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An artificial bee colony-based hybrid approach for waste collection problem with midway disposal pattern

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Abstract

This paper investigates a waste collection problem with the consideration of midway disposal pattern. An artificial bee colony (ABC)-based hybrid approach is developed to handle this problem, in which the hybrid ABC algorithm is proposed to generate the better optimum-seeking performance while a heuristic procedure is proposed to select the disposal trip dynamically and calculate the carbon emissions in waste collection process. The effectiveness of the proposed approach is validated by numerical experiments. Experimental results show that the proposed hybrid approach can solve the investigated problem effectively. The proposed hybrid ABC algorithm exhibits a better optimum-seeking performance than four popular metaheuristics, namely a genetic algorithm, a particle swarm optimization algorithm, an enhanced ABC algorithm and a hybrid particle swarm optimization algorithm. It is also found that the midway disposal pattern should be used in practice because it reduces the carbon emission at most 7.16% for the investigated instances.

Keywords

Hybrid artificial bee colony algorithm, Waste collection problem, Carbon emissions, Midway disposal pattern

1. Introduction

Municipal Solid Waste (MSW) collection is an important public service and logistics activity [1]. It consists of the processes of gathering wastes from different areas, loading and transporting by vehicles, and dumping at disposal facilities [2]. Effective MSW collection and disposal are recognized as one of urgent requirements for sustainable social development [3]. The Waste Collection Problem (WCP) aims to generate effective MSW collection solutions by yielding effective waste collection routes for different vehicles [4], which is one type of vehicle routing problems (VRPs) in essence [2], [5].

Research on WCP has received increasing attention in recent years. In Tung and Pinnoi's study [2], vehicles were applied to collect wastes from different collection points under time window constraints and the full-load wastes were dumped at a landfill. The objectives were to optimize the travel times and distances of vehicles. Kim et al. [6] investigated a WCP with the objective of minimizing the number of vehicles and the total travel time by extending the Solomon's insertion algorithm [7]. Multiple disposal facilities, collection time windows of customers and driver rest periods were considered in their model. Louati [1] proposed a general MSW collection model with the consideration of multiple transfer stations, collection points and heterogeneous vehicles. Comparing to the practical model, total travel distances and operational hours were reduced by applying this new model. Some researchers have considered other objectives including minimizing the total travel cost, the total transportation cost, the labor cost, the travel distance and the number of vehicles used [5], [8], [9], [10]. In recent years, WCPs with sustainability-related constraints and objectives have received increasing attention. Apaydin and Gonullu [11] focused on the exhaust emission reduction of vehicles in solid waste collection processes by using a software to optimize the waste routes. Faccio et al. [12] presented a vehicle routing model for solid waste collection, which is helpful to reduce engine emissions, traffic congestion and noise.

However, some realistic features in WCP have not been considered in previous studies. For example, the emissions and fuel consumptions were calculated usually based on the travel distance without consideration of the wastes loaded on vehicles in the collection process, which results in inaccurate emissions and fuel consumptions. In addition, the waste disposal pattern was considered to be a fully-loaded disposal pattern (FDP), by which wastes were dumped only when the vehicle is fully-loaded [5,6]. In some realistic situations, when vehicles have collected a certain amount of wastes (not fully-loaded) from several waste collection points, they could empty themselves by dumping the wastes to the nearest disposal facility dynamically, which is the so-called *midway disposal pattern* (MDP). According to the emission model proposed by Franceschetti et al. [13], vehicles with lower weight of wastes could generate the less carbon emissions in waste collection. Thus, after those vehicles empty themselves and start to collect other points in MDP, their carbon emissions could decrease largely since their total load drops dramatically. It is thus crucial to decide when the vehicle should empty itself and which disposal facility should be visited since the MDP is helpful to reduce carbon emissions. However, MDP has not been considered in WCP, which allows the vehicle to dump wastes dynamically, even if the vehicle is not fully loaded.

This paper thus investigates a WCP with MDP and the total carbon emission cost minimization objective, which is termed as WCP-MDP. The investigated problem can be considered as a VRP with dynamic disposal trips. It is well known that VRPs are NP-hard [14–17]. Realistic features in waste collection, such as multiple disposal facilities and midway disposal pattern, further increase the complexity of the WCP-MDP. Various approaches have been developed for WCPs and VRPs, including linear programming [18], mixed integer programming [2,19], heuristics [10,20], and meta-heuristics such as ant colony optimization algorithm (ACO) [4,21], genetic algorithm (GA) [22,23], particle swarm optimization algorithm (PSO) [3,24], artificial bee colony algorithm (ABC) [25,26] and variable neighborhood descent algorithm (VND) [27,28]. Due to the NP-hard nature, the WCP-MDP problem cannot be solved effectively by mathematical programming techniques and traditional heuristics within an affordable time [29]. Metaheuristics have the potentials to provide optimal or near-optimal solutions to complex NP-hard problems within a reasonable time [30–36]. In the waste collection and VRP literature, various metaheuristics have been used to solve WCPs and VRPs, among which GA and PSO are the most commonly used ones. It is well-known that different parameter settings for metaheuristics could lead to different optimization results. The metaheuristics with less parameters are thus usually easier to use. Comparing to PSO and GA, ABC provides a simpler parameter mechanism for global search, which only needs to set two parameters and has a mechanism to accelerate the convergence [26]. ABC has been adopted to solve effectively a wide variety of optimization problems in recent years [37–43]. Many studies have reported the comparison results between ABC and other popular metaheuristics such as GA and PSO, which show that ABC can provide better solutions within less computation time [38,44]. We refer interested readers to two comprehensive surveys on ABC algorithms [37,45]. However, no research has reported the application of ABC to WCPs. This paper thus develops an ABC-based solution approach to handle the investigated WCP-MDP.

