrical transport distances between all delivery points and the depot.

2.3 Notations

The number of delivery points is denoted by \( N \), and the delivery points are numbered from 1 to \( N \). The depot is numbered 0. In this paper, the numbers that identify delivery points are called “dpIDs.” The number of units is denoted by \( M \), and the \( i \)th unit is denoted by \( U_i \). The number of delivery points in \( U_i \) is denoted by \( N_i \). A route for \( U_i \) is denoted by a vector \( r_i \).

\[ r_i = (r_i[0], r_i[1], \ldots, r_i[N_i], r_i[N_i + 1]) \]  

where \( r_i[j] \) is the dpID of the \( j \)th visited delivery point in \( U_i \). As the depot is both the starting and terminal point of the route, \( r_i[0] \) and \( r_i[N_i + 1] \) are set to 0. The cargo weight to be delivered to delivery point \( n \) is denoted by \( w_n \) (1 ≤ \( n \) ≤ \( N_i \)). The total weight of all the cargos on the truck being transported from \( r_i[k - 1] \) to \( r_i[k] \) is denoted by \( W_i[k] \) (1 ≤ \( k \) ≤ \( N_i + 1 \)), as defined by

\[ W_i[k] = \sum_{n \in U_i} w_n - \sum_{j=1}^{k-1} w_{r_i[j]} \]  

The transport distance between delivery points \( i \) and \( j \) is denoted by \( d_{ij} \) (0 ≤ \( i \) ≤ \( N \), 0 ≤ \( j \) ≤ \( N \)). All \( d_{ij} \) are set to 0. The total transport distance \( d_i \) for \( U_i \), the weighted average cargo weight \( w_i \) for \( U_i \), and the amount of fuel consumption per ton-kilometer \( y_i \) for \( U_i \) are respectively calculated as

\[ d_i = \sum_{j=0}^{N_i+1} d_{r_i[j-1], r_i[j]} \]  

\[ w_i = \frac{1}{d_i} \sum_{k=1}^{N_i} W_i[k] \times d_{r_i[k-1], r_i[k]} \]
\[
\ln y_i = 2.71 - 0.812 \ln \frac{u_i}{z_i} - 0.654 \ln z_i
\]  

(7)

where \(z_i\) is the maximum load of the truck assigned to \(U_i\). The total \(CO_2\) emissions that result from transporting cargo along routes \(r_1, r_2, \ldots, r_M\) is calculated as

\[
f(r_1, \ldots, r_M) = \sum_{i=1}^{M} w_i \times d_i \times y_i \times \alpha \times 10^{-3}
\]  

(8)

VRCAP-MCMCE can be considered as an optimization problem that finds the vectors \(r_1, r_2, \ldots, r_M\), which minimize the objective function in equation (8) while minimizing the outsourcing fee. The total outsourcing fee \(g(U_1, \ldots, U_M)\) is the sum of the charter fee of trucks that are assigned to units \(U_1, \ldots, U_M\).

\[
g(U_1, \ldots, U_M) = \sum_{i=1}^{M} g'(z_i)
\]  

(9)

where \(g'(z_i)\) is the charter fee of a truck whose maximum load is \(z_i\).

3. Method for VRCAP-MCMCE Based on Harmony Search

3.1 Adjustment Operators

In our previous paper [7], a method for solving VRCAP-MCMCE was proposed. First, a tentative cargo allocation with a low outsourcing fee is defined using a simple and easy procedure. Then, the cargo allocation is adjusted so that \(CO_2\) emissions are reduced while the outsourcing fee is kept at or below the original tentative allocation. In other words, the cargo allocation is adjusted so that the total transportation costs for the subcontractors are reduced. Repeated adjustments lead to reductions in both cost and \(CO_2\) emissions. This method is called the “gradual method” in the following sections.

The gradual method is not a global search but a hill-climbing method that adjusts a tentative cargo allocation. In order to search a solution space globally and efficiently, an evolutionary computation algorithm is applied.

The cargo allocation of a solution candidate is adjusted by the following two operators in a gradual method.

- Select one cargo from a truck, and allocate to the other truck.
- Select one cargo from two trucks respectively, and exchange them.