Traditional metaheuristics could trap into local optimum for large-scale optimization problems. In recent years, various hybrid optimization techniques have been developed by integrating the search mechanism of global search and local search, which exhibited superior optimization performances to popular metaheuristics (e.g., GA, PSO and ACO) in various real-world applications [46–49]. The performance of hybrid optimization techniques are affected by the algorithms nested for its global search and local search. As aforementioned, ABC is a good candidate to perform the global search. In addition, VND is an effective local search approach [50], which has exhibited good performances in various applications [51,52]. Thus, it is desirable to develop a hybrid optimization approach by integrating the global search capability of ABC and the local search capability of VND since ABC and VND-based hybrid approach has not been reported in the literature.

This paper contributes to the literature by (1) extending waste collection research by considering the realistic midway disposal pattern, and (2) developing an ABC-based hybrid approach to solve this problem effectively. The rest of this paper is organized as follows. In Section 2, the mathematical model of the investigated WCP-MDP is formulated. Section 3 presents the ABC-based hybrid approach. In Section 4, numerical experiments are presented and experimental results are analyzed firstly to validate the effectiveness of the proposed approach. Then we examine the carbon emission reduction generated by the MDP, and the timing of applying VND. Finally, Section 5 concludes the paper and suggests future research directions.

2. Problem statement

2.1. Problem description

The WCP-MDP can be defined on a directed graph $G(C, A, D)$, where $C = \{0, \ldots, c\}$ is the node set of collection points, $D = \{c+1, c+2, \ldots, n\}$ is the set of disposal facilities. Let N denotes the set of nodes consisting of all collection points and all disposal facilities, i.e., $N = C \cup D$. In addition, $A = \{(i, j) \mid \forall i, j \in N, i \neq j\}$ is the set of arcs among all collection points and disposal facilities. Each vehicle is assigned to a route with a sequence of nodes (including waste collection points and disposal facilities). Each collection point of the assigned route is served once and all wastes are loaded and dumped. This research sets that a vehicle can visit disposal facilities at most twice in a single tour. That is, each vehicle perform the midway disposal only once at most. This setting is reasonable in real-world waste collection practice. First, the number of disposal facilities is usually very limited in each single waste collection area due to cost concerns. Second, the service area of each vehicle is usually limited and too many disposal facilities are unnecessary. The carbon emission EC_{ij} of traveling on arc (i, j) is equal to $\alpha \cdot S_{ij}$, where α(\$/kg) is the cost of unit carbon emission, S_{ij}(kg) is the carbon emission incurred on arc(i, j). This research adopts a shadow price of carbon, \$120 per ton carbon emission [53]. That is, the cost of unit carbon emission α equals to 0.12\$/kg.

The objective is to minimize the summation of carbon emission costs (unit: \$) of all vehicles. The decision variable of the WCP-MDP is denoted by x_{ijk}. x_{ijk} is 1 if vehicle k collects wastes from two different nodes i and j, otherwise it is 0. y_{ik} is an intermediate variable. It is 1 if node i is collected by vehicle k, otherwise it is 0. Notations used in this section are listed out in Appendix A.

Given a waste collection task, the carbon emission S_{ij} on arc (i, j) is equal to the product of the fuel emission factor θ and the fuel consumption δ_{ij} on this arc [54], i.e., $S_{ij} = \theta \cdot \delta_{ij}$. The fuel emission factor θ is a constant, which is defined as the amount (kilogram) of CO_2 emitted per liter of fuel (diesel). The fuel consumption δ_{ij} (liters) is defined by the comprehensive emissions model developed by Franceschetti et al. [13], from which the following equation can be derived (detail is shown in Appendix B):

$$S_{ijk} = \rho_1 l_{ijk} + \rho_2 l_{ijk} w_{ijk} \tag{1}$$

where ρ_1 and ρ_2 are pre-given parameters, l_{ijk} is the travel distance (m), and w_{ijk} is the total weight of vehicle (kg) composed of the curb weight and the vehicle load.

2.2. Mathematical model

The mathematical model of the WCP-MDP is formulated as follows:

Minimize

$$F(x_{ijk}) = \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{K}\left(\alpha \cdot S_{ijk} \cdot x_{ijk}\right) \quad (2)$$

subject to

$$\sum_{i=0}^{n} x_{ijk} = y_{jk}, \qquad \forall j \in N, k \in K \quad (3)$$

$$\sum_{j=0}^{n} x_{ijk} = y_{ik}, \qquad \forall i \in N, k \in K \quad (4)$$

$$\sum_{k=1}^{K} y_{ik} = 1, \qquad \forall i \in C \quad (5)$$

$$\sum_{k=1}^{K} y_{0k} = K \quad (6)$$

$$\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ijk} = |P| - 1, \quad P \subseteq \{1, \dots, n\}; 2 \le |P| \le n-1; \forall k \in K \quad (7)$$

$$\sum_{i=1}^{c} x_{ijk} \le 2, \qquad \forall j \in D, k \in K \quad (8)$$

$$\sum_{j=0}^{c} x_{ijk} \ge 1, \qquad \forall i \in D, k \in K \quad (9)$$

$$L_{jk} = q_j + \sum_{i=0}^{n}(x_{ijk}L_{ik}), \quad \forall i \to j, j \in C, k \in K \quad (10)$$

$$L_{jk} \le Q, \qquad \forall j \in C, k \in K \quad (11)$$

$$L_{ik} = 0, \qquad \forall i \in D, k \in K \quad (12)$$

$$w_{ijk} = M + L_{ik}, \qquad \forall i, j \in N, k \in K \quad (13)$$

$$S_{ijk} = \rho_1 l_{ijk} + \rho_2 l_{ijk} w_{ijk}, \quad \forall i, j \in N, k \in K \quad (14)$$

$$x_{ijk}, y_{ik} \in \{0, 1\}, \qquad \forall i, j \in N, k \in K \quad (15)$$

The objective function of the model is given in (2) which minimizes the total carbon emission cost of all vehicles. Constraints (3)–(4) guarantee that each vehicle arrives and departs from any node when it serves this node. Constraint (5) ensures that each collection point is served once. Constraint (6) ensures that all vehicles commence from the depot. Constraint (7) ensures sub-tour elimination. Constraint (8) enforces the vehicle to visit the disposal facility at most twice, while constraint (9) ensures that the vehicle visits the next collection point or returns to the depot from the disposal facility. Constraint (10) denotes the accumulated weights of any collection point. Constraint (11) ensures that the total amount of wastes collected in a route do not exceed the maximum load of each vehicle. Constraint (12) ensures all the wastes on a vehicle are dumped in the disposal facility. Constraint (13) calculates the total load of vehicle on arc(i, j). The carbon emission on arc(i, j) is calculated by constraint (14). Constraint (15) indicates the value ranges of variables x_{ijk} and y_{ik}.

3. The artificial bee colony-based hybrid approach

This section presents the ABC-based hybrid approach for the WCP-MDP problem. This approach consists of a hybrid artificial bee colony algorithm and a midway disposal trip selection heuristic, which is termed as HABC-MDT. The selection heuristic decides where and when the vehicle needs to dump wastes. To achieve a good optimum-seeking performance, the HABC hybridizes the enhanced artificial bee colony algorithm (EABC) developed by Szeto et al. [55] and the variable neighborhood decent (VND) algorithm developed by Hansen et al. [27].

3.1. Overview of the hybrid artificial bee colony algorithm

This section describes how the proposed HABC is used to solve the WCP-MDP. The flow chart of proposed HABC-MDT is presented in Fig. 1. First, the parameters are initialized in step 1. The initial population G_{ip} for the investigated WCP-MDP are generated by random permutation in step 2. The fitness of each individual in the initial population is evaluated by the MDT procedure described in Section 3.4 in step 3. Then some neighborhood operators (i.e., random swap, random insertion, reversing a sequence et al.) described in the EABC [55] are randomly chosen to generate new populations G_{np} based on the current population in step 4. This step aims to improve the diversity of new populations in the early stage of HABC. The MDT procedure is reused to evaluate the new solutions in step 5. Then, in step 6, the improved solutions are updated to form the new population by employing the roulette wheel selection method described in [56]. In step 7, the abandon condition is checked. If a predetermined number (*limit*) of operations is reached, some bad individuals which have never generated any improved solutions are replaced by randomly generated solutions; otherwise, it returns to step 4. The loop in steps 4–7 is terminated until the maximal number of neighborhood operations, denoted by *limit*, are reached or the improved solution is found. Next, the VND is employed for local search improvement of current population by intensifying the exploitation of candidate solutions in step 8. In step 9, the MDT procedure, same to steps 3 and 5, is used to evaluate the new solutions obtained by local search. Then, the greedy selection is applied to obtain the new generation in step 10. After each cycle, the termination condition is checked in step 11. If a specified maximum number t_{max} of iterations is reached or no better individual is generated in some consecutive iterations, the iterative process of the HABC algorithm is terminated. The best candidate individuals S_{best} are returned as the best solutions generated by the HABC algorithm in step 12.

3.2. Initial solutions and evaluation function

We adopt giant tours to represent the sequences of waste collection points, i.e. a random permutation of points without delimiters. When this representation is applied for WCP-MDP, a decoding procedure which divides the random permutation into several sub-tours is needed. We adopt the optimal splitting procedure proposed by Prins [15] to split the giant tour into sub-tours. These sub-tours are then used for local search by applying the neighborhood structures, which are described in Section 3.3.

The evaluation function is defined as $f(\mathbf{x}) = e(\mathbf{x}) + \psi \cdot p(\mathbf{x})$, where $\mathbf{x}$ denotes a candidate solution, $e(\mathbf{x})$ is the carbon emission cost of this solution, $p(\mathbf{x})$ is the total violation of the capacity constraint. The second term in the evaluation function is used to handle capacity constraint (11), in which the penalty coefficient ψ is a self-adaptive parameter. It gradually enlarges with the increase of the number of iterations, the detail of which will be described in Section 4.1.

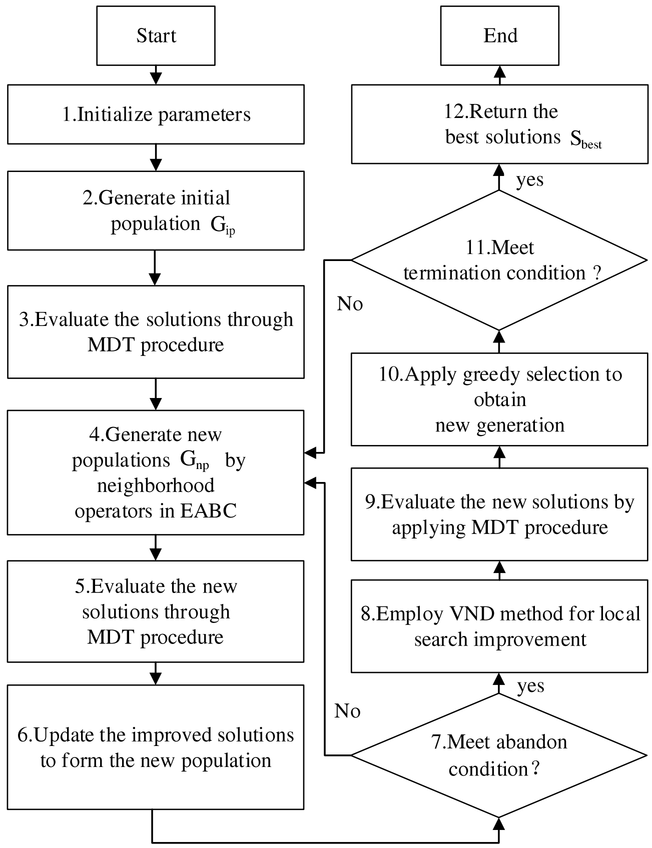

Fig. 1. Flow chart of proposed HABC-MDT.

3.3. Neighborhood structures

In the proposed HABC-MDT approach, variable neighborhood descent (VND) algorithm is used as the local search process for seeking better solutions based on the sub-tours obtained by the HABC algorithm. Five neighborhood structures proposed in [49] are applied to perform local search, namely *Crossover*, *Swap (1, 1)*, *Shift (1, 0)*, *2-Opt* and *Exchange*. The first three neighborhood structure are implemented as inter-route structure while the other two are applied as intra-route procedure within one sub-tour. These structures are used according to the sequence presented in [49].