As it is possible to find valid solutions by the gradual method, these adjustment operators should be adopted. A harmony search algorithm is the evolutionary computation algorithm that can adopt these operators most easily.

3.2 Harmony Search Algorithm

The harmony search algorithm imitates a musician’s improvisation process [3]. Searching for a perfect state of harmony is analogous to solving an optimization problem. When a musician is improvising, he/she plays music using any one of the following three methods.

i. Select any famous piece from his/her memory.

ii. Adjust slightly the pitch of a known piece.

iii. Compose a new piece.

In the harmony search algorithm, a candidate solution is represented as a harmony, and a set of harmonies is called a harmony memory. New candidates are generated using the following three operators, each of which corresponds to one of the above-mentioned improvisation methods, in the same order.

i. Choose one harmony from the harmony memory, and copy the value of the relevant variable.

ii. Choose one harmony from the harmony memory, and adjust the value of the relevant variable.

iii. Randomly generate a new value of the relevant variable.

Diversification and intensification are necessary for an optimization algorithm. Diversification encourages a search for various candidate solutions. Intensification encourages quick convergence to the optimal solution. In the harmony search algorithm, diversification is controlled by the pitch adjustment and randomization operations, and intensification is represented by the harmony memory.

The pseudocode of the harmony search algorithm is presented in Fig. 1. \(H\) is the number of harmonies in the harmony memory, \(K\) is the number of repetitions, \(V\) is the number of variables in a harmony, \(R_c\) is the harmony memory considering rate, \(R_a\) is the pitch adjusting rate, and \(h(s)\) is an evaluation value of a harmony \(s\).

3.3 Harmony Search Algorithm for Cargo Allocation

This paper proposes a cargo allocation method based on a harmony search algorithm. \(N\) delivery points are divided into \(M\) units so that \(CO_2\) emissions are minimized while minimizing the outsourcing fee by the proposed method.
A harmony represents a cargo allocation. In a harmony, all trucks that the subcontractors own are located in line in order of the serial number for each maximum load of truck. Each truck contains dpIDs whose cargos are allocated to the truck. Trucks that have no allocated cargos are empty. Fig. 2 shows an example of a harmony for the case where the subcontractors own three 10 ton trucks, two 4 ton trucks, and two 2 ton trucks. When a truck is treated as a variable, the number of variables in a harmony V is set to 7. Here, cargos for the delivery point with the dpID “1” and “3” are allocated to the 10 ton truck with the serial number “1.” Hyphen “-” means that the truck is empty.

The entire procedure is as follows:

Step 1. Generate a tentative cargo allocation.

(a) Calculate a route that includes all the delivery points using Dijkstra’s algorithm. The starting point is set to the farthest delivery point from the depot. The dpIDs are renumbered according to the servicing order of this initial route.

(b) Each truck is given a serial number based on the truck’s maximum load.

(c) Each cargo is allocated to a truck in the order of the newly assigned dpID. The largest available truck that has sufficient space available for the cargo is selected. When there are two or more trucks whose maximum load are same, the truck with the smallest serial number is selected.

Step 2. Initialize a harmony memory using the tentative cargo allocation.

(a) Adjust the tentative cargo allocation by applying one of the adjustment operators described in Section 3.1, and make it a harmony of an initial harmony memory.

(b) Calculate a delivery route for each truck and the corresponding CO₂ emissions of the harmony.

(c) Calculate the evaluation value of the harmony.

(d) Repeat (a) - (c) H times.

Step 3. Generate a new harmony, and calculate a delivery route for each truck and the corresponding CO₂ emissions of the harmony.

Step 4. Calculate the evaluation value of the harmony.

Step 5. If the evaluation value is lower than that of the worst harmony in the harmony memory, exchange them.

Step 6. Repeat Step 3 - 5 K times.

In (a) of Step 1, the dpIDs are renumbered to prevent the solution from being affected by the dpID numbering. If cargo allocation is performed based on only cargo weights, the transport distance will become large meaninglessly. Cargos for delivery points that are located near one another should be allocated to the same truck. By allocating cargos in the order of dpID in (c), cargos for neighboring delivery points are likely to be allocated to the same truck. In addition, by giving priority to a larger truck in (c), the number of the trucks to be used, i.e., the outsourcing fee decreases.