3.4. Midway disposal trip selection heuristic

Given the route (denoted by R) of vehicle k, the MDT selection heuristic is used to decide when to dump the wastes and selects the optimal disposal facilities df dynamically in evaluation process. The inputs of this procedure contain the number of disposal facilities (denoted by D), the number (denoted by C_k) of collection points in route R, the matrix (denoted by MD) of distances between any two nodes, the sequence of collection points in the route R and other data required. In the collection process, when vehicle k decides to dump wastes after a collection point cp_1, it needs to select an optimal disposal facility, and then collects wastes in next collection point cp_2. We define the optimal disposal facility as the disposal facility with the minimal total distance from it to the two adjacent collection points cp_1 and cp_2.

The pseudo-code of this procedure is shown in Fig. 2. First, all the parameters needed in this procedure are initialized in line 2. Then, the for-end-loop in lines 3–10 is used to calculate the carbon emission costs (CEC), generated by selecting the best disposal facility after each collection point, based on Eq. (1). The collection

Pseudo-codes of MDT selection heuristic	**line**
Begin	1
Parameter Initialization: MD, C_k, D	2
For $t = 1, \ldots, C_k$ do	3
$cdf := \text{Select\_min}(cp_t, cp_{t+1})$	4
$EC_1^t := \text{Cal\_cost}(R_{0\to 1}, R_{1\to t}, R_{t\to cdf})$	5
$sdf := \text{Select\_min}(C_k, 0)$	6
$EC_2^t := \text{Cal\_cost}(R_{cdf\to t+1}, R_{t+1\to C_k}, R_{C_k\to sdf})$	7
$EC_3^t := \text{Cal\_cost}(R_{sdf\to 0})$	8
$EC_{MDP}^t := EC_1^t + EC_2^t + EC_3^t$	9
End for	10
$EC_{MDP} := \min_t EC_{MDP}^t$	11
End	12

Fig. 2. Pseudo-code of MDT selection heuristics.

point in R is indexed by t. For collection point t, lines 4–9 calculate the resulting total CEC EC_{MDP} if the waste collected is dumped immediately after this point. In line 4, we select out the disposal facility, with the minimal total distance to collection points cp_t and cp_{t+1}, as the current disposal facility cdf. We use $R_{i\to j}$ to denote a sub-route from point i to point j. The route of each vehicle from the depot to the disposal facility cdf can be divided into three sub-routes: the depot 0 to point 1 ($R_{0\to 1}$), point 1 to point t ($R_{1\to t}$), and point t to the current disposal facility ($R_{t\to cdf}$). The resulting total CEC generated between the depot and cdf, denoted by EC_1^t, is calculated in line 5 by summing up the CECs in the three sub-routes. Next, the vehicle dumps all collected wastes in the current disposal facility and then visits the remaining collection points in $R_{t+1\to C_k}$ to collect wastes. In line 6, the same method used in line 4 is reused to find a selected disposal facility (sdf) which has a total minimal distance to the last collection point C_k and the depot. Then the CEC EC_2^t, generated between cdf and sdf, is calculated in line 7. EC_2^t is 0 if no sdf is selected. Line 8 calculates the CEC EC_3^t generated between sdf and the depot. The total CEC EC_{MDP}^t for collection point t is calculated in line 9. The best CEC EC_{MDP} of MDP for route R is set to the minimal EC_{MDP}^t in line 11. That is, $EC_{MDP} = \min_t EC_{MDP}^t$. By so doing, for each collection route, we select the disposal facilities for which the minimal total CEC is generated in the tour. If t equals C_k, the vehicle visits all collection points in $R_{1\to C_k}$ and dumps wastes only once and then returns to depot. This pattern is a typical FDP, and its resulting CEC (EC_{FDP}) is the summation of EC_1^t and EC_3^t.

4. Computational experiments and discussions

4.1. Experimental data and setting

To validate the effectiveness of the presented hybrid approach for the WCP-MDP, we have conducted a series of experiments for various WCP-MDP instances based on publicly available CVRP benchmark data sets (http://neo.lcc.uma.es/vrp/vrp-instances/capacitated-vrp-instances/). The problem instances consider different nodes and vehicles, ranging from 33 to 51 and 5 to 7 respectively. For each problem instance, a group of nodes is selected randomly to represent the disposal facilities. The number of disposal facilities is assumed to equal to the number of vehicles for a specific instance. The capacity of vehicles, the demand of each node and the coordinate of these nodes are given in each dataset.

As for the parameters setting, the size BS of the bee colony, the predetermined number ($limit$) of abandoning a specific solution

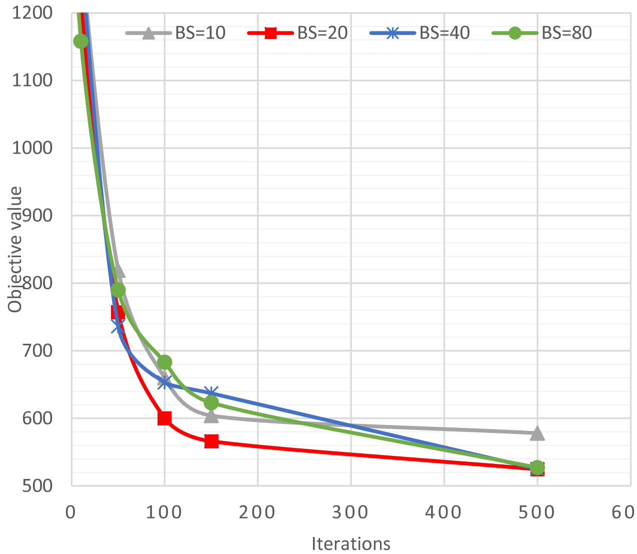

Fig. 3. Comparison of objective value changes at different values of *BS*.

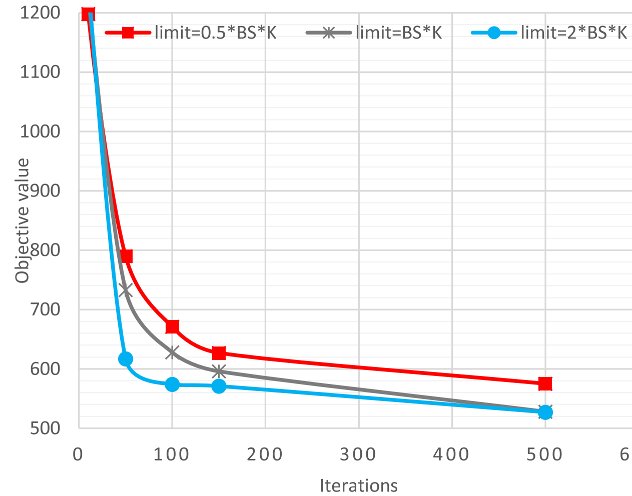

Fig. 4. Comparison of objective value changes at different values of *limit*.

and the probability Φ of implementing VND are set as 20, $BS \times K$ and 0.3, respectively. Here K denotes the number of vehicles. The detailed analyses for these parameters are presented in the Section 4.2. To make the penalty coefficient ψ in the evaluation function increase with the number of iterations, it is defined as the product of the current number of iterations and a positive coefficient (e.g., 0.1) [26]. The experiments were carried out on a laptop with Intel Core i7-6500U CPU @2.5 GHz and 4 GB RAM and using MATLAB version R2013b.

4.2. Parameter analysis

As mentioned in Section 4.1, two parameters are required to be tuned in the ABC algorithm for achieving better performance, *BS* and *limit*. In principle, a larger *BS* generally results in more parallel searches and a diversified exploration. However, the computational time increases with *BS*, especially when the number of iterations and *limit* are both large. Thus, setting appropriate values for *BS* and *limit* is critical to the optimum-seeking process. We conducted a series of experiments to observe and compare the effects of different values of *BS* and *limit* on the values of objective to be optimized (i.e., the total travel distance in CVRP).

Take CVRP instance 'E-n51-k5' as an example, the best known objective value is 524.61. Figs. 3 and 4 show the comparison results of objective value changes with iterations at different values of *BS* and *limit* respectively. As shown in Fig. 3, the setting of bee colony size $BS = 10$ leads to the objective value of 578.23, which is not close to the best solutions. On the other hand, setting $BS = 20$ is sufficient to acquire the best known solution, which also consumes the less computational time than setting $BS = 40$ or 80.

We then test the performance of HABC algorithm with different values of *limit* at $BS = 20$. To set the value of *limit*, there is a tradeoff between the optimization efficiency and the computational time. It can be found from Fig. 4 that the larger *limit* leads to the faster convergence speed. However, the computational time for getting the best solution increases with the value of *limit*. The value of *limit* is thus set to the product of *BS* and the number of vehicles, which is consistent with Zhang's [26] finding.

Furthermore, we investigate the effects of probability of VND Φ and size of bee colony *BS* on solution quality and computational time of HABC. Two different bee colony sizes are considered ($BS = 20, 40$) since $BS = 10$ could lead to a much inferior optimization performance and $BS = 80$ is too time-consuming. Three different values of Φ are considered, which are 0.1, 0.3 and 0.6. To determine their best combination, a series of experiments are conducted to compare the optimization performances for each combination of *BS* and Φ. Table 1 reports the average objective value (AOV) of solutions, the average computational time (ACT) and the average deviation from the best known solution (DFB) to instance 'E-51n-k5' for each combination. It can be found from Table 1, increasing *BS* from 20 to 40 improves the solution quality slightly while leading to dramatically increases in computational time, i.e., almost two times larger than those obtained at $BS = 20$. In addition, at $\Phi = 0.3$, the average solution obtained by the HABC is slightly better than those at $\Phi = 0.1$or 0.6 regardless of *BS*. Therefore, to balance the computational time and the optimum-seeking performance, and to obtain a competitive algorithm with other algorithm, we adopted the combination of $BS = 20$ and $\Phi = 0.3$ for the HABC algorithm used.

4.3. Experimental results & comparison

4.3.1. Performance comparison

To highlight the effectiveness of the proposed HABC-MDT approach, this research compared the optimum-seeking performances of the proposed approach with four different hybrid approaches in terms of various WCP-MDP instances. Similar to the proposed approach, the four approaches hybridize different optimization techniques with the MDT selection heuristics, which are GA-based MDT (GA-MDT) approach, PSO-based MDT (PSO-MDT) approach, EABC-based MDT (EABC-MDT) approach and HPSO-based MDT (HPSO-MDT), respectively. The optimization techniques are used to generate the better waste collection routes while the MDT selection heuristic is applied to select the disposal trip based on the obtained collection routes. The only difference of these approaches is that different optimization techniques are used. The four optimization techniques are (1) GA [57], (2) PSO [49], (3) Enhanced ABC [55], and (4) hybrid PSO with VND (HPSO) [49], respectively. GA and PSO are selected because they are two of the most commonly used meta-heuristics for complex combinational optimization problems. EABC and HSPO are selected because they are representative techniques for capacitated VRPs. Of course, many other meta-heuristics or hybrid algorithms can also be used for comparison, but comparing more approaches are not the focus of this paper.

The parameters of GA, PSO are provided in Table 2, while the parameter setting of EABC is the same as the proposed HABC. To

Table 1
Optimization performance comparison at different *BS* and Φ.

Probability of VND	Size of bee colony (*BS*)					
	20			40		
Φ	AOV	ACT (min)	DFB (%)	AOV	ACT (min)	DFB (%)
0.1	527.93	5.05	0.63	526.79	12.37	0.42
0.3	**525.83**	**11.07**	**0.23**	**525.63**	**26.65**	**0.19**
0.6	527.26	22.07	0.51	526.05	39.65	0.27

Table 2
Parameters used in GA and PSO.