When a new harmony is generated in Step 3, the following Operation A or B is used. The operation to use is selected according to the provided probability distribution.

Operation A. Adjust one harmony selected from the harmony memory as in a gradual method.

• Select one cargo from a truck, and allocate to the other truck.

• Select one cargo from two trucks respectively, and exchange them.

• Reallocation cargos except those on one truck selected randomly.

Operation B. Generate a new harmony by applying the harmony search operators that treat a truck as a variable.

• Choose one harmony from the harmony memory, and copy the truck concerned.

• Choose one harmony from the harmony memory, and add or reduce or exchange one cargo loaded on the truck concerned.

• Generate a new truck randomly.

Since Operation B causes a larger change than Operation A, probability P(k) is defined as equation (10). The larger the repetition count is, the more frequently Operation A is used.

\[
P(k) = 0.5 \times \frac{k}{K} + 0.5
\]  

The evaluation value \( h(s) \) of a harmony s is defined as the weighted sum of the total outsourcing fee \( g(U_1, \ldots, U_M) \) [JPY] and total CO₂ emissions \( f(r_1, \ldots, r_M) \) [kg-CO₂].

\[
h(s) = \beta \cdot g(U_1, \ldots, U_M) + f(r_1, \ldots, r_M) \cdot 10^3
\]  

The lower the evaluation value is, the better the harmony. Here, \( U_1, \ldots, U_M \) are units that are represented as a set of dpIDs allocated to trucks in a harmony s. \( r_1, \ldots, r_M \) are vectors that represent delivery routes based on a harmony s. Delivery routes are searched using the method proposed in our previous paper [5]. \( \beta \) should be set so that the outsourcing fee takes priority over CO₂ emissions.

4. Experiments

To confirm the effectiveness of the proposed method, experiments were conducted using both actual and synthetic data. VRCAP-MCMCE is solved by the gradual and the proposed method. The parameters for the proposed method are listed in Table 1.
### 4.1 Evaluation with Actual Data

We collected actual data from a cargo carrier in Inashiki city, Japan. The data contained all the transport distances between all combinations of the depot and the 32 customers. The locations of the depot and the delivery points are shown in Fig. 3. Three scenarios, case1, case2, and case3, were defined for potential cargo weights, as listed in Table 2. The subcontractors own two 2 ton trucks, two 1 ton trucks, and two lightweight trucks. The maximum load of a lightweight truck is 350 kg. The cost to charter each size of truck is set to 30,000 JPY, 25,000 JPY, and 22,000 JPY, respectively.

Route and cargo allocation for each situation were searched using the gradual and the proposed method ten times. Table 3 shows the total transport distance, the total CO\(_2\) emissions, the outsourcing fee, and number of trucks required for the tentative cargo allocation obtained before adjustment and the final cargo allocation obtained after adjustment for all three cargo weight scenarios. The required trucks in tentative cargo allocation did not change after performing the adjustment procedure for any of the three scenarios using both methods. The CO\(_2\) emissions of the cargo allocations obtained by the proposed method were lower than those obtained by the gradual method. Thus, a delivery route with lower CO\(_2\) emissions and the same outsourcing fee can be obtained stably by the proposed method.

The standard deviations of CO\(_2\) emissions before adjustment in case2 and case3 are lower than those in case1. In case2 and case3, the standard deviations of CO\(_2\) emissions by the proposed method are lower than those by the gradual method. Especially, in the case where the stable tentative cargo allocation is obtained, a better solution can be certainly obtained by the proposed method.

The delivery routes for case1 before and after adjustment are shown in Fig. 4 and 5, respectively. The figures show enlarged maps of the delivery points shown in Fig. 3. The circled dpIDs are the delivery points for heavier cargos. The dpIDs indicated with arrows correspond to the first visited point, \(r_1[1]\). Although a route between two delivery points is denoted by a straight line, the trucks actually move along roads. The lines (a) (b), the lines (c) (d), and the line (e) correspond to the delivery routes for the 2 ton trucks, 1 ton trucks, and lightweight truck, respectively.

Heavier cargo is typically delivered early in each route to reduce CO\(_2\) emissions. It is important to note that the delivery points that were assigned to the same unit as the delivery point for heavier cargo were changed by the adjustment. Before adjustment, delivery point 6 was assigned to a unit that included delivery points located far from the depot. After adjustment, however, delivery point 6 belonged to the same unit as delivery points 14 and 15, which are closer to the depot than delivery point 6. Lighter cargos are unloaded on the way to delivery point 6 according to this allocation. In addition, delivery point 25 was originally assigned to a unit that included delivery point 30, creating a long route with few deliveries. After the cargo allocation adjustment, delivery point 25 was included in the same unit as delivery point 24, which is in the same neighborhood.

The cargo allocations for the lightweight truck obtained by the gradual method and proposed method are very different. In the case of the proposed method, cargos destined for two delivery points that are near to the depot are allocated to the lightweight truck, and cargos with delivery points that are far from depot are allocated to 2 ton trucks. This results in lower CO\(_2\) emissions.

### 4.2 Evaluation with Synthetic Data

To confirm the effectiveness of our method when applied to a large number of delivery points, an experiment with synthetic data was also conducted. One hundred delivery points are located on the grid in the \(xy\)-plane within \(0 \leq x \leq 9\) and \(0 \leq y \leq 9\). The depot is located at the point \(x = 5\) and \(y = 30\), that is far from delivery points. The transport distance between two delivery points is defined as the Manhattan distance. Each division of the \(x\)-axis and \(y\)-axis is 6 km and 3 km, respectively.

The cargo weight for each delivery point is defined randomly, creating a long route with few deliveries. After the cargo allocation adjustment, delivery point 6 was assigned to a unit that included delivery points located far from the depot. After adjustment, however, delivery point 6 belonged to the same unit as delivery points 14 and 15, which are closer to the depot than delivery point 6. Lighter cargos are unloaded on the way to delivery point 6 according to this allocation. In addition, delivery point 25 was originally assigned to a unit that included delivery point 30, creating a long route with few deliveries. After the cargo allocation adjustment, delivery point 25 was included in the same unit as delivery point 24, which is in the same neighborhood.

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### Table 1 Parameters

| Parameter                        | Value      |
|----------------------------------|------------|
| maximum number of repetitions, \(K\) | 30000      |
| harmony-memory-considering rate, \(R_s\) | 0.85       |
| pitch-adjusting rate, \(R_a\)     | 0.30       |
| size of harmony memory, \(H\)     | 30         |
| weight for evaluation value, \(\beta\) | 10000      |

### Table 2 Cargo weight scenarios

| Scenario | Cargo weight                                      |
|----------|--------------------------------------------------|
| case1    | \(w_1 = w_{12} = 750\) kg, others = 150 kg      |
| case2    | \(w_1 = w_{13} = 750\) kg, others = 150 kg      |
| case3    | \(w_1 = w_{18} = 750\) kg, others = 150 kg      |

### Fig. 3 Locations of the depot and delivery points

### Fig. 4 Routes for case1 before adjustment
### Table 3 Effects of adjustment with the actual data

| Scenario | Adjust       | Transport distance [km] | CO₂ emission [kg-CO₂] | Outsourcing fee [JPY] | Number of trucks |
|----------|-------------|-------------------------|-----------------------|----------------------|------------------|
|          |             | Ave.  | S D  | Ave.  | S D  |          | 2 t | 1 t | lightweight |
| case1    | before      | 355.61 | 0.46 | 137.14 | 0.21 | 132,000 | 2   | 2   | 1           |
|          | gradual     | 340.40 | 0.51 | 133.02 | 0.24 | 132,000 | 2   | 2   | 1           |
|          | proposed    | 340.27 | 0.90 | 132.95 | 0.32 | 132,000 | 2   | 2   | 1           |
| case2    | before      | 360.02 | 0.22 | 138.03 | 0.07 | 132,000 | 2   | 2   | 1           |
|          | gradual     | 342.78 | 1.74 | 133.61 | 0.64 | 132,000 | 2   | 2   | 1           |
|          | proposed    | 340.82 | 0.87 | 132.76 | 0.11 | 132,000 | 2   | 2   | 1           |
| case3    | before      | 360.05 | 0.26 | 138.29 | 0.09 | 132,000 | 2   | 2   | 1           |
|          | gradual     | 342.79 | 1.25 | 133.67 | 0.58 | 132,000 | 2   | 2   | 1           |
|          | proposed    | 342.02 | 1.06 | 133.23 | 0.22 | 132,000 | 2   | 2   | 1           |