Approaches	Parameters	Settings
GA	Crossover rate	0.75
	Mutation rate	0.1
	Population size	20
PSO	Swarm size	20
	First inertia weight	0.9
	Last inertia weight	0.4
	Personal best position acceleration constant	0.5
	Global best position acceleration constant	0.5

ensure a fair comparison, the five optimization approaches use the same termination condition, which is controlled only by the same computation time $T_{\max}$. The value of $T_{\max}$ is the average computation time of executing repetitively the HABC-MDT approach for each instance 30 times. To reduce the contingency of iterative processes in the five optimization approaches, the five approaches are run repetitively 30 times to obtain the statistical results of objective values for each instance.

Table 3 shows the comparison results generated by the five approaches. Due to the page limit, we only present the results of 10 representative problem instances since other instances showed similar results. The best solutions of HABC-MDT for each instance are shown in the column 'Sol.'. The columns of 'Min', 'Mean' and 'Max' denote the minimum, average and maximum deviation of the objective value of solutions obtained by other approaches from the value of HABC-MDT best solutions for each instance, respectively. According to these results, the HABC-MDT obtained the better solutions than the other four approaches in all instances in terms of minimum, average and maximum results in 30 runs. We have used t-test to examine the performance difference between the proposed method and other four methods for the 10 problem instances. Table 4 shows the results of statistical test at significance level of 5%. The proposed HABC-MDT generates the significantly better results than other four approaches do for almost all instances. The only two exceptions occur for problem instances 'A-n44-k6' and 'A-n48-k7' when we compare the HABC-MDT with the HPSO-MDT. We further use a boxplot to present the statistical distribution of the results generated by the five approaches. Fig. 5 presents the cumulative results over all problem instances. To make the cumulative results comparable, we use the min–max normalization method to transform the objective values of all problem instances into the range of [0, 1] since different problem instances have different best objective values. In Fig. 5, the boxplots represent the quartiles for normalized carbon emission costs generated by five approaches respectively, which indicates that the HABC-MDT obtains the lower minimum, median and maximum than other approaches do. Fig. 6 shows the evolutionary trajectories of the minimum of the objective values over iterations in the optimization processes of five approaches. It indicates that the HABC-MDT gets converged more quickly than other approaches do since the HABC-MDT can obtain the lower carbon emissions in each iteration. In summary, HABC-MDT outperforms the other four approaches for handling the investigated WCP-MDP instances.

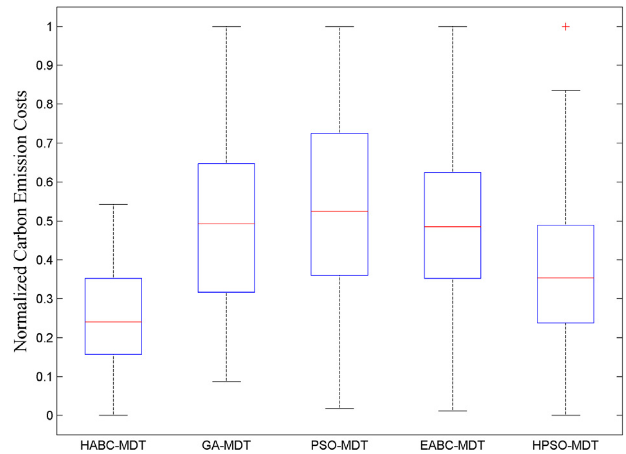

Fig. 5. Boxplot results of different algorithms.

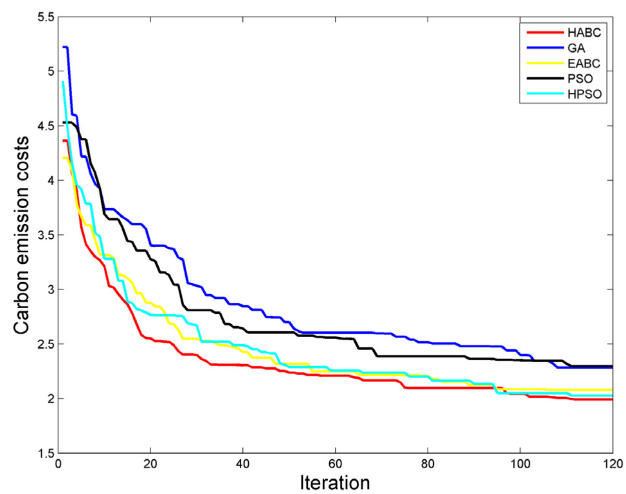

Fig. 6. Changes of minimal objective values over iterations.

4.3.2. Optimum-seeking performance of hybrid artificial bee colony algorithm

To evaluate the optimum-seeking performance of the proposed HABC algorithm, this research compared the optimization results of this algorithm and the best known solutions based on a series of CVRP benchmark instances. The proposed HABC algorithm found the best known solutions to the 10 CVRP instances in Table 3 and 'set B' instances with less than 51 nodes (i.e., problem instances from 'B-n31-k5' to 'B-n50-k7' in webpage: http://neo.lcc.uma.es/vrp/vrp-instances/capacitated-vrp-instances/). Note that 50 collection nodes is usually big enough in real-world waste collection problems. According to these results, the HABC approach has a good capability of seeking the global optima for the investigated CVRP instances. As mentioned in Section 1, the WCP-MDP is actually a CVRP with the consideration of MDP. Therefore, the proposed hybrid approach can solve the investigated problem effectively by providing optimal solutions to this problem since it combines the HABC with the MDT selection heuristics.

4.4. Carbon emission reductions generated by midway disposal pattern

To evaluate the effects of MDP on carbon emission reductions, a series of experiments have been conducted on the same 10 WCP-MDP instances to compare the carbon emission differences

Table 3
Comparison of different algorithms for solving WCP-MDP.