Figure 5 Routes for case1 after adjustment

![Transport distance: 339.94 km
CO₂ emission: 132.80 kg-CO₂
(a) Gradual method](image1)

![Transport distance: 338.84 km
CO₂ emission: 132.43 kg-CO₂
(b) Proposed method](image2)

Figure 6 Locations of the delivery points and cargo weights [kg] in the synthetic data

![Fig. 6 Locations of the delivery points and cargo weights [kg] in the synthetic data](image3)

Figure 7 shows the change in the evaluation value of the best harmony in the harmony memory. This indicates that better solutions are certainly found in the early stage by the proposed method than by the gradual method.

The best delivery routes before and after adjustment are shown in Fig. 8 and 9, respectively. Delivery points in each neighborhood belong to the same unit before adjustment. However, widely separated delivery points are included in the same unit after adjustment. This phenomenon is a result of the fact that smaller trucks are being employed in order to decrease the total CO₂ emissions.

Indicates the cargo weight associated with that delivery point. The subcontractors own five 10 ton trucks, five 4 ton trucks, and five 2 ton trucks. The cost to charter each size of truck is set to 50,000 JPY, 40,000 JPY, and 30,000 JPY, respectively.

Route and cargo allocation for this situation were searched using the gradual and the proposed method ten times. VRCAP-MCMCE was solved using the gradual and proposed method ten times. Table 4 shows the total transport distance, the total CO₂ emissions, the outsourcing fee and number of trucks required for the tentative cargo allocation obtained before adjustment and the final cargo allocation obtained after adjustment. The required trucks were five 10 ton trucks and two 4 ton trucks in the tentative cargo allocation. This became five 10 ton trucks, one 4 ton truck, and one 2 ton truck after performing the adjustment procedure using both methods. Thus, cargo allocations with a lower outsourcing fee were found. The average and standard deviation of CO₂ emissions by the proposed method are lower than those by the gradual method. The CO₂ emissions of the solutions that were obtained stably by the proposed method were lower than those obtained by the gradual method.

Fig. 7 shows the change in the evaluation value of the best harmony in the harmony memory. This indicates that better solutions are certainly found in the early stage by the proposed method than by the gradual method.

The best delivery routes before and after adjustment are shown in Fig. 8 and 9, respectively. Delivery points in each neighborhood belong to the same unit before adjustment. However, widely separated delivery points are included in the same unit after adjustment. This phenomenon is a result of the fact that smaller trucks are being employed in order to decrease the total CO₂ emissions.
Table 4  Effects of adjustment with the synthetic data

| Adjust   | Transport distance [km] | CO$_2$ emission [kg-CO$_2$] | Outsourcing fee [JPY] | Number of trucks |
|----------|-------------------------|-----------------------------|----------------------|------------------|
|          | Ave. | $SD$ | Ave. | $SD$ |                     |                  |
| before   | 1685.40 | 21.37 | 1279.45 | 16.54 | 330,000 | 5 | 2 | 0 |
| gradual  | 1564.80 | 24.71 | 1176.45 | 18.17 | 320,000 | 5 | 1 | 1 |
| proposed | 1546.80 | 13.09 | 1160.81 | 8.31  | 320,000 | 5 | 1 | 1 |

5. Conclusion

In this paper, we proposed a method based on a harmony search algorithm for solving VRCP-MCMCE. The experimental results show that solutions with lower CO$_2$ emissions can be obtained by the proposed method. Therefore allocating cargo to trucks using the proposed method does not increase the cost for the cargo carrier, but does decrease the costs for the subcontractors. In addition, this method also allows the CO$_2$ emissions resulting from delivery activities to be reduced.

In the future, it is necessary to develop new adjustment operators and examine the applicability of other evolutionary computation algorithms.

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