Instance	HABC-MDT		GA-MDT			PSO-MDT			EABC-MDT			HPSO-MDT		
	Sol. ($)	Tmax (s)	Min (%)	Mean (%)	Max (%)	Min (%)	Mean (%)	Max (%)	Min (%)	Mean (%)	Max (%)	Min (%)	Mean (%)	Max (%)
A-n33-k5	**1.92**	**288.0**	5.64	8.83	13.69	4.42	9.14	15.27	4.18	7.74	11.05	4.25	6.94	9.50
A-n34-k5	**2.25**	**286.4**	1.41	5.87	11.23	1.41	6.59	11.40	1.81	7.80	12.67	2.27	8.25	16.18
A-n36-k5	**2.27**	**305.3**	9.69	15.22	18.57	9.96	16.44	22.61	12.73	17.66	22.61	1.50	13.20	18.88
A-n37-k5	**2.13**	**304.1**	2.23	9.03	20.79	0.35	7.12	15.13	2.02	5.44	10.82	0.00	5.18	8.15
A-n38-k5	**2.22**	**385.7**	2.28	10.47	18.81	4.97	11.52	21.75	0.30	15.48	25.57	4.97	9.98	15.23
A-n39-k5	**2.52**	**448.9**	3.52	7.64	13.73	4.46	18.88	36.59	3.45	11.95	19.88	0.73	8.78	20.05
A-n44-k6	**3.05**	**424.0**	4.03	8.92	19.05	3.77	10.70	19.38	4.42	9.78	14.13	2.90	6.34	14.03
A-n45-k6	**3.38**	**351.8**	8.44	15.71	21.64	8.44	20.50	34.11	9.62	19.24	31.36	0.00	13.47	20.33
A-n48-k7	**3.27**	**354.8**	17.08	21.09	26.72	11.87	23.07	36.08	10.37	16.61	20.94	6.54	12.83	23.25
E-n51-k5	**1.96**	**402.8**	16.93	23.51	30.34	7.60	18.03	32.53	7.30	14.99	24.00	1.51	7.88	12.31

Table 4
Statistical test results for performance comparisons between the HABC-MDT and other approaches.

Instances	Results of t-test with HABC-MDT							
	GA-MDT		PSO-MDT		EABC-MDT		HPSO-MDT	
	H	p-value	H	p-value	H	p-value	H	p-value
A-n33-K5	1	0.00	1	0.00	1	0.00	1	0.00
A-n34-k5	1	0.00	1	0.00	1	0.00	1	0.00
A-n36-k5	1	0.00	1	0.00	1	0.00	1	0.00
A-n37-k5	1	0.00	1	0.00	1	0.00	1	0.00
A-n38-k5	1	0.00	1	0.00	1	0.00	1	0.00
A-n39-k5	1	0.04	1	0.00	1	0.00	1	0.01
A-n44-k6	1	0.00	1	0.00	1	0.00	0	0.92
A-n45-k6	1	0.00	1	0.00	1	0.00	1	0.00
A-n48-k7	1	0.00	1	0.00	1	0.00	0	0.70
E-n51-k5	1	0.00	1	0.00	1	0.00	1	0.00

H: Indicates whether the proposed algorithm is significantly better. 1-significant, 0-not significant
p-value: The p-value of t-test.

Table 5
Carbon emission reductions by the midway disposal pattern in 30 repetitive runs.

Instances	Carbon emission saving (%)		
	Minimum	Mean	Maximum
A-n33-K5	1.14	2.09	3.99
A-n34-k5	1.88	2.96	5.27
A-n36-k5	2.60	3.54	4.94
A-n37-k5	2.85	3.84	5.68
A-n38-k5	3.20	4.21	6.43
A-n39-k5	3.49	4.70	6.77
A-n44-k6	3.30	4.26	5.76
A-n45-k6	3.11	4.05	5.62
A-n48-k7	3.88	4.85	6.45
E-n51-k5	4.34	5.54	7.16

between MDP and FDP. For each problem instance, thirty waste collection scenarios are generated by the normal distribution with specific mean value and standard deviation, each of which has different waste amounts in collection points. It is reasonable for simulating the real-world waste collection because the waste amounts in the same collection point could be different each day. On the other hand, for a single scenario, there are some special conditions which may contribute to the better results of carbon emissions reduction led by MDP. For example, some collection points with many wastes are exactly near to the optimal disposal facility. However, these special conditions cannot demonstrate the effectiveness of general MDP. To eliminate the contingency of these conditions on the carbon emissions reduction led by MDP, experiments are conducted based on the thirty different waste collection scenarios.

Table 5 shows the results based on these experimental settings. Columns of 'Minimum', 'Mean' and 'Maximum' present respectively the minimum, mean and maximum of carbon emission reduction percentages, generated by two different disposal patterns in 30 repetitive runs. It can be found from this table that the MDP generates the less carbon emission and the reduction percentages are between 1.14% and 7.16% for different instances. On the whole, the reduction percentage increases with the increase of the number of collection points. The reason is, we think, that more carbon emissions are generated in the collection routes if more wastes are collected.

4.5. Timing of employing VND

This research hybridizes a global search process (ABC algorithm) with a local search process (VND method) to seek the best solutions in the solution space, which results in the increase of computation time in the optimization process. A feasible way to reduce the computation time is to reduce the times of running the local search process by selecting an appropriate timing for activating this process during the optimum-seeking process. That is, it is crucial to determine the beginning iteration of employing VND in the EABC. To obtain the best beginning iteration of VND, three instances are randomly selected from 10 WCP-MDP instances to evaluate the differences of carbon emission cost at different timings of employing VND. The beginning iterations of employing VND are set to 1, 30, 60, 90 and 120, respectively while the terminal iteration is set as 120. Table 6 compares the resulting objective values and the average computation time (ACT) in these different settings. It can be found that the relative differences in carbon emission cost (RDC) are rather small. Take the beginning iterations '30' and '60' as example. For three different instances shown in the first column, the RDCs between beginning iteration '1' and '30' are '−1.44%', '1.20%' and '1.77%' respectively; while the RDCs between beginning iteration '1' and '60' are '−0.48%', '−0.3%' and '0.44%' respectively. However, the relative differences in average computation time (RDT) are distinctly large for all instances. In addition, with the increase of the beginning iteration of using VND, the ACT can get an up to 61.01% reduction. It is interesting that, at VND = 90, the large reduction in ACT does only slightly decrease of the optimization performance by 0.30% to 1.77%. The reason is, we think, that this strategy has little influence on the optimum-seeking performance because of the strong robustness of the proposed HABC-MDT. Please note that when the beginning iteration of VND is set to 120, the HABC procedure is actually conducted without VND procedure since the terminal iteration is also set as 120. Comparing to the setting of other beginning iterations (i.e., 1, 30, 60, 90), the setting of the beginning iteration = 120 leads to the larger increase of RDC, although it also results in the larger RDT. It is because the VND procedure contributes to intensify the exploitation of optimal solution and also consume some

Table 6
Beginning iteration of employing VND.

Instance	Beginning iteration of VND									
	1		30		60		90		120	
	CE cost ($)	ACT (min)	RDC (%)	RDT (%)	RDC (%)	RDT (%)	RDC (%)	RDT (%)	RDC (%)	RDT (%)
A-n33-k5	2.09	6.22	**−1.44**	−4.02	**−0.48**	−5.63	**0.96**	−30.87	**9.09**	−62.66
A-n44-k6	3.32	14.49	**1.20**	−15.11	**−0.30**	−33.47	**0.30**	−44.93	**9.04**	−78.81
E-n51-k5	2.26	13.00	**1.77**	−19.00	**0.44**	−28.62	**1.77**	−61.01	**14.16**	−83.88

computational time. In summary, VND is a valuable component in the proposed approach since it is helpful to largely improve the optimization results.

5. Conclusions

This paper addressed a WCP with the consideration of midway disposal pattern. To the best of the authors' knowledge, this paper is the first to consider the effects of the midway disposal pattern in WCP, which is helpful to select a better disposal mode and reduce carbon emissions in real-world waste collection. An enhanced artificial bee colony (EABC)-based hybrid approach, which hybridized an ABC algorithm, a VND method and a MDT selection heuristic, was developed to handle the WCP-MDP. To evaluate the effectiveness of the proposed hybrid approach, we have carried out a series of experiments from three perspectives. The first one was to compare the performance of HABC-MDT with other four approaches in solving the WCP-MDP. The computational results show that the proposed approach is superior to the other four approaches (GA-MDT, PSO-MDT, EABC-MDT and HPSO-MDT) in terms of the carbon emission cost saving for all WCP-MDP instances used. The second was to demonstrate the optimum-seeking performance of HABC based on 10 CVRP instances, the results showed that the proposed HABC had good capacity in handling the WCP-MDP, which can also be used as an effective alternative to handle VRPs. The third one was to compare the carbon emission difference generated by the midway disposal pattern (MDP) and by the fully-loaded disposal pattern (FDP) in waste collection. The experimental results over 10 WCP-MDP instances showed that the MDP reduced the carbon emission by up to 7.16%, comparing with that generated by the FDP.

Future research will use the proposed hybrid ABC algorithm to handle the larger-scale waste collection problems or other similar combinatorial optimization problems. The performance of proposed HABC will be further compared with many other popular hybrid approaches. To develop more efficient algorithms is also a promising direction based on recently developed metaheuristics such as thermal exchange optimization. Another promising direction is to address the disposal facility location decision and the effects of more midway disposals in one single tour on the performances of waste collection solutions.

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Appendix A. Notations

i	node in graph, $i \in N$
k	vehicle, $k \in K$
q_i	waste collection demand of collection point i
K	the set of homogeneous vehicles
d_{ijk}	travel distance of vehicle k from node i to node j
w_{ijk}	total load (include curb weight M) of vehicle k from node i to node j
L_i	the accumulated load of vehicle in collection point i
Q	maximum load capacity of vehicle
EC_{ij}	the carbon emission cost of traveling on arc(i, j)
S_{ij}	carbon emission incurred on arc(i, j)
α	the cost of unit carbon emission
x_{ijk}	$= 1$ if vehicle k collects wastes from nodes i and j, otherwise it is 0
y_{ik}	$= 1$ if node i is collected by vehicle k, otherwise it is 0.

Appendix B. Measurement of carbon emissions

The fuel consumption δ_{ij} (liters) is defined by the comprehensive emissions model developed by Franceschetti. It is formulated as follow:

$$\delta_{ij} = \frac{\xi}{\kappa\psi}\left(\mathrm{kN_eV}\frac{l}{v} + \frac{0.5C_d\varphi Alv^2 + (g\sin\phi + gC_r\cos\phi)wl}{1000\varepsilon\varpi}\right) \quad (16)$$

where ξ is fuel-to-air mass ratio, κ is the heating value of a typical diesel fuel (kJ/g), ψ is a conversion factor from grams to liters from (g/s) to (liter/s), k is the engine friction factor (kJ/rev/liter), N_e is the engine speed (rev/s), V is the engine displacement (liter), φ is the air density (kg/m^3), A is the frontal surface area (m^2), v is the speed of a vehicle (m/s). g is the gravitational constant (equal to 9.81 m/s^2), ϕ is the road angle, C_d and C_r are the coefficient of aerodynamic drag and rolling resistance, ε is vehicle drive train efficiency and ϖ is an efficiency parameter for diesel engines.

This research considers δ_{ij} as a function of variables l and w. We can thus set two parameters to simplify the model as follows:

$$\rho_1 = \frac{\theta\xi}{\kappa\psi}\cdot\left(\frac{kN_eV}{v} + \frac{0.5C_d\varphi Av^2}{1000\varepsilon\varpi}\right) \quad (17)$$

$$\rho_2 = \theta\xi\cdot\frac{(g\sin\phi + gC_r\cos\phi)}{1000\kappa\psi\varepsilon\varpi} \quad (18)$$

We then have,

$$S_{ij} = \rho_1 l + \rho_2 lw \quad (19)$$

where S_{ij} is the total amount of carbon emission for diesel engines (kg), l is the travel distance (m), and w is the total weight of vehicle (kg) which contains the curb weight and the vehicle load. The carbon emission of vehicle k for collecting wastes on arc (i, j) is formulated as follows.

$$S_{ijk} = \rho_1 l_{ijk} + \rho_2 l_{ijk} w_{ijk} \quad (20)$$

